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COMMUNICATIONS

President's Message

Robert Mercer

Society Conference

I want to wish everyone a Happy New Year (Decade, Century, and Millennium). To start the new millennium the society has made an important change: we are sponsoring an annual rather than biennial conference. Our next conference will be held 7-9 June 2001 in Ottawa. The program chairs are Stan Matwin and Eleni Stroulia. It will, as in the recent past, be held in conjunction with our sister societies as AI/GI/VI 2001. The conference will be held following the 11th Annual PRECARN-IRIS Conference which is in Ottawa 4-5 June 2001.

Annual General Meeting

One feature of having an annual conference is that our Annual General Meeting can be held annually in a location where we can expect many of our members to be. These meetings provide a forum to discuss society issues. The time and location will be announced before the conference. I hope to see you at the conference and the AGM.

Conférence de la Société

Je veux souhaiter à chacun une bonne et heureuse année (décennie, siècle, et millénium). Pour innaugurer le nouveau millénium la société a fait un changement important: nous commanditons une conférence annuelle plutôt que bisannuelle. Notre prochaine conférence sera tenue 7-9 juin 2001 à Ottawa. Les directeurs du programme sont Stan Matwin et Eleni Stroulia. Comme dans le passé, elle sera tenu en même temps que nos sociétés soeurs, en tant que AI/GI/VI 2001. La conférence sera tenue après la 11ème conférence annuelle de PRECARN-IRIS qui se déroule à Ottawa le 4-5 juin 2001.

Assamblée Générale Annuelle

Un des aspects positifs de l'adoption d'une assemblée annuelle est que notre assemblée générale peut être tenue annuellement dans un endroit qui rassemble la majorite'e de nos membres. Ces réunions fournissent un forum pour discuter de the`mes propre a` la société. Les jours et l'emplacement seront annoncés avant la conférence. J'espère vous voir à la conférence et à l'AGM.

Collaborative Filtering: Dealing with Information Overload by Recommending Quality Items

Sonny Han Seng Chee

Résumé

Le monde géré en réseau a transformé l'expression la surcharge de l'information en cliché. Les techniques automatisées telles que l'information filtrant (SI), bien qu'utile, ne peuvent pas filtrer les éléments non pertinents parce qu'elles ne capturent pas des jugements subjectifs de qualité ou de préférence. Le filtrage de colaboration (FC) est une technique prometteuse, complimentaire au SI, cherchant a` automatiser le processus de collaboration entre humains, dans la recommandation d'élément de haute qualité. Dans nos vies quotidiennes, nous sommes tous au courant de l'efficacité d'une recommandation d'un amis de confiance, pour un bon restaurant ou un film drôle, en nous dirigeant vers les marchandises et les services qui apparient notre goût particulier. De nombreux dévelopements ont été réalisées depuis la publication de la première automatisation de systèmes de FC, néanmoins, de nombreux défis existent. Dans cette brève étude, nous revisons quelques résultats de filtrage de collaboration importants.

Abstract

The networked world has transformed the phrase "information overload" into a cliché. Automated techniques such as information filtering (IF), though useful, cannot filter irrelevant items because they fail to capture subjective judgments of quality or preference. Collaborative filtering (CF) is a promising complimentary technique to IF that seeks to automate the collaborative process that humans engage to recommend high quality items to each other. In our daily lives, we are all familiar with the effectiveness of a trusted friend's recommendation for a 'good' restaurant or a 'funny' movie in directing us towards goods and services that match our particular tastes.

Numerous advances have been achieved since the publication of the first automated CF systems and yet numerous challenges exist. In this brief survey, we review some important collaborative filtering results.

1 Introduction

In our daily life, virtually all of us have asked a trusted friend to recommend a movie or a restaurant. The underlying assumption is that our friend shares our taste and if she recommends an item then we are likely to enjoy it. If a friend consistently provides good recommendations then she becomes more trusted, if she provides poor recommendations then she becomes less trusted and eventually ceases to be an advisor. Collaborative filtering (CF) describes a variety of processes that automate the interactions of human advisors; a collaborative filter recommends items based upon the opinions of a clique of human advisors. Amazon[1] and CDNow[2] are two well known e-commerce sites that use collaborative filtering to provide recommendations on books, music and movie titles; this service is provided as a means to promote customer retention, loyalty and sales [14].

Example 1: A ratings database records a patron's reaction after viewing a video. Users collaborate to predict movie preference by computing the average rating for a movie from among their friends. A subset of the database is shown below where Sam and Baz have indicated a common set of friends. The average rating of *Matrix* is 3 while *Titanic* is 14/4. Therefore, *Titanic* would be recommended over *Matrix* to Sam and Baz.

		Titles				
		Speed (A)	Amour (R)	MI-2 (A)	Matrix (A)	Titanic (R)
Users	Sam	3	4	3		
	Bea	3	4	3	1	1
	Dan	3	4	3	3	4
	Mat	4	2	3	4	3
	Gar	4	3	4	4	4
	Baz	5	1	5		

Table 1: Higher scores Table1: Higher scores indicate a higher level of enjoyment in this ratings database.

1. http://www.amazon.com
2. http://www.cdnow.com

This simplistic approach falls well short of automating the human advisory circle. In particular, the group average algorithm implicitly assumes that all advisors are equally trusted and consequently, their recommendations equally weighted. An advisor's past performance is not taken into account when making recommendations. However, we know that in off-line relationships, past performance is extremely relevant when judging the reliability of recommendations. Equally problematic is that the group average algorithm will make the same recommendation to all users. Baz, who has very different viewing tastes from Sam, as evidenced by his preference for action over romantic movies (as indicated by the letter A and R following each of the titles) will nevertheless be recommended *Titanic over Matrix*. Collaborative filters aim to overcome these shortcomings to provide recommendations that are personalized to each user and that can adapt to a user's changing tastes.

Collaborative filters take a list of item endorsements or a ratings history, as input for computation. The type of computation can be used to categorize CF algorithms as memory-based or model-based algorithms [4]. Memory-based algorithms identify advisors from similarities between rating histories and then generate a recommendation on an as-yet-unseen item by aggregating the advisors' ratings. Memory-based collaborative filters differ in the manner that ratings are defined, the metric used to gauge similarity, and the weighting scheme to aggregate advisors' ratings.

In the well-known correlation-based collaborative filter [11], that we call CorrCF for brevity, a 5-point ascending rating scale is used to record user reactions after Usenet items. Pair-wise similarity, $w_{u,a}$, between the user, u, and his potential advisor, a, is computed from Pearson correlation of their rating histories:

$$w_{u,a} = \sum_{i \in Y_{u,a}} \frac{(r_{u,i} - \bar{r}_u)(r_{a,i} - \bar{r}_a)}{\sigma_u \sigma_a |Y_{u,a}|} \quad (1)$$

Here, $r_{u,i}$ and $r_{a,i}$ are the user and advisor ratings for item i, while $\bar{r}_u$ and $\bar{r}_a$ are the mean ratings of each user.

The standard deviations of each user's rating history are denoted by σ_u and σ_a. Then $Y_{u,a}$ is the set of items that both the user and his advisor have rated. A recommendation, $p_{u,j}$, is generated by taking a weighted deviation from each advisor's mean rating:

$$p_{u,j} = \bar{r}_u + \frac{1}{\alpha} \sum_{i \in Y_{u,a}} (r_{a,i} - \bar{r}_a) \cdot w_{u,a} \quad (2)$$

Here, α is a normalizing constant such that the absolute values of the correlation coefficients, $w_{u,a}$, sum to 1.

Example 2: We apply *CorrCF* to generate personalized recommendations for Sam and Baz. The tables below summarize the similarity scores between members in the ratings database subset (computed via (1)) and the predicted rating score for each movie (computed via (2)). Notice that the recommendations are in-line with our intuition – Sam is recommended *Titanic* over *Matrix* while Baz is recommended *Matrix* over *Titanic*.

Similarity Scores

		Users	
		Sam	Baz
Users	Bea	1	-1
	Dan	1	-1
	Mat	-0.87	0.87
	Gar	-1	1

Movie Predictions

		Titles	
		Matrix	Titanic
Users	Sam	2.69	2.73
	Baz	4.40	3.91

Table 2: Similarity and movie predictions computing with *CorrCF*.

The computation of the similarity coefficients can be viewed as an operation to fill in the entries of an n by n matrix where each cell stores the similarity coefficient between each user and his n-1 potential advisors. Each row of the matrix requires a minimum of one database scan to compute and to fill the entire matrix of n rows therefore requires $O(n^2)$ operations. The computation of these similarity coefficients is the performance bottleneck in all previously published memory-based algorithms.

Model-based collaborative filters infer a user model from the rating histories. Recommendations are computed quickly once the model is constructed although the time to train the model may be high. Beyond recommendations, the model itself is valuable as it may show correlations in the data that can explain the rationale for recommendations [10]. Model algorithms are often not amenable to incremental update.

2 Collaborative Filtering Systems

The term collaborative filtering originates from the Tapestry email system [5]. Tapestry allows users to manually craft filter expressions on the identities of the participants and the document annotations they have supplied. A limitation of Tapestry is that an explicit relationship has to exist between participants. John, for example, would need to know *a priori* that Sally provided annotations matching his own style and judgement. Otherwise, John would have no reason to filter on Sally's annotations.

The GroupLens Usenet news filtering system is one of the first collaborative filters [11] to remove this *relationship* requirement. Recommendations are automatically generated by aggregating the ratings of a clique of advisors, often with whom we have no prior personal relationship with. GroupLens identified advisors by the Pearson correlation of their voting histories.

In [15], the constrained Pearson correlation is introduced to account for the implicit positivity and negativity of the rating scale in the Ringo music recommendation service. They also provide an innovative solution that inverts the basic CF approach; music albums are treated as 'participants' that can recommend users to other music album participants.

In Personality Diagnosis (PD) [10], the ratings of a single best advisor are the basis for recommendations. PD infers the probability that a potential advisor has the same preferences as the user and the advisor with the highest probability is then taken as the best advisor. PD assumes that true preferences are obscured by random factors such as the user's mood and the context of other items evaluated in the same session.

2.1 Accuracy

The effectiveness of collaborative filters has traditionally been measured by its accuracy and degree of coverage. Coverage is defined as the percentage of prediction requests that a filter can fulfill. Accuracy has been measured with a number of metrics that can be classified into decision support based and statistically based metrics.

Reversal rate, F-number, and ROC sensitivity are examples of decision-support accuracy metrics. Reversal rate is the percentage of times the recommendations are very contrary to the user's actual rating. On a 5 point scale it could be defined as the percentage of predictions that deviate more than 3 points from the actual rating [13]. F-number is an information retrieval measure of accuracy that combines precision and recall, given by F = 2·precision·recall/(precision+recall) [12]. Precision is the percentage of documents that are retrieved that are relevant and recall is the percentage of all relevant documents that are retrieved. In one CF application with an ascending 5 point rating scale, items with a score exceeding 4 were classified as relevant [2]. An F-number of 1 indicates perfect accuracy; every item that the user rated as relevant was correctly classified and only items that were relevant were presented to the user. ROC sensitivity is a signal processing measure first used by [13] to measure the decision support accuracy of the MovieLens movie recommendation system. The area under the sensitivity vs. 1-specificity curve gives the ROC sensitivity [16]. Sensitivity is the probability that a randomly selected relevant item will be categorized as a relevant item by the filter. Specificity is the probability that a randomly selected irrelevant item will be categorized as an irrelevant item by the filter. A ROC sensitivity of 0.5 indicates an indiscriminate filter that is no better than random predictions. A score of 1 indicates a perfect filter.

A popular statistical accuracy metric is the mean absolute error (MAE) [11] [15], which is the average absolute difference between the filter's recommendation and the user's actual vote. The mean square error (MSE) [11] penalizes a filter for large errors. The rationale is that users' confidence in a system will be greatly diminished by predictions that are significantly different from their expectations. Correlation between recommendations and actual ratings measures the degree to which the filter's predictions track the user's actual rating behaviour [11] [15]. Goldberg et al. [6] proposes the normalized mean absolute error (NMAE), which normalizes the MAE by the rating scale. The NMAE has an intuitive explanation; it reflects the expected fractional deviation of predictions from actual ratings. The NMAE for a random filter applied to a random user, for example is 0.33 [6], which means that on average, we expect a prediction to be off by 33%. Despite the myriad of accuracy metrics [7] reports that comparisons of different algorithms tend to be consistent regardless of the metric chosen.

Recently, several techniques have been proposed to increase the accuracy of collaborative filters. Breese et al. [4] adjust the similarity coefficients to more accurately capture user proximity with case amplification and inverse user frequency (IUF). Case amplification increases the influence of strong advisors by increasing their similarity weights with a power factor. Inverse user frequency captures the notion that infrequently rated items are more discerning of a person's tastes than items that are commonly perused. If Sam and Baz, for example, have both watched the popular movie *Titanic*, it is less indicative of similarity than say if they both watched a less popular film such as *Pitch Dark*. IUF weights each rated item by $f_j=\log(n/n_j)$, where n is the total number of users and n_j is the number of users who have rated item j. IUF is analogous to the IR technique of adjusting the similarity weights by inverse term frequency. Improvements in accuracy with case amplification were mixed while IUF delivered an average improvement of 6.5%.

Herlocker et al. [9] limit the number of advisors that contribute to a prediction. They theorize that when a prediction is computed from an unrestricted set of users, the multitude of poor advisors overwhelm the effect of the good advisors on the prediction. They limit the number of advisors by thresholding the minimum similarity and taking the top m advisors. Both approaches improve the accuracy, but the first approach reduces the coverage; the number of predictions that can be computed.

2.2 Rating Sparsity

When the rating density is low, most CF systems have difficulty generating accurate recommendations [11] [7]. Rating sparsity is an open issue that has received significant research attention. Sarwar et al. [13] and [7] attempt to ameliorate this issue by using bots and agents to artificially increase the rating density. Bots assign ratings based on criteria such as the number of spelling errors, the length of the Usenet message, the existence of included messages [13] or the genre of the movie title [7]. Agents are trained, using IF techniques, to mimic the rating distribution of each user. An agent regenerates its ratings as it becomes better trained which may force large portions of the similarity matrix to be updated [7], thereby raising a potential performance bottleneck in a 'live' system. In both of these works, the relevancy of the bots' and agents' ratings to a particular user is decided by the CF system as it identifies potential advisors.

In the Fab system, rating sparsity is dealt with by computing user similarity from profiles rather than item-ratings [3]. A TF-IDF vector is built up from the documents that the user has rated and matched against other profiles using cosine distance.

In their recent paper, Goldberg et al. [6] describe Eigentaste, which for certain domains does not suffer from the sparsity problems. They note that rating sparsity is introduced during the profiling stage when users are given the freedom to select the items they rate. In contrast, the Eigentaste algorithm forces participants to rate all items in a *gauge set*. The dimensionality of the resulting dense rating matrix is reduced using principal component analysis to the first two dimensions. All of the users are then projected onto this eigen-plane and a divisive clustering algorithm is applied to partition the users into neighbourhoods. When a new user joins the system their neighbourhood is located by projecting their responses to the gauge set onto the eigen-plane. A recommendation is generated by taking neighbourhood's average rating for an item.

Eigentaste is however limited in that it requires the definition of a gauge set. In the Jester recommendation service, the gauge set consists of a set of jokes. After reading a joke, each user can immediately supply a rating. However, there are few domains where the items of interest can be consumed so quickly and evaluated. The authors suggest that short textual descriptions can serve as unbiased surrogates for movies or books. However, they do not discuss how these descriptions can be constructed.

2.3 Early Raters

A collaborative filter does not provide any benefit to a user if she is the first person in her neighbourhood to rate an item. [1] has speculated that even if the cost of rating an item were zero, most users will prefer to benefit from others ratings rather than supply ratings themselves. Without a compensation mechanism, CF systems depend upon the altruism of their members to overcome the early rater problem.

2.4 Scalability

The commercial interest in CF has motivated a large amount of research, which has focussed primarily on improving the accuracy of the predictions while making only passing reference to performance and scalability issues. The two classes of CF algorithms have comparable accuracy but differ in their space and time requirements. Memory algorithms require more space but less time to train in comparison to model-based algorithms [4]. The fastest memory-based algorithms as we discussed earlier have quadratic complexity at best [11] [15] [10]. The recently published Eigentaste algorithm has $O(j^2n)$ complexity, where n is the size of the dataset. For small values of j, the size of the gauge set, Eigentaste can be very fast. However it can be applied only in limited circumstances where every participant has the same set of common experiences.

Chee et al. [20] recently published an efficient algorithm, *RecTree* (RECcomendation Tree) which is generally applicable and scales by $O(n\log_2(n))$. *RecTree* solves the scalability problem by using a divide-and-conquer approach. The *RecTree* algorithm partitions the data into cliques of approximately similar users by recursively splitting the dataset into child clusters. Splits are chosen such that the intra-partition similarity between users is maximized while the inter-partition similarity is minimized. This yields relatively small cohesive neighbourhoods that *RecTree* uses to restrict its search for advisors and which represent the bottleneck in memory-based algorithms. *RecTree* achieves its

$O(n\log_2(n))$ scale-up by creating more partitions to accommodate larger datasets — essentially scaling by the number of partitions rather than the number of users.

Prediction accuracy deteriorates when a large number of lowly correlated users contribute to a prediction. Herlocker et al. [9] suggest that a multitude of poor advisors can dilute the influence of good advisors on computed recommendations. The high intra-partition similarity between users makes *RecTree* less susceptible to this dilution effect, yielding a higher overall accuracy.

The chain of intermediate clusters leading from the initial dataset to the final partitioning is maintained in the *RecTree* data structure, which resembles a binary tree. Within each leaf node, computing a similarity matrix between all members of that clique identifies advisors. *RecTree* then generates predictions by taking a weighted deviation from each clique's advisor ratings using (2).

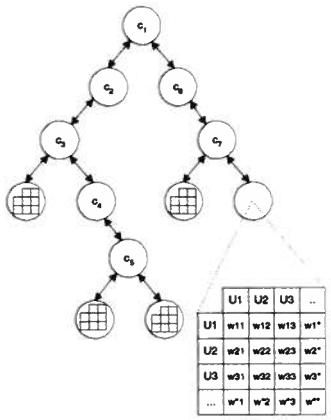

Figure. 1: The *RecTree* data structure

3 Conclusion

Collaborative filtering is a tool for dealing with the overwhelming wealth of information in the networked world. CF incorporates human subjectivity such that the recommended items match an individual's tastes and not just pre-stated preferences. Whereas information filtering may recommend a number of car magazines to a car enthusiast, CF will recommend only the car magazines that will appeal to that user. CF is a promising technology that continues to enjoy considerable commercial success and active research.

It is worth noting that many e-commerce sites provide a simplified form of collaborative filtering that is based on the complementary technologies of data warehousing and on-line analytical processing (OLAP). OLAP and data warehousing are the dual technologies that support rapid aggregation of measures across a large of number of dimensions. Often-seen examples of OLAP style collaborative filtering are the factoids that attempt to cross-sell/up-sell products: *Item X has been downloaded Z times*. These rudimentary filters make the implicit assumption that all users are equally good advisors to the user. A more sophisticated approach would be to mine patterns from the database, data warehouse [8], or multi-media database [17] and use these as the basis of a recommendation to the user.

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Institute for Computing, Information and Cognitive Systems at UBC

Sidney S. Fels and Dinesh K. Pai

Résumé

Nous décrivons l'ICICS, un nouvel institut de recherche multidisciplinaire à UBC. Nous traçons brièvement les lignes principales des sphères de recherches dont plusieurs constitues un interèt marké pour la communauté Canadienne de AI, et présente l'infrastructure pour la recherches fournie par l'ICICS.

Abstract

We describe ICICS, a new multidisciplinary research institute at UBC. We briefly outline the research foci, many of which are of interest to the Canadian AI community, an introduce the research infrastructure provided by ICICS.

1 Introduction

The Institute for Computing, Information & Cognitive Systems (ICICS) is a new institute at the University of British Columbia, funded by the Canada Foundation for Innovation, provincial, university and other sources, with a total budget of $22.1M. ICICS will include the existing Centre for Integrated Computer Systems Research (CICSR). In addition, it will include researchers in life sciences, social and behavioral sciences, in addition to engineering, mathematical and physical sciences. The existing CICSR facilities will be part of ICICS; in addition there will be new equipment infrastructure and new construction of approximately 30,000 net assignable square feet (nasf)zs and renovations to the existing space of about 5000 nasf. By the time the ICICS facility is fully functional in 2002, as a conservative estimate, we expect a group of 120 faculty members, 30 collaborators and academic visitors and over 450 graduate students to be participating as researchers in ICICS.

2 Vision

The central vision for ICICS focuses on communicating human experience in the context of our evolving global community of people and machines. As information technology becomes ubiquitous, it will also become human-centered, communicating experience as well as exchanging knowledge. ICICS will foster multi-disciplinary research in the science and technology required to encode, process, store, retrieve, represent, recognize, transmit, and synthesize experience. ICICS researchers hope to enable computers to listen to our spoken language, sense our gaze (attention), and interpret our body language. Thus we take advantage of the human ability to communicate experience and intent through a variety of channels simultaneously.

3 Research Focus

The main areas of research focus are:

Focus A: Modelling Humans and Their Environments

1. Human Motion Modeling
2. Human Tissue Modeling, Simulation & Visualization
3. 3-D Articulator Model for Speech Synthesis
4. Learning and Attentional Processes

Focus B: Creating Human Experience and Multi-modal Interfaces

1. Interactive Visualization of Complex Systems
2. Multimodal Simulation
3. Haptic Displays
4. Auditory Displays
5. Video Synthesis & Authoring Tools for Multimedia

Focus C: Multi-Agent Systems

1. Networks of Constraint-based Agents
2. Telerobotic System Agents
3. Canada-Singapore Collaboration in Intelligent Machines and Control
4. Automatic Control of Drug Delivery Systems

Focus D: Global Information Systems

1. Data Bases and Data Mining
2. The Next Generation Active Internet
3. Ubiquitous Reconfigurable Wireless Networks and Services
4. Pervasive Computing and the Smart Home
5. People's Multimedia over Internet

Focus E: New Computational Paradigms

1. Quantum Computing
2. Biomolecular Computing

4 ICICS Infrastructure

ICICS space and equipment infrastructure divides into three overlapping components for research in human communication technologies, multi-agent information systems and rapidly evolving global information systems. In terms of space, the largest component is the new human communications technology laboratories. This complex has four functions:

- conveying experience to machines;
- conveying experience to people;
- processing of experience;
- observation of people in new human-machine environments.

The specific categories are for interactive, multimedia experiments and developments, a virtual reality room, human observation and measurement lab, and a fully instrumented system demonstration lab.

For research in multi-agent technology additional space and equipment will be available. A recent development in human-machine systems is the concept of an agent, familiar to AI. Computer systems are accorded increasing autonomy: they have goals, intentions and plans. The agents may be human operators, software systems, machines and other synthetic agents. Existing space in the CICSR building will be expanded to accommodate new research in collaborative systems of networked agents. Any system of networked agents has to honour constraints, thus issues of authority, trust, negotiation, adaptability and control are central. Infrastructure for research in this expanding area primarily relies on a robust high bandwidth intra- and inter-building communication network and sets of manipulators and robots.

In addition to the communication infrastructure noted above, both space and equipment is provided for research in global information systems. Research is being pursued in several aspects of emerging Internet technology, such as data mining, people's multimedia, ubiquitous wireless networks and new languages. Space provision is made both for the core communication infrastructure and a parallel router/switching facility to permit information systems research without compromising the needs of other ICICS researchers.

This comprehensive infrastructure for research in innovative human communication technologies will provide a unique opportunity for a multi-disciplinary research effort to develop the scientific foundations of computing, information and cognitive systems.

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SCEIO

AI 2001

The Fourteenth Canadian Conference on Artificial Intelligence

June 7 - 9, 2001
Ottawa, Canada

The purpose of this conference is to provide a forum where Canadian and international researchers and practitioners in Artificial Intelligence can present their work, exchange scientific ideas and results and explore possibilities for collaboration.

Conference Format

This year, the format of the AI conference will emphasize interaction among the participants. Following each group of papers on a given topic, there will be in-depth discussion of the topic area, the work described in the presentations, and the implications for future research. We expect the AI 2001 attendees to actively participate in the discussion, so that they can explore the potential relevance of the presented work in their own research and give constructive feedback to the presenters.

Details: http://www.cs.ualberta.ca/~stroulia/AI2001/

Program Chairs:

Dr. Stan Matwin
E-mail: stan@site.uottawa.ca
URL: http://www.site.uottawa.ca/~stan/

Dr. Eleni Stroulia
E-mail: stroulia@cs.ualberta.ca
URL: http://www.cs.ualberta.ca/

ISI 2001

International Congress on Information Science Innovations

March 17-21, 2001

to be held at the American University in

Dubai, U.A.E.

http://www.icsc.ab.ca/isi2001.htm

32nd International Symposium on Robotics

ISR 2001

April 19-21, 2001

Seoul, Korea

http://isr2001.kist.re.kr/Teams/isr2001/

The Fourteenth International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems

(IEA/AIE-2001)

June 4-7, 2001 Budapest, Hungary

details available at

http://www.sztaki.hu/conferences/ieaaie2001/

or from

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Sponsored by the International Society of Applied Intelligence and cooperated with major international organizations, including ACM/SIGART, AAAI, INNS, IEE, CSCSI, JSAI, SWT, ERCIM, and SZTAKI.

International ICSC Congress on

COMPUTATIONAL INTELLIGENCE: METHODS & APPLICATIONS

CIMA 2001

June 19-22 2001

Bangor, Wales, U.K.

http://www.icsc.ab.ca/cima2001.htm

IJCAI 2001

17th International Joint Conference on Artificial Intelligence

August 4 - 10, 2001

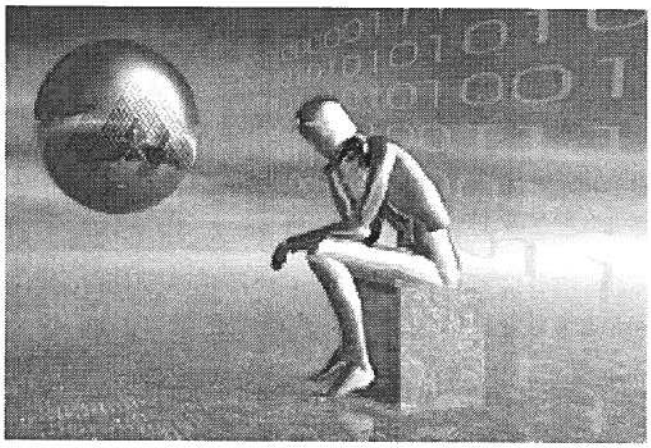
Seattle, Washington, USA

Washington State
Convention & Trade Center

Sponsored by the International Joint Conferences on Artificial Intelligence
Co-sponsored by the American Association
for Artificial Intelligence

Information: http://www.ijcai-01.org

The Eleventh Annual PRECARN • IRIS Conference



June 4-5, 2001

Ottawa Congress Centre

For up-to-date conference details, visit the PRECARN/IRIS Website:

www.precarn.ca/events/11thConference

Sponsored by PRECARN Associates Inc. and the Institute for Robotics and Intelligent Systems (IRIS)

VI 2001

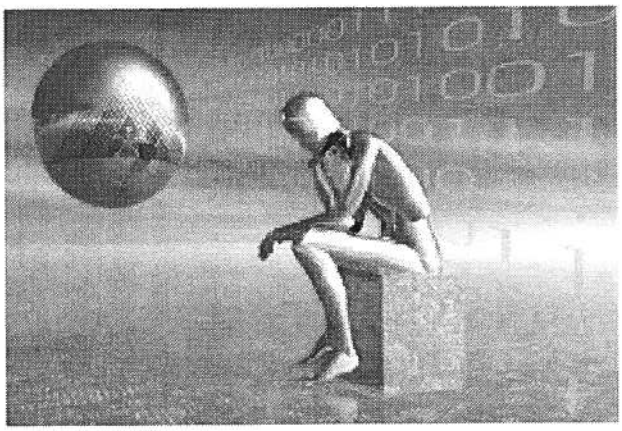
Vision Interface Annual Conference

http://www2.vit.iit.nrc.ca/~vi2001/

June 7-9, 2001

Ottawa, Canada

11th Annual Canadian Conference On Intelligent Systems



The Eleventh Annual PRECARN • IRIS Conference

June 4-5, 2001

Ottawa Congress Centre

www.precarn.ca/events/11thConference

What the Conference is About

The 11th Annual Canadian Conference on Intelligent Systems is Canada's leading forum for the exchange of ideas and information in 'intelligent systems' technologies. The Conference brings together world experts in intelligent systems from industry, research organizations and universities to discuss the results of their research, the latest technological developments and applications of these technologies.

Intelligent systems are able to sense their environment, interpret and draw logical conclusions, and then act accordingly. Applications of intelligent systems span the Canadian economy, ranging from the Natural Resources Sector (mining, forestry and energy), to the Manufacturing Sector, and the Service Sector (education, financial services and entertainment).

The timing of the 11th Annual Canadian Conference on Intelligent Systems has been coordinated to run sequentially with the 2001 Conferences of AI (Artificial Intelligence), GI (Graphics Interface), and VI (Vision Interface) which are being held in Ottawa, June 7-9, 2001.

Why You Should Attend

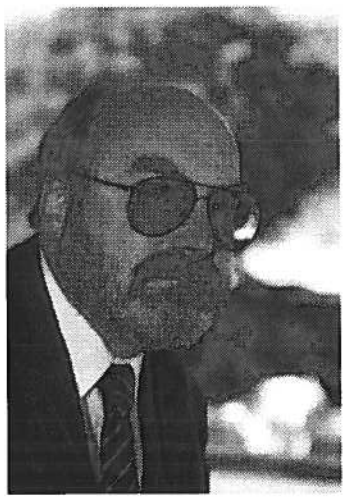
At the conference you will have an opportunity to meet researchers, graduate students and senior managers in the fields of artificial intelligence, expert systems, knowledge-based systems, telerobotics and automation. On display will be demonstrations of leading-edge technologies and their applications, many of which address specific industry problems and concerns.

There will be a **Career Fair** providing industry and students with the opportunity to meet. The **Exhibit Hall** will feature the latest technologies from Canada's IT companies. **Technical sessions** will run sequentially to give participants the chance to attend all events.

Who Should Attend

- industry research managers, and researchers
- industry business development people
- university professors, post-doctoral fellows, research associates and students
- federal and provincial government researchers and research managers

Conference Opening and Keynote Address



David Snowden
European Director,
Institute of Knowledge Management

"Knowledge, Complexity and Learning"

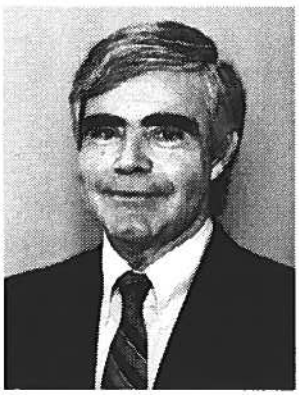
Monday, June 4, 2001,
9:15 am - 10:00 am

State-of-the-Art Sessions: PRECARN and IRIS Projects

Come and learn the latest advances in intelligent systems, presented by researchers and project leaders from both the IRIS and PRECARN networks. These presen-

tations are geared to be informative, yet succinct, giving an overview of the spectrum of both theoretical and applied, intelligent systems research within our networks. Attending these presentations should provide a very clear understanding of where intelligent system research is heading in the world and how these systems are currently being applied within industry. Each presenter will also have an exhibit and/or demo, where you will be invited to discuss his or her research results in greater detail.

Plenary



Aristides A.G. Requicha
Professor of Computer Science and Electrical Engineering, University of Southern California

"Nanorobotics"

Tuesday, June 5, 2001,
9:00 am - 10:00 am

Dr. Requicha's current research is focused on the science and engineering required to interact with the nanometer-scale world. He directs USC's Laboratory for Molecular Robotics, an interdisciplinary center whose ultimate goal is to control the structure of matter at the molecular scale. The lab is now developing systems for manipulating nanoscale objects using Scanning Probe Microscopes (SPMs) as sensory robots. Applications in nanoelectronics, nanoelectromechanical systems (NEMS) and nanobiotechnology are being investigated. This work is evolving towards the construction and deployment of autonomous nanorobots.

PRECARN Collaborative R&D Opportunities

There are many organizations that sponsor collaborative research. A select group of presenters will share information on the support that is available from their organizations. These include: Natural Sciences and Engineering Research Council (NSERC), National Research Council Canada, Canadian Space Agency, Department of National Defense, Centre de recherche informatique de Montrèal (CRIM), and of course, PRECARN Associates.

Awards Luncheon

One of Canada's best-known science journalists, Mr. McDonald has been with the program since 1992. His extensive background in science broadcasting includes numerous science documentaries for CBC Radio's "Ideas" series and location stories and investigative reports for CBC's "As It Happens" and "Morningside".

Bob McDonald,
Journalist and Host of CBC Radio's "Quirks & Quarks"

"Science and Society; a Love-Hate Relationship"

Tuesday, June 5, 2001, 12:00 pm - 2:00 pm

Bob McDonald has also produced, written, and hosted over one hundred educational videos, written for the Globe and Mail, and before joining "Quirks & Quarks" was the host of CBC televison's children's science program "Wonderstruck". He is also the author of two books based on the program: "Wonderstruck I" and "Wonderstruck II". In the summer of 1999, he published an audio book of Jules Verne's "From the Earth to the Moon", in celebration of the 30th anniversary of humankind's walk on the moon. Fall 2000 saw the release of his latest book, "Measuring the Earth with a Stick: Science as I've seen it".

PRECARN Associates Inc.: Building Canada's Intelligent Systems Sector

The PRECARN Network is a member-owned, not-for-profit industrial consortium supporting the development of intelligent systems technologies.

What we do

PRECARN helps Canadian companies bridge the 'innovation gap' between university and government research and commercial applications. Our Mission is to make Canadian firms more globally competitive through increased development and use of intelligent systems technologies and expertise.

PRECARN funds, coordinates and promotes collaborative research conducted by industry, university and government researchers. With support from Industry Canada, other federal departments and provincial government agencies, PRECARN plays a key role in Canada's growing Intelligent Systems Sector. Since our founding in 1988, the intelligent systems industry has swelled from only a handful of companies to more than 250 firms that employ 23,000 people and generate $3.8 billion in annual revenue. By 2005, the number of companies is expected to reach 700.

In today's global knowledge-based economy, innovation is too complex, and international competition too fierce, for firms to 'go it alone'. By collaborating-with universities, government research laboratories, and other firms, such as suppliers and developers-companies increase their capacity to innovate and are able to bring their products to market faster.

PRECARN fosters this collaboration by building nationwide relationships among players with complementary capabilities. Through these linkages, companies gain access to technology, expertise, resources and markets.

(IRIS) Institute for Robotics and Intelligent Systems: Strengthening the University Connection

Managed by PRECARN, IRIS is one of the federally-funded Networks of Centres of Excellence.

While PRECARN focuses on industry-led research, IRIS focuses on university-based research, and is a network comprised of over 100 researchers, 600 students, and 22 universities across Canada. The program currently comprises 19 projects within a variety of sectors: natural resources, manufacturing, health care and information technology.

IRIS's mission is to promote high-quality, collaborative applied research in intelligent systems that is of strategic importance to Canadian industry. It works to strengthen the R&D interaction between universities and industry. As a direct result of IRIS-supported research, 23 high-technology startup companies have been launched that still exist today.

To find out more information on PRECARN and IRIS, please visit us on the website at www.precarn.ca, or contact our Communications Office at:

PRECARN Associates Inc.
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Tel: (613) 727-9576
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E-Mail: info@precarn.ca.

CSCSI/SCEIO Membership Application

I wish to join CSCSI/SCEIO and receive *Canadian Artificial Intelligence /Intelligence Artificielle au Canada*

Yes ___ / No ___ Web Access Only ($30.00* Cdn./yr.)

Yes ___ / No ___ Printed Copy and Web Access ($40.00* Cdn./yr.)

I am a student

Yes ___ / No ___ Web Access Only ($15.00* Cdn./yr.)

Yes ___ / No ___ Printed Copy and Web Access ($15.00* Cdn./yr.)

I am a member of CIPS

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E-mail: aff@cips.ca

For more information, contact CIPS or a member of the CSCSI/SCEIO executive.

Canadian Artificial Intelligence
Intelligence Artificielle au Canada

The editor welcomes contributions from members and non-members. Possible formats include, but are not limited to:

- commentary, in the form of letters or short articles, on any AI issue of concern to you (e.g. research priorities, funding, educational trends, cultural, political, or ethical aspects of AI)
- interdisciplinary work
- survey papers
- reports on new work by students
- abstracts
- web site reviews
- news
- humour

Submission information • Guide de soumission

Canadian Artificial Intelligence / Intelligence Artificielle au Canada welcomes submissions on any matter related to artificial intelligence. Please send your contribution, preferably in electronic form, with an abstract and biography to:

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Editor, *Canadian AI / IA au Canada*
School of Computing Science
Simon Fraser University
Burnaby, British Columbia, Canada
V5A 1S6 or — agrbavec@cs.sfu.ca
Phone (604) 291-3208
Fax (604) 291-3045

Please contact the editor as early as possible to obtain complete submission guidelines.
Submission deadline: May 1, 2001.

Sample issues and articles can be viewed at: http://cscsi.sfu.ca/cai.html

Advertising rates are available upon request from the editor.

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