# User Modeling and Adaptive User Interfaces

#### Introduction

- Types of Adaptation
  - Adaptable
  - Adaptive
  - Mixed Initiative
- Definition of Adaptive Interfaces: "Interactive systems that invoke machine learning to improve their interaction with humans (Langley, 1999)."

### Adaptive vs. Adaptable

#### Adaptive

- System adapts itself to tasks & users
- Knowledge is contained in the system
- Little or no effort is needed from the user [+]
- Loss of user control [-]

#### Adaptable

- Users can change functionality
- Knowledge is extended by user
- User is in control [+]
- User must do substantial work [-]

Fisher G, "User Modeling in Human-Computer Interaction", UMUAI 11, pp. 65-86, (2001).

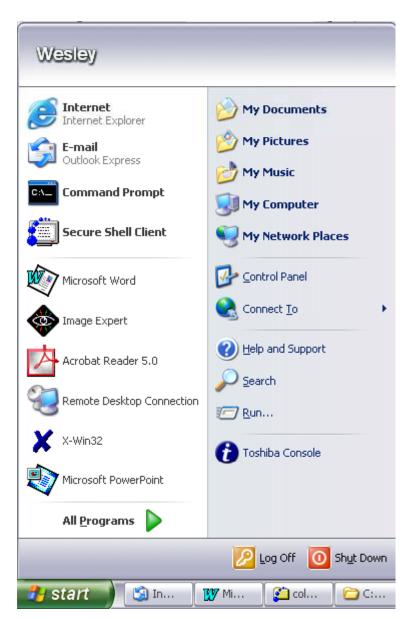
# Why have adaptive systems?

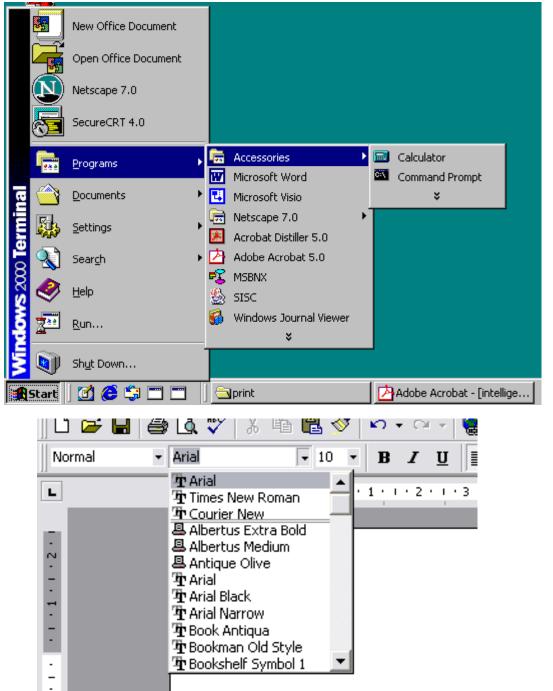
To enhance the user experience

- Information filtering
  - Individual interests
  - Shared interests
  - Tailored content & navigation

# **Adaptive Menus**

- Commercial applications
  - MS Office font split menu
  - MS Office adaptable menus
  - Windows 2000 start menu
  - XP start menu frequent application list





#### **User Models**

- "...An explicit representation of the properties of an individual user; it can be used to reason about the needs, preferences or future behaviour of the user. (Ross, 2000)"
- Data collection
  - Self Reporting (eg. Some movie recommenders)
  - Detecting user actions (eg. tracking clicks, frequency of actions)

# **User Modeling**

#### Beneficial in:

- Personalization
- Filtering systems
- Adaptive systems
- Adaptive user interfaces
- Recommender systems

# **User Modeling**

- Sometimes called User Profiling
- Methods of capturing user preferences and behaviour
  - Handcrafted stereotypical models
  - Handcrafted models based on traditional questionnaires (expert systems)
  - <u>Learned (statistical) models based on use of system</u>
- Can be collaborative or individual

# Collaborative profiling

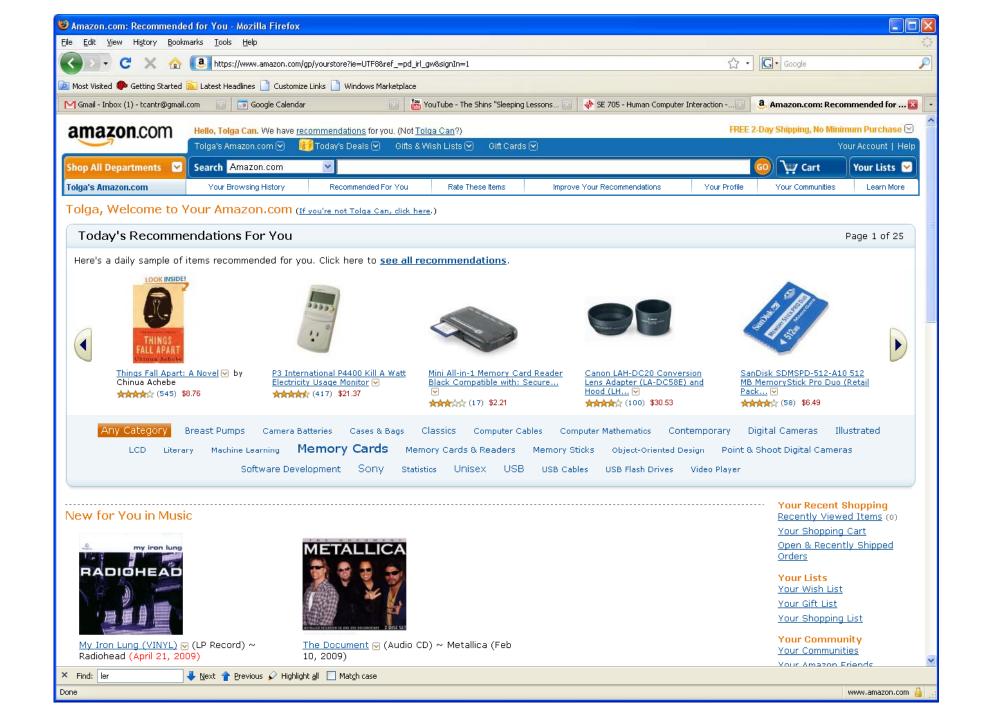
Based on the items you've purchased and the behaviour of other customers who've bought the same items, Recommendations change immediately when you purchase or rate a title, Can change recommendation by clicking – 'not interested' or 'own it' -http://www.amazon.co.uk

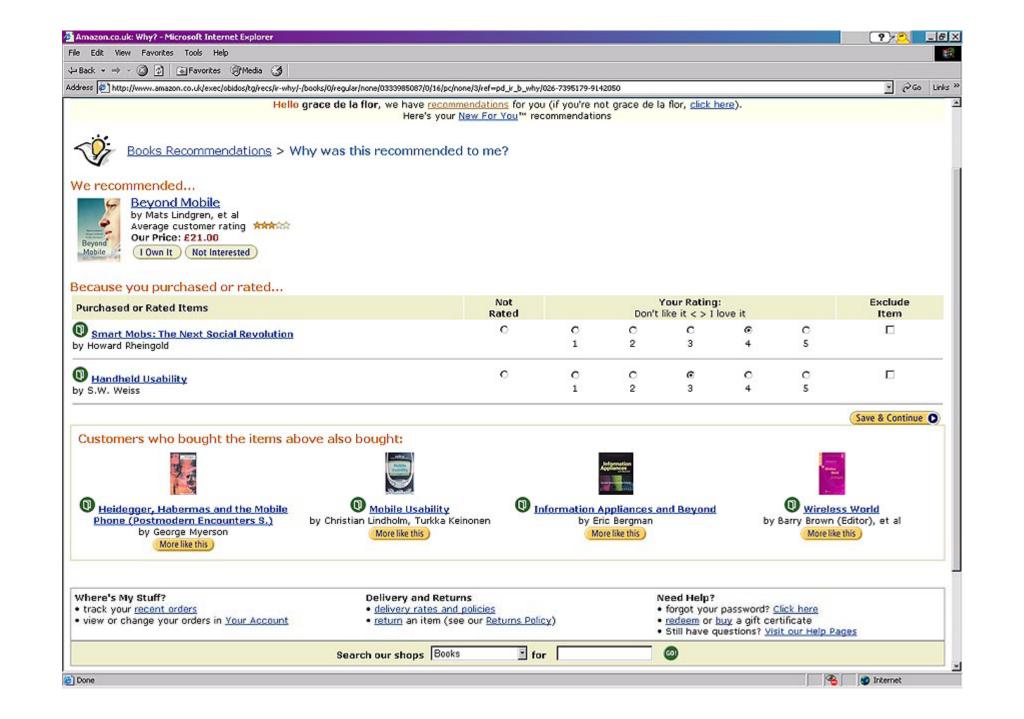
#### Collaborative filtering

- Association by user and object
- Explicit data, shopping history
- Implicit data, stereotypes

#### Issues

May create inaccurate stereotypes





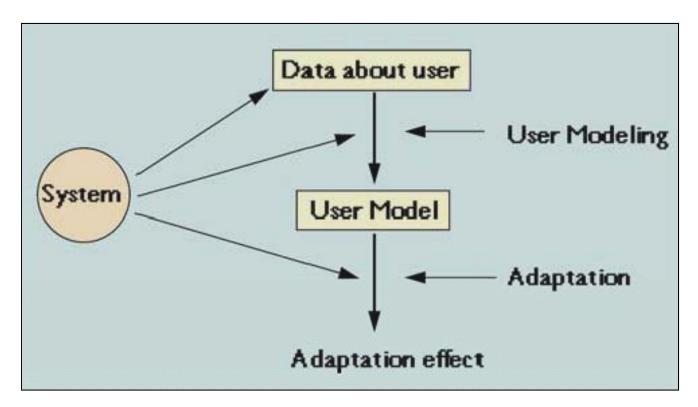
# Data Used to Develop User Profiles

- Explicit data:
  - Questions/answers
  - User preferences, options chosen
- Implicit data (less obtrusive):
  - Navigation
    - Keystroke and mouse traces
    - Click stream from web browsing
  - Content
    - Record of purchases/actions

# **User Modeling: The Basics**

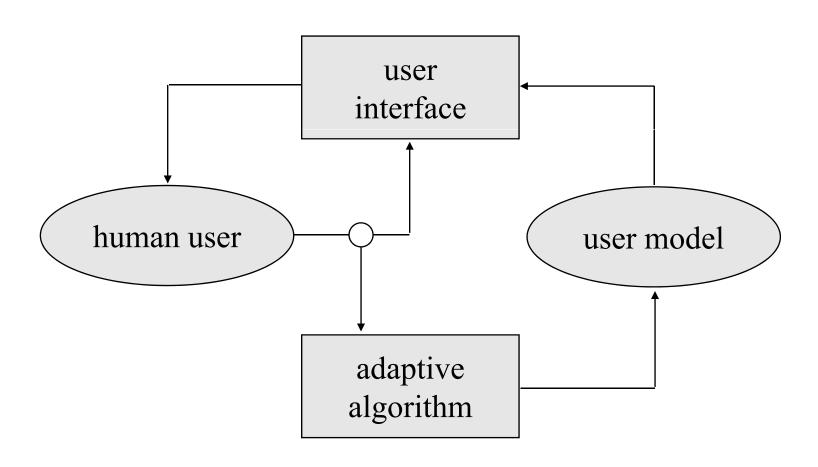
- Collect implicit and explicit data
- Process data and develop a mathematical or logical model to predict user preferences or product interests
- Apply user models to adapt the format or content of a system's interface
- Such systems are named adaptive user interfaces or intelligent user interfaces
- Examples: Amazon, Google, ...

# **User Modeling & Adaptation**



Brusilovsky P., Maybury M. *From adaptive hypermedia to the adaptive web*. Pages: 30 – 33. Communications of the ACM May 2002/Vol. 45, No. 5

#### **Elements of an Adaptive Interface**

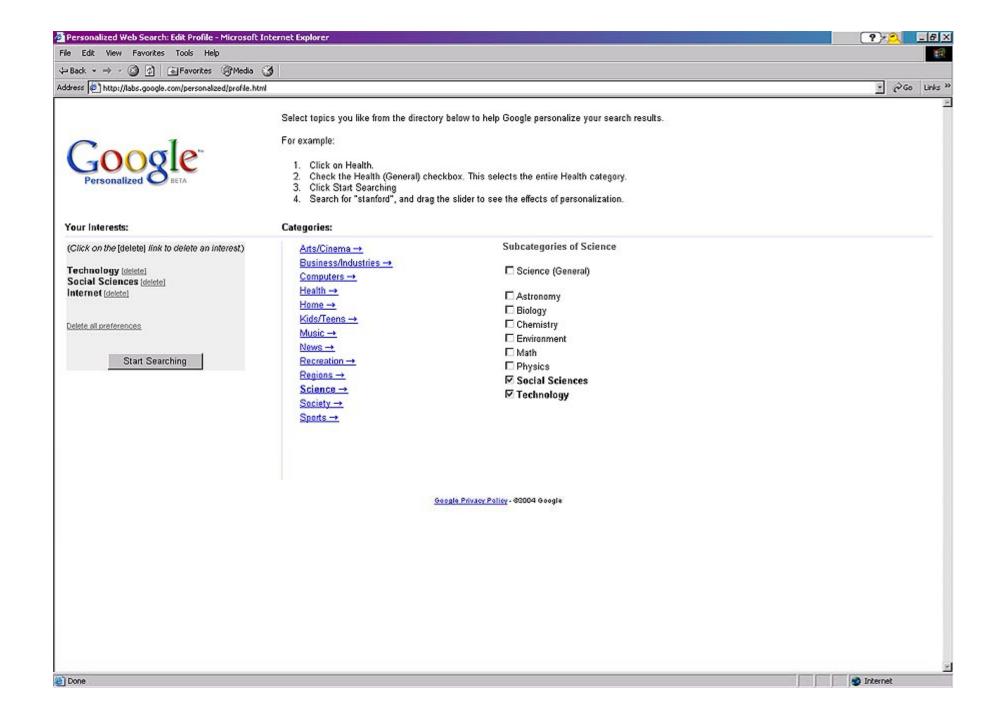


### **Implicit Data**

- Server logs & Cookies
   Patterns of use
  - IP address
  - Time stamp
  - Referring URL
  - Operating system
  - User ID & session number
  - Number of visit/pages viewed
    - » Data collection
    - » Pattern discovery
    - » Automated user model

#### **Explicit Data**

- User Profiles & Preferences
   Supplied data
  - Age
  - Gender
  - Location
  - Content preferences
  - Layout preferences
  - Shopping history
    - » User input
    - » Pattern discovery
    - » Informed user model



#### Using a Hidden Markov Model to Learn User Browsing Patterns for Focused Web Crawling Hongyu Liu, Jeannette Janssen and Evangelos Milios

Technical Report CS-2005-05

Dalhousie University

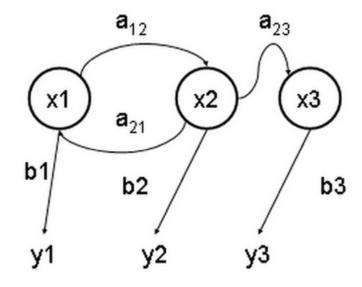
June 3rd, 2005

#### **Abstract**

A focused crawler is designed to traverse the Web to gather documents on a specific topic. It can be used to build domain-specific Web search portals and online personalized search tools. The focused crawler must use information gleaned from previously crawled page sequences to estimate the relevance of a newly seen URL. In this paper, we present a new approach for prediction of the important links to relevant pages based on a Hidden Markov Model (HMM). The system consists of three stages: user data collection, user modelling via sequential pattern learning and focused crawling. In particular, we first collect the Web pages visited during a user browsing session. These pages are clustered, and the link structure among pages from different clusters is used to learn page sequences that are likely to lead to target pages. The learning is done using HMM. During crawling, the priority of links to follow is based on a learned estimate of how likely the page is to lead to a target page. We compare performance with Context-Graph crawling and Best-First crawling and experiments show that this approach performs better than other strategies.

#### **Hidden Markov Model**

 Hidden Markov models are probabilistic finite state machines. A hidden Markov model λ is determined by the following parameters:



- A set of finite number of states:  $S_i$ ,  $1 \le i \le N$
- The probability of starting in state  $S_i$ ,  $\pi_i$
- The transition probability from state  $S_i$  to  $S_j$ ,  $a_{ij}$
- The emission probability density of a symbol  $\omega$  in state  $S_i$

#### What is hidden?

- With a hidden Markov model, we usually model a temporal process whose output we can observe but do not know the actual underlying mathematical or physical model.
  - We try to model this process statistically.
- Here the states of the hidden Markov model are hidden to us. We assume that there is some underlying model (or some logic) that produces a set of output signals.

#### **Problems associated with HMMs**

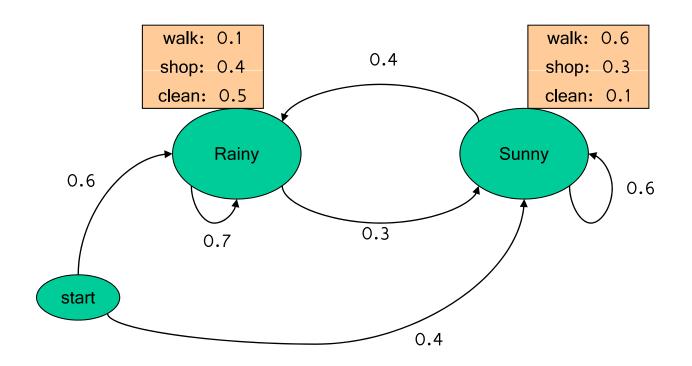
- There are three typical questions one can ask regarding HMMs:
  - Given the parameters of the model, compute the probability of a particular output sequence. This problem is solved by the forwardbackward procedure.
  - Given the parameters of the model, find the most likely sequence of hidden states that could have generated a given output sequence. This problem is solved by the Viterbi algorithm.
  - Given an output sequence or a set of such sequences, find the most likely set of state transition and output probabilities. In other words, train the parameters of the HMM given a dataset of output sequences. This problem is solved by the Baum-Welch algorithm.

# **Example (from Wikipedia)**

- You have a friend to whom you talk daily on the phone. Your friend is only interested in three activities: walking in the park, shopping, and cleaning his apartment. The choice of what to do is determined exclusively by the weather on a given day. You have no definite information about the weather where your friend lives, but you know general trends. Based on what he tells you he did each day, you try to guess what the weather must have been like.
- There are two states, "Rainy" and "Sunny", but you cannot observe them directly, that is, they are *hidden* from you. On each day, there is a certain chance that your friend will perform one of the following activities, depending on the weather: "walk", "shop", or "clean". Since your friend tells you about his activities, those are the *observations*.

# **Example (from Wikipedia)**

 You know the general weather trends in the area, and what your friend likes to do on the average. In other words, the parameters of the HMM are known.

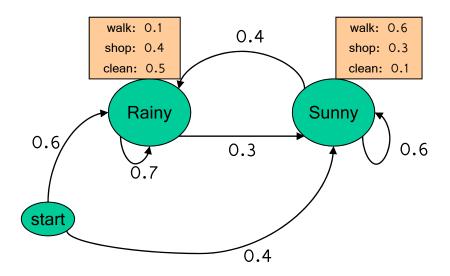


# **Example (from Wikipedia)**

 Now, you talked to your friend for three days, and he told you that on the first day walked, the next day he shopped and the last day he cleaned.

What is the most likely sequence of days that could have produced this outcome? (Solved by the Viterbi algorithm)

What is the overall probability of the observations? (Solved by forward-backward algorithm)



# Viterbi algorithm

- It is a dynamic programming algorithm. It is based on the following assumptions:
  - At any time the process we are modeling is in some state
  - We have finite number of states
  - Each state produces a single output
  - Computing the most likely hidden sequence up to a certain point t must depend only on the observed event at point t, and the most likely sequence at point t − 1.
- These assumptions are satisfied by a first order HMM.

# Forward algorithm

- Forward and backward algorithms are used to compute the probability of the sequence being emitted from an HMM by summing up the probabilities over all possible paths.
- Modification on Viterbi DP equations:
  - Instead of using max, sum all options

# **Baum-Welch Algorithm**

 The Baum-Welch algorithm is an expectationmaximization (EM) algorithm. It can compute maximum likelihood estimates and posterior mode estimates for the parameters (transition and emission probabilities) of an HMM, when given only emissions as training data.

#### **Using the Learned Model**

Another essential step in the development process can be stated:

Given: An approach to learning a user model for some task;

*Find:* Some way to invoke the model that helps the user perform the task more effectively.

This decision includes making clear design choices about:

when and how to present the model's predictions to user;

how to handle cases in which these predictions are wrong.

The ideal adaptive interface lets the user take advantage of good predictions and ignore bad ones.

#### **Gaining User Acceptance**

A final important facet of the development process can be stated:

Given: A complete adaptive user interface for some task;

Find: Ways to get people to try the system and to become long-term users.

Attracting first-time users involves marketing much more than technology, but, without it, a good system may be ignored.

However, a system that is well-designed and easy to use is more likely to retain users over long periods.

#### **Examples of Adaptive User Interfaces**

Adaptive interfaces have been developed for many different tasks:

- Command and form completion
- Email filtering and filing
- News selection and layout
- Browsing the World Wide Web
- Selecting movies and TV shows
- On-line shopping
- In-car navigation
- Interactive scheduling
- Dialogue systems

These efforts cover a wide spectrum but also raise common issues.

#### The Task of Route Selection

A decision-making task that confronts drivers can be stated as:

- Given: The driver's current location C;
- Given: The destination D that the driver desires;
- Given: Knowledge about available roads (e.g., a digital map);
- Find: One or more desirable routes from C to D.

Computational route advisors already exist in both rental cars and on the World Wide Web.

However, they do not give *personalized* navigation advice to individual drivers.

#### An Approach to Route Selection

Here is a one approach to learning route preferences, though not the first we considered:

- Formulation: Learn a "subjective" function to evaluate entire routes
- Representation: Global route features computable from digital maps
- Data collection: Preference of one complete route over another
- *Induction:* A method for learning weights from preference data
- *Utilizing model:* Apply subjective function to find "optimal" route

This method learns a user model with respect to the entire route.

#### **The Adaptive Route Advisor**

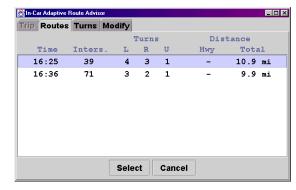
The proposed approach is implemented in the *Adaptive Route Advisor* (Fiechter, Rogers, & Langley, 1999), which:

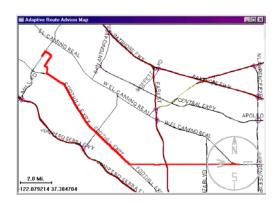
models driver preferences in terms of 14 global route features gives the driver two *alternative* routes he might take lets the driver *refine* these choices along route dimensions uses driver choices to refine its model of his preferences invokes the driver model to recommend future routes

Note that providing drivers with choices lets the system collect data on route preferences in an unobtrusive manner.

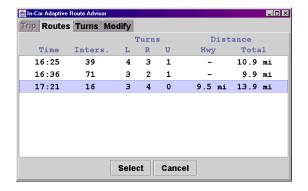
#### The Adaptive Route Advisor

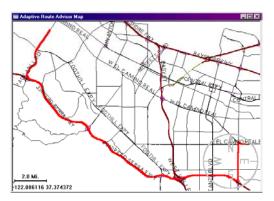






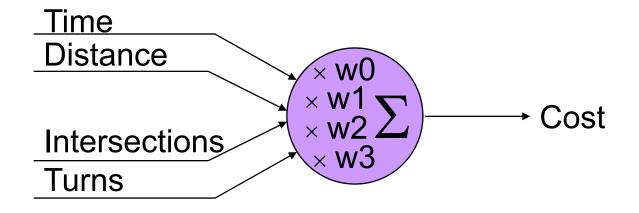






## **Driver Model and Training Cases**

The Adaptive Route Advisor represents the driver model as a weighted linear combination of route features.

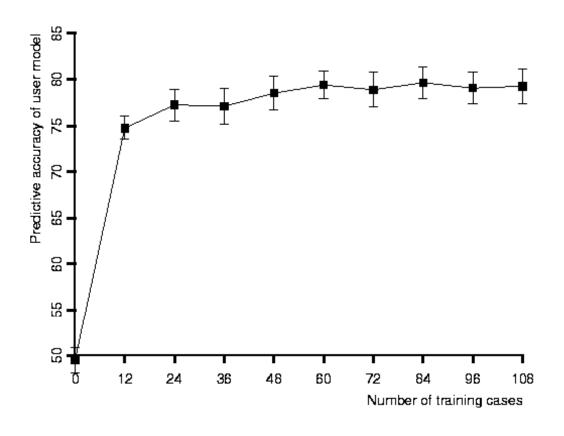


Training data: [x0, x1, x2, x3] is better than [y0, y1, y2, y3].

The system uses each training pair as constraints on the weights found during the learning process.

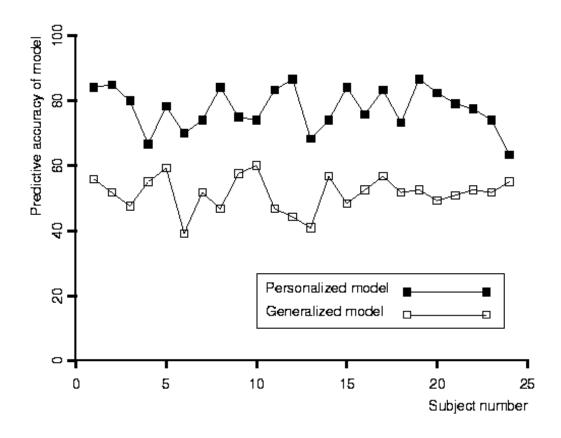
### **Experimental Results on Route Advice**

Experiments with 24 subjects show the Route Advisor improves its predictive ability rapidly with experience.



### **Experimental Results on Route Advice**

Analyses also show that personalized user models produce better results than generalized models, even when given more data.



## The Adaptive Email Reader

- Consider an email program that highlights emails that the user is particularly likely to read.
- Email Characteristics (Boolean)
  - Known The sender is known to the reader
  - New This email is not part of an existing thread
  - Short The email is short
  - Home The email is being read from home
  - Reads Dependent variable: Whether the user reads the message

# **Another example**

- Many games can be complex for players to learn/manage
- Need for interfaces that do more than simply act as a means for players to input commands/actions
- Intelligent interfaces between players and games will enable games to reason about the needs, desires and motivations of players and to react accordingly.
- Intelligent vs. Adaptive interfaces?
- Next:
  - describe some possible benefits of such an interface in game playing
  - discuss some of the challenges that will have to be overcome to make them a reality in mainstream game production

## **Assistance with Micro-Management**

- Strategy games: Macro and micro-management
  - As empires grow, more and more time on micro-management (chore) and less on macro-management (fun)
- Some games already make use of agents to help in these tasks
  - "Civilization" advisors
- Intelligent Interface assistants learn during the game
  - Make micro-management decisions similar to the players'
- RPGs: Re-distributing items & selling off acquired loot
  - Take minutes of play time and dozens of mouse clicks
    - Repeated dozens of times in a single session of play
  - Interfaces that learn how a given player likes to distribute equipment or to propose lists of items to sell could drastically reduce the time spent by players on 'housekeeping'

## **Assistance in Task Execution**

- If interface can detect what a player is trying to do, it can offer help in completing the task
  - Not to have the computer play the game for the player!
  - Scope for assistance that reduces the need for players to carry out all tasks by themselves (similar to micro-management)
- Example: Squad-based game
  - With intelligent interface analyzing the players' intent, squad members would be able to pro-actively offer to carry out tasks
  - Decrease the need for the player to manage other characters
    - Control task reduced to accepting or rejecting offers of help
    - In place of sequences of commands and key combinations
  - Increase perceived intelligence of the computer controlled squad members, and degree of immersion in the game overall?

## From Tutorials to Mentors

- Currently: Interactive Tutorials
  - Often first stages or levels of a game
  - Cycle through a range of actions and activities.
- Possible for players to forget how to perform infrequent actions
  - Or when game has not been played for some time
  - Pro-active help can be offered to explain how tasks may be carried out
  - Learn: Offer guidance based on previous activity of player
  - As simple as pop-up dialogs, or better...
- Embodied Mentor characters and sidekicks
  - E.g. Mentors in educational and massively multiplayer games
  - Can allow richer interaction with mentor where possible
    - Allow players to kill them off when they get too annoying?

# **Enhancing Gameplay**

- Enhancing and Adapting Gameplay
  - Instead of helping the player, an intelligent interface can adapt a game in other ways
    - Adapting the gameplay to suit the player
- Adaptive Difficulty
  - Very simple non-Al methods exist in range of games (e.g. catch-up slowdown in racing games)
  - Al methods being presented at this workshop
  - Intelligent interfaces which monitor players can help a game decide when to adapt the difficulty
  - May e.g. learn from the player to adapt AI strategies in response

# Challenges

- Offer help without being intrusive or irritating
  - To some, Clippy is annoyance deactivated as soon as possible
  - Need an off switch An escape clause, not a solution
- Be able to reliably interpret not just players' intentions, but their emotional state
  - Understand player preferences and motivations
  - Progress on measuring the emotional state of players without additional non-game peripherals to monitor the player
  - Additional means of observing players ("EyeToy" or heart-rate monitors)
    may help, but cannot be assumed
- Keep game difficulty at the right level of player challenge
  - Players dislike games being too easy as well as too hard
- Careful balancing: just enough intervention
  - To maintain interest in the game
- With benefits unproven, not many developers will be keen to implement Intelligent Interfaces

#### Web

Results 1 - 10 of about 10,200 for office assistant paperclip. (0.19 seconds)

#### Annoyances.org - Kill the Office Paperclip!

... t have to tell you how annoying that stupid little animated **paperclip** character is ... next to **Office** Tools, and click the box next to **Office Assistant**; for **Office ...** www.annoyances.org/exec/show/article08-100 - 11k - 7 Jul 2004 - Cached - Similar pages

#### Annoyances.org - Question about 'Kill the Office Paperclip!' ...

Question about 'Kill the **Office Paperclip!**' Monday, February 18, 2002 at 1:47 am ... **office** 2000 Word, Excel or Powerpoint, I get the **Office Assistant** popup window ... www.annoyances.org/exec/forum/win98/t1014025646 - 19k - <u>Cached</u> - <u>Similar pages</u> [More results from www.annoyances.org]

#### Getting rid of that (\*)#'@^ paperclip! - Taming the Office ...

How can I get rid of that ^\$#\*@& paperclip? This page last revised: 20 May 2004 11:18:16 -0500. ... Call up the Office Assistant Help è Microsoft Word Help . ... www.addbalance.com/word/officeassistant.htm - 22k - Cached - Similar pages

#### CNN - Microsoft's paper-clip assistant killed in Denver - October ...

... at the Professional Developers Conference here Wednesday, as Microsoft product managers coolly and deliberately killed the Microsoft **Office Assistant**. ... www.cnn.com/TECH/computing/9810/16/clipdeath.idg/ - 24k - <u>Cached</u> - <u>Similar pages</u>

#### Office The Office Assistant Paperclip Help

... Help menu. To edit the features of "The **Office Assistant,**" right-click on the **paper clip** when it appears and choose the Options tab. ... www.appsynthesis.com/techtips/articles/ 009%20Office%202000%20-%20The%20Office%20Assistant%20(Paper clip).htm - 9k - Cached - Similar pages

#### Office Assistant - Wikipedia, the free encyclopedia

... com/dragonfire/clippy.html); Academic paper on why people hate the **Office Assistant** (http://xenon.stanford.edu/~lswartz/paperclip/). ... en.wikipedia.org/wiki/Office\_Assistant - 9k - <u>Cached</u> - <u>Similar pages</u>

#### Office Assistant - encyclopedia article about Office Assistant. ...

... XP was the removal of Clippy and the Office Assistant from the software, although

## **Challenges of Adaptive Interfaces**

Adaptive user interfaces have clear attractions but also pose some challenges to developers:

formulation of user modeling as an induction task engineering of representation to support learning process unobtrusive collection of training data from users effective application of learned user model requirement for some form of *online* learning necessity for induction from *few* training cases

These challenges overlap with other applications of machine learning, but also raise some new issues.

# **Criticisms of Adaptive Interfaces**

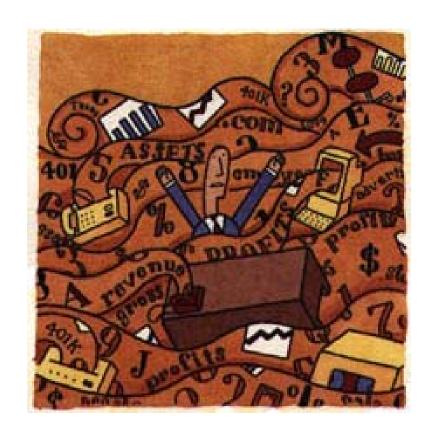
- Loss of Control
- Transparency
- Predictability
- Trust
- Redesigning a system can often overcome the problems addressed by adaptive features (Breuker, 1990)

## The Internet's Dilemma

- A lot more information
- A lot harder to find the piece you desire
- How can users be provided the information they want without being overwhelmed?
- How can E-Commerce companies help their customers find the products and services they desire?

### The Need for Intelligent Assistance

As information and choices become more available, users need help in finding, and selecting among, the many alternatives.



This has led to the development of *recommendation systems*, which attempt to locate and recommend relevant items.

### The Need for Personalized Assistance

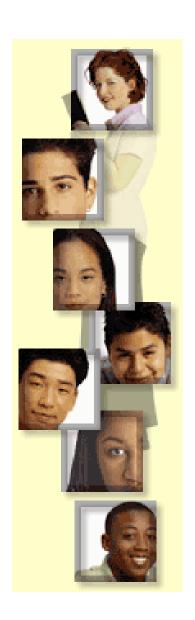
At the same time, society is becoming ever more diversified.

Differences in private and professional preferences are growing.

Internet users are becoming increasingly selective about what they want to see and purchase.

We need *personalized* systems that can give users the information or product they want.

But personalized response requires some *model* or *profile* of the user.



## The Solution

- Track the categories that users visit and use the information to predict the next best category
- Adapt the content of the web pages so as to recommend the next best category
- Assumption: Users will follow similar trajectories when shopping for similar purposes

# **Testing Strategy**

- User testing (Effectiveness)
  - Model vs. Random
- User Testing (Usefulness)
  - · Will links be used?

# **User Testing (Effectiveness)**

- 10 test subjects given 4 shopping scenarios (e.g. Xmas, wedding)
  - Adaptive interface was disabled (no recommendations)
  - Used to develop user profile models
- 10 different subjects given 4 shopping scenarios
  - 2 scenarios with random recommendations
  - 2 scenarios with learned recommendations
- Users were asked to rate the links they were provided with by the recommendation utility:
  - 0 (Useless)
  - 1 (Somewhat Useful)
  - 2 (Very Useful)

# **User Testing (Effectiveness)**

	0 – Useless	1 – Somewhat Useful	2 – Very Useful
Random	69.9%	24.4%	5.8%
Model	42.1%	32.8%	25.1%

	1 or more Very Useful	1 or more Very OR Somewhat Useful
Random	15.4%	63.5%
Model	49.2%	93.4%

## Results

Model was capable of creating successful profiles

Users seemed to benefit from the suggested links

### The Promise of New Sensors

Adaptive interfaces rely on user traces to drive their modeling process, so they stand to benefit from developments like:

GPS and cell phone locators
robust software for speech recognition
accurate eye and head trackers
real-time video systems
wearable body sensors (GSR, heart rate)
portable brain-wave sensors

As such devices become cheap and widespread, they will give us new sources of data and support new types of adaptive services.

### **Conclusions**

In summary, adaptive interfaces integrate ideas from machine learning, intelligent agents, and human-computer interaction.

This approach to automated personalization of online services:

has many examples already in regular and successful use, but many unexplored niches for research and application, and challenges involving integration rather than new methods.

These adaptive systems promise to change the way we interact with, and think about, computer software.