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EXHIBIT 3 A

Exhibit 3-A

Claim Chart of Dunja Mladenic, "Personal WebWatcher: design and implementation", *Technical Report IJS-DP-7472*, Department of Intelligent Systems, J. Sefan Institute, Slovenia (1996) ("MLADENIC").

as prior art to

Asserted Claims of U.S. Patent No. 6,9981,040 ("'040 Patent")
and
Asserted Claims of U.S. Patent No. 7,685,276 ("'276 Patent")

'040 Patent	MLADENIC
Claim 1	
A computer-implemented method for providing automatic, personalized information services to a user u, the method comprising:	Personal WebWatcher is based on the WebWatcher described in *WebWatcher: A Tour Guide for the World Wide Web*, by Joachims, Freitag, and Mitchell (1997); *WebWatcher: Machine Learning and Hypertext*, by Joachims, Freitag, Mitchell and Armstrong (1995); and *Web Watcher: A Learning Apprentice for the World Wide Web*, by Armstrong, Freitag, Joachims, and Mitchell (1995) ("Armstrong"). "[u]nlike WebWatcher, Personal WebWatcher (PWW) is structured to specialize for a particular user, modeling his/her interests." (Mladenic at 3). At a high level, Personal WebWatcher uses a corpus of documents and interactions that correspond to a specific user, rather than a set of documents and interactions that correspond to a web site, as WebWatcher does. As one would expect, using an individual user's documents for training data results in a system that is customized to that individual user. Personal WebWatcher then provides automatic, personalized services to the user by highlighting links that the user may be interested in. As seen in Figure 3 below, PWW places "eyeballs" next to selected links:

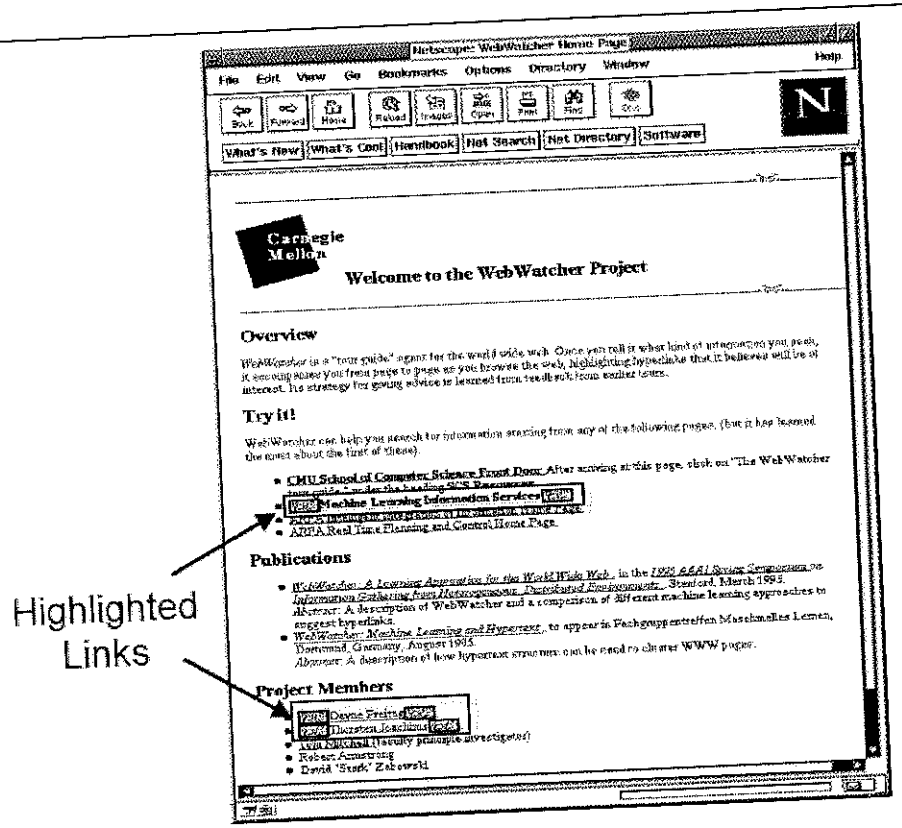
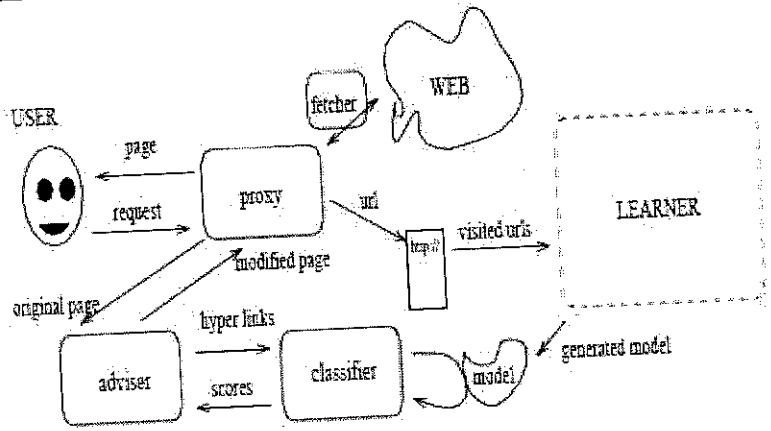
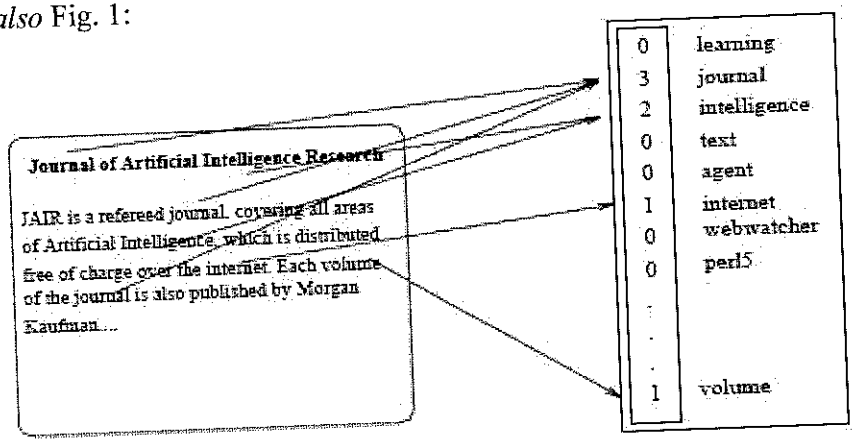


Figure 3: Example of HTML page presented to the user by PWW.

See also Mladenic at 2 ("Personal WebWatcher is a system that observes users of the WWW and suggests pages they might be interested in.... Web Watcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough."), Fig. 2:

	
a) transparently monitoring user interactions with data while the user is engaged in normal use of a computer;	MLADENIC, p. 2: "Personal WebWatcher is a system that observes users of the WWW and suggests pages they might be interested in. It learns user interests from the pages requested by the user." p. 3: "Unlike WebWatcher, Personal WebWatcher(PWW) is structured to specialize for a particular user, modeling her/his interests. It "watches over the user shoulder" the similar way WebWatcher does, but it avoids involving the user in its learning process." *See also*: **CULLISS** at 3:46-56; 5:18-21; 7:14-20. **REFUAH** at Abstract; 3:3-11; 5:34-50; 19:20-22. **SCHUETZE** at 5:36-40; 11:12-14; 18:11-17; 28:65 – 29:6. **WASFI** at Abstract, 60. Autonomy Press Release, at 2

	Autonomy Technology Whitepaper, AUT00069-70 Autonomy Agentware User Guide, at AUT00119 **MONTEBELLO** at 3.
b) updating user-specific data files, wherein the user-specific data files comprise the monitored user interactions with the data and a set of documents associated with the user;	MLADENIC, p. 3: "It solely records the addresses of pages requested by the user and highlights hyperlinks that it believes will be of interest." p. 8: "Both versions fetch visited documents and documents one step behind the hyperlinks of visited documents and store them as positive or negative examples of user interests, depending whether the user visited the document or not." p. 8: "Hyperlinks whose documents were visited by the user are considered to be positive examples, and all other to be negative examples of the user interests. The idea is that all hyperlinks were presented to the user and the user chose to visit some of them that meet her/his interests." *See also*: **CULLISS** at 3:13-35; 5:36-48; 7:14-42. **REFUAH** at Abstract; 5:34-50; 6:5-15; 8:31-39; 20:31-37. **SCHUETZE** at 10:14-18; 10:32-39; 11:12-17; 28:65 – 29:6; 34:34-37; *See generally* 17:47 – 18:27. **WASFI** at 58, 60, 61. Autonomy Press Release, at 1 Autonomy Technology Whitepaper, at AUT00069-70 **MONTEBELLO** at 3-4.

c) estimating parameters of a learning machine, wherein the parameters define a User Model specific to the user and wherein the parameters are estimated in part from the user-specific data files;	Personal Web Watcher treats a web page as a "bag of words," meaning that "all words from the document are taken and no ordering of words or any structure of text is used." (Mladenic at 3-4.) *See also* Fig. 1:  Figure 1: Bag-of-words representation using frequency vector. MLADENIC, p. 7: PWW uses a learner module, which uses "a Naïve (Simple) Bayesian classifier on frequency vectors to generate a model of user interests, that is used for advising hyperlinks." p. 8: "[Personal WebWatcher] fetch[es] visited documents and documents one step behind the hyperlinks of visited documents and store[s] them as positive or negative examples of user interests, depending on whether the user visited the document or not." p. 9: "LEARNER transforms documents into examples in two phases : (1) (docs2exs and docs2addexs in Figure4) parsing each document, assigning an index to each word and representing it in three files as a line of word indices containing: all words, only headline words, only underlined words. (2) (exs2vec in Figure4) calculating score (e.g. information gain) for each word, selecting some top words and represent documents as bag-of-words keeping frequency for each of the top words." p. 10: "The model of user interests is designed to predict if some document is positive or negative example of user interests."

	pp. 10-11: "The model of user interests is generated "off-line," usually during the night and thus its generation is not so critical in time as its usage for prediction. One of the simplest idea for learning is to use hyperlinks that occurred on the documents presented to the user as training examples and learn to predict if a new hyperlink is positive or negative example of the user interests....But during the learning phase we can afford using more time than when adding advice, so why not retrieving document behind hyperlinks, instead of using the extended hyperlink representation? In that case, we can learn the model of user interests directly from documents whose interestingness we are trying to predict." *See also*: **CULLISS** at 3:57-65; 4:54 – 5:10. **REFUAH** at 2:9-35; 6:49-64; 8:30-58; *See generally* 14:21 – 15:45. **SCHUETZE** at 27:44-64. *See also* 27:65 – 28:14. **WASFI** at 58, 61, 63. Autonomy Press Release, at 1 Autonomy Technology Whitepaper, at AUT00069-70 Autonomy Agentware User Guide, at AUT00002 **MONTEBELLO** at 3, 4.
d) analyzing a document d to identify properties of the document;	Personal Web Watcher treats a web page as a "bag of words," meaning that "all words from the document are taken and no ordering of words or any structure of text is used." (Mladenic at 3-4.) *See also* Fig. 1:

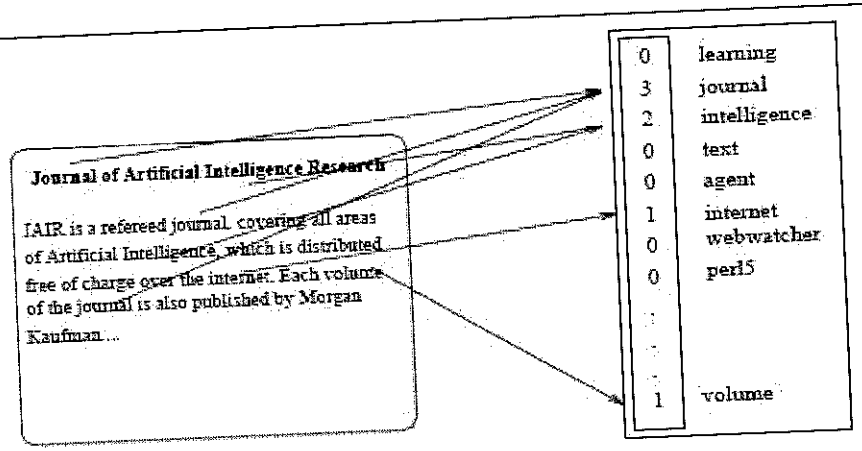


Figure 1: Bag-of-words representation using frequency vector.

MLADENIC, p. 4: "We decided to use the bag-of-words representation using frequency of word and observe success of given advice (whether user selected the advised hyperlink). In case of poor system performance, some additional information from HTML-structure could be added, for example, frequency of word in headlines of a given document."

p. 4: "Some later versions of the WebWatcher system change slightly the way of constructing text for learning, e.g., adding words in the document retrieved behind hyperlink."

p. 10: PWW is "actually predicting interestingness of document based on the hyperlink pointing to it, and not document itself" because "retrieving documents behind the requested hyperlinks is usually time consuming."

p. 12: "Documents are currently represented using the bag-of-words approach (see Section 3.1) and feature selection is performed using mutual information approach (see Section 3.2)."

See also:

CULLISS at 2:43-46; 5:36-48; 10:47-52.

	REFUAH at 7:53 – 8:6; 20:31-37; 21:6-30. **SCHUETZE** at 3:40-44; 5:59-63; 10:20-31; Fig.1. *See generally* 11:42 – 15:19. **WASFI** at 61. Autonomy Press Release, at 1 Autonomy Technology Whitepaper, at AUT00068-69, AUT00071 Autonomy Agentware User Guide, at AUT00002, AUT00117 **MONTEBELLO** at 3, 4.
e) estimating a probability P(u|d) that an unseen document d is of interest to the user u, wherein the probability P(u|d) is estimated by applying the identified properties of the document to the learning machine having the parameters defined by the User Model; and	MLADENIC, p. 5: "Since we are more interested in positive class (interested documents) and we want to have words that are frequent, it might be better to include in the weighting formula the probability of a word occurring in the positive class or frequency of the word, (a formula) where w is a selected word, c is the positive class and TF(w) is the frequency of the word w." p. 7: "We decided to test different learning algorithms on PWW data (see Section 5), since it is not clear which algorithm is the most appropriate. The current version of PWW uses a Naive (Simple) Bayesian classifier on frequency vectors to generate a model of user interests, that is used for advising hyperlinks." p. 7: "The current version of PWW uses a Naïve(Simple) Bayesian classifier on frequency vectors to generate a model of user interests, that is used for advising hyperlinks." p. 8: "Both versions [of the document analyzer used in PWW] fetch visited documents and documents one step behind the hyperlinks of visited documents and store them as positive ***or negative*** examples of user interests, depending whether the user visited the document ***or not***." p. 10: "The model of user interests is designed to predict if some document is positive or negative

example of user interests."

p. 12, Table 2:

UserId and data source	probability of interestingness	number of examples	data entropy
usr150101			
Doc	0.094	1 333	0.449
HL	0.104	2 528	0.480
usr150202			
Doc	0.107	3 415	0.492
HL	0.053	4 798	0.301
usr150211			
Doc	0.089	2 038	0.436
HL	0.044	2 221	0.259
usr150502			
Doc	0.100	1 272	0.468
HL	0.100	2 198	0.468

See also:

CULLISS at 2:43-51; 5:36-62.

REFUAH at 3:56 – 4:4; 17:32 – 18:4.

SCHUETZE at 18:62 – 19:10.

WASFI at 60, 61.

Autonomy Press Release, at 1-2

	Autonomy Technology Whitepaper, at AUT00069, AUT00071 Autonomy Agentware User Guide, at AUT00119 **MONTEBELLO** at 4.
f) using the estimated probability to provide automatic, personalized information services to the user.	MLADENIC, p. 2: "Web Watcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough." pp. 7-8: "A limited number of hyperlinks that are scored above some threshold are recommended to the user, indicating their scores with graphical symbols placed around each advised hyperlinks. For example, in Figure 3 three hyperlinks are suggested by PWW: "Machine Learning Information Services" and two project members (Dayne Freitag, Thorsten Joachims)." p. 12: "Our experiments are performed on data collected for four users participating in the HOMENET project [14] with the data characteristics given in Table 2." *See also*: **CULLISS** at 2:39-51. **REFUAH** at Abstract, 2:63 – 3:11; 3:47-55; 17:21-43; 18:56-65; 23:11-28. **SCHUETZE** at 1:29-33; 7:54-60. **WASFI** at 61. Autonomy Press Release, at 1 Autonomy Technology Whitepaper, at AUT00068 Autonomy Agentware User Guide, at AUT00002, AUT00004, AUT00116-117

	MONTEBELLO at 4.
Claim 11	
11. The method of claim **1** further comprising estimating a posterior probability P(u|d,q) that the document d is of interest to the user u, given a query q submitted by the user.	MLADENIC, p. 2: "WebWatcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough. The idea is that the user provides a few keywords describing a search goal and WebWatcher highlights related hyperlinks on the current page and/or adds new hyperlinks to the current page." *See also*: **CULLISS** at 2:39-51, 9:41-49, 10:1-7, 10:47-52. **REFUAH** at 17:21-43. **SCHUETZE** at 21:57 – 22:16, 22:31-48, 30:58 – 31:13.
Claim 22	
22. The method of claim **1** wherein the monitored user interactions include a sequence of interaction times	*See also*: **MLADENIC** at 2. **REFUAH** at 5:57-58. **WASFI** at Abstract, 57. Autonomy Press Release, at 1 Autonomy Agentware User Guide, at AUT00124
Claim 32	
32. A program storage	*See* citations for claim 1[preamble].

device accessible by a central computer, tangibly embodying a program of instructions executable by the central computer to perform method steps for providing automatic, personalized information services to a user u, the method steps comprising:	
a) transparently monitoring user interactions with data while the user is engaged in normal use of a client computer in communication with the central computer;	*See* citations for claim 1[a].
b) updating user-specific data files, wherein the user-specific data files comprise the monitored user interactions with the data and a set of documents associated with the user;	*See* citations for claim 1[b].
c) estimating parameters of a learning machine, wherein the parameters define a User Model specific to the user and wherein the parameters are estimated in part from the user-specific data files;	*See* citations for claim 1[c].

d) analyzing a document d to identify properties of the document;	*See* citations for claim 1[d].
e) estimating a probability P(u|d) that an unseen document d is of interest to the user u, wherein the probability P(u|d) is estimated by applying the identified properties of the document to the learning machine having the parameters defined by the User Model; and	*See* citations for claim 1[e].
f) using the estimated probability to provide automatic, personalized information services to the user	*See* citations for claim 1[f].
Claim 34	
34. The program storage device of claim **32** wherein analyzing the document d provides for the analysis of documents having multiple distinct media types.	MLADENIC, p. 2: "WebWatcher can be describes as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough." p. 10: "The model of user interests is designed to predict if some document is positive or negative example of user interests. It is used to advice hyperlinks on the HTML document requested by the user." *See also*: **CULLISS** at 1:22-28, 2:19-24.

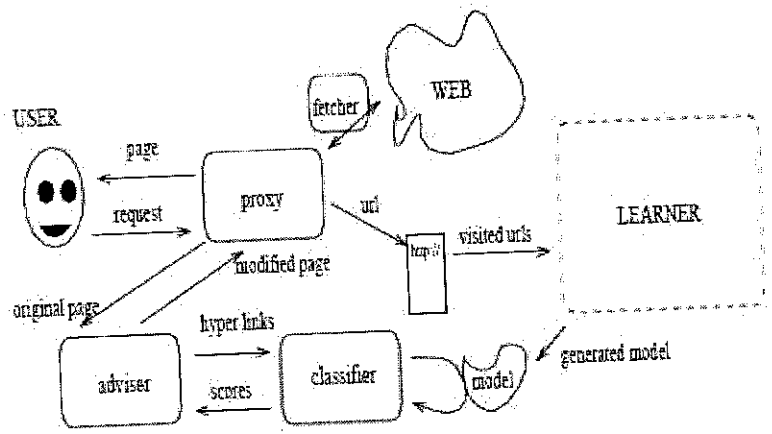
	REFUAH at 1:63 – 2:2. **SCHUETZE** at 4:12-35, 5:48-58. *See generally* "Summary of the Invention", 5:43 – 8:32. **WASFI** at 57, 58.
'276 Patent	MLADENIC
Claim 1	
A computer-implemented method for providing personalized information services to a user, the method comprising:	*See* citations for '040 Patent, claim 1[preamble].
a) transparently monitoring user interactions with data while the user is engaged in normal use of a browser program running on the computer;	*See* citations for '040 Patent, claim 1[a]. MLADENIC, p. 2: "Personal WebWatcher is a system that observes users of the WWW and suggests pages they might be interested in. It learns from the pages requested by the user. The learned model of user interests is then used to suggest hyperlinks on new HTML-pages requested by and presented to the user via Web browser that enables connection to [a] "proxy," e.g. Netscape." p. 7: "Personal WebWatcher consists of two main parts: a proxy server that interacts with the user via Web browser and a learner that provides the user-model to the server." p. 7: "Proxy waits in an infinite loop for a page request from the browser." *See also*: **REFUAH** at 5:57-58.

	WASFI at Abstract, 57.
b) analyzing the monitored data to determine documents of interest to the user;	*See* citations for '040 Patent, claim 1[b].
c) estimating parameters of a user-specific learning machine based at least in part on the documents of interest to the user;	*See* citations for '040 Patent, claim 1[c].
d) receiving a search query from the user;	MLADENIC, p. 1: "For example, Armstring et al. [2] developed WebWatcher, a system that assists user[]s in locating information on the World Wide Web [by] taking keywords from the user, suggesting hyperlinks and receiving evaluation." p. 2: "WebWatcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough. The idea is that the user provides a few keywords describing a search goal and WebWatcher highlights related hyperlinks on the current page and/or adds new hyperlinks to the current page." *See also*: **CULLISS** at 2:39-51. **REFUAH** at 1:63 – 2:2; 3:12-24. **SCHUETZE** at 21:57 – 22:16; 22:31-48. Autonomy Agentware User Guide, at AUT00002 **MONTEBELLO** at 3.

e) retrieving a plurality of documents based on the search query;	MLADENIC, p. 1: "For example, Armstring et al. [2] developed WebWatcher, a system that assists user[]s in locating information on the World Wide Web [by] taking keywords from the user, suggesting hyperlinks and receiving evaluation." p. 2: "WebWatcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough. The idea is that the user provides a few keywords describing a search goal and WebWatcher highlights related hyperlinks on the current page and/or adds new hyperlinks to the current page." *See also*: **CULLISS** at 2:39-51. **REFUAH**, 1:63 – 2:2; 3:12-24. **SCHUETZE**, 21:57 – 22:16; 22:31-48. **MONTEBELLO** at 3.
f) for each retrieved document of said plurality of retrieved documents: identifying properties of the retrieved document, and applying the identified properties of the retrieved document to the user-specific learning machine to estimate a probability that the retrieved document is of interest to the user; and	*See* citations for '040 Patent, claim 1[d, e].

g) using the estimated probabilities for the respective plurality of retrieved documents to present at least a portion of the retrieved documents to the user.	*See* citations for '040 Patent, claim 1[f]. MLADENIC, p. 2: "The idea is that the user provides a few keywords describing a search goal and WebWatcher highlights related hyperlinks on the current page and/or adds new hyperlinks to the current page."
Claim 3	
3. The method of claim **1**, wherein transparently monitoring user interactions with data comprises monitoring user interactions with data during multiple different modes of user interaction with network data.	MLADENIC, p. 3: "Unlike WebWatcher, Personal WebWatcher(PWW) is structured to specialize for a particular user, modeling her/his interests. It "watches over the user shoulder" the similar way WebWatcher does, but it avoids involving the user in its learning process." *See also*: **CULLISS** at 2:43-46, 3:29-35, 3:46-56. **REFUAH** at 5:34-50. **SCHUETZE** at 18:11-17. **WASFI** at 58, 61. Autonomy Press Release, at 1
Claim 5	
5. The method of claim **1**, further comprising analyzing the monitored data to determine documents not of interest to the user, and wherein estimating parameters of a	MLADENIC, p. 8: "Hyperlinks whose documents were visited by the user are considered to be positive examples, and all the other to be negative examples of the user interests. The idea is that all hyperlinks were presented to the user and the user chose to visit some of them that meet her/his interests." *See generally* pp. 10-11. *See also*:

user-specific learning machine further comprises estimating parameters of a user-specific learning machine based at least in part on the documents not of interest to the user.	**CULLISS** at 3:57-65, 4:61-64, 5:4-10. **REFUAH** at 22:6-14. **SCHUETZE** at 17:47-67. **WASFI** at 58. **TAN** at 4.2.1, 4.3.2. Autonomy Press Release, at 1 Autonomy Technology Whitepaper, at AUT00070 Autonomy Agentware User Guide, at AUT00123
Claim 6	
6. The method of claim **1**, wherein monitoring user interactions with data for a document comprises monitoring at least one type of data selected from the group consisting of information about the document, whether the user viewed the document, information about the user's interaction with the document, context information, the user's degree of interest in the	MLADENIC, p. 8: "Hyperlinks whose documents were visited by the user are considered to be positive examples, and all the other to be negative examples of the user interests. The idea is that all hyperlinks were presented to the user and the user chose to visit some of them that meet her/his interests." *See also*: **CULLISS** at 2:43-46, 3:27-35. **REFUAH** at 5:34-50, 14:54-59. **SCHUETZE** at 5:36-40, 11:12-14, 18:11-17. **WASFI** at Abstract, 60, 61.

document, time spent by the user viewing the document, whether the user followed at least one link contained in the document, and a number of links in the document followed by the user.	
Claim 7	
7. The method of claim **1**, wherein said plurality of retrieved documents correspond to a respective plurality of products.	MLADENIC, p. 2: "Personal WebWatcher is a system that observes users of the WWW and suggests pages they might be interested in." p. 2: "Web Watcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough." p. 8, Figure 2: 

	See also: **CULLISS** at 9:55- 10:13. *See generally* 9:55 – 11:33. **REFUAH** at 1:63 – 2:2, 3:56 – 4:4, 7:24-32, 18:35-39, 18:40-55. **SCHUETZE** at 35:66 – 36:8.
Claim 21	
21. The method of claim **1**, wherein using the estimated probabilities for the respective plurality of retrieved documents to present at least a portion of the retrieved documents to the user comprises presenting to the user at least said portion of the retrieved documents based on the estimated probability that the retrieved document is of interest to the user and the relevance of the retrieved document to the search query.	MLADENIC, p. 2: "WebWatcher can be described as an agent that assists users in locating information on the WWW. It learns by observing a user on her/his way through the WWW and suggests interesting hyperlinks whenever it is confident enough. The idea is that the user provides a few keywords describing a search goal and WebWatcher highlights related hyperlinks on the current page and/or adds new hyperlinks to the current page." *See* citations for claim 1[g].
Claim 22	
22. The method of claim **1**, wherein identifying properties of the retrieved	MLADENIC, p. 2: "[Personal WebWatcher] can also suggest pages related to the current page using information stored in the structure of hypertext without considering the text itself."

document comprises identifying properties selected from the properties consisting of a topic associated with the retrieved document, at least one product feature extracted from the retrieved document, an author of the retrieved document, an age of the retrieved document, a list of documents linked to the retrieved document, a number of users who have accessed the retrieved document, and a number of users who have saved the retrieved document in a favorite document list.	p. 3: "It solely records the addresses of pages requested by the user and highlights hyperlinks that it believes will be of interest." p. 4: "We decided to use the bag-of-words representation using frequency of word and observe success of given advice (whether user selected the advised hyperlink). In case of poor system performance, some additional information from HTML-structure could be added, for example, frequency of word in headlines of a given document." p. 10: "Since the prediction should be performed while the user is waiting for an HTML-document, we are actually predicting interestingness of [sic] document based on the hyperlink pointing to it, and not the document itself... [b]ut during the learning phase we can afford using more time than when adding advice, so why not retrieving [sic] documents behind hyperlinks, instead of using the extended hyperlink representation?" p. 12: "Documents are currently represented using the bag-of-words approach (see Section 3.1) and feature selection is performed using mutual information approach (see Section 3.2)." *See generally* 3-6. *See also*: **CULLISS** at 2:26-37. **REFUAH** at 7:53 – 8:6, 9:50-59, 20:19-30, 21:6-30. *See generally* 20:19- 21:36. **SCHUETZE** at 6:58 – 7:15, 10:40-56, Fig. 3. *See generally* 17:47 – 18:27. **WASFI** at 61.

EXHIBIT 3 B

Exhibit 3-B

Claim Chart of Autonomy's Agentware

as prior art to

Asserted Claim of U.S. Patent No. 6,9981,040 ("'040 Patent")
and
Asserted Claims of U.S. Patent No. 7,685,276 ("'276 Patent")

'040 Patent	AGENTWARE
Claim 1	
A computer-implemented method for providing automatic, personalized information services to a user u, the method comprising:	Autonomy's Agentware is a piece of software that "enables automatic personalization of Web content as well as flexible management of unstructured information." (Autonomy White Paper at 11.) Autonomy's Agentware employs "agents," or small programs that "locate information based on concepts and context, thereby selecting the most relevant information according to the individual's preferences." (Autonomy PR at 1). These personalized agents can learn about a user's interests in a variety of ways, including by "simply observing a user's actions." Accordingly, agents "do not require [the user] to fill out lengthy questionnaires or rate his likes and dislikes." Agents can "analyze a text and identify the key concepts within the document because [they] understand[] how the frequency and relationships of terms correlate with meaning." (Autonomy WP at 1). Once an agent has been trained, "it can compare [a pattern] to the documents it finds on the Internet. Autonomy does not use keyword searches, but actually identifies the concepts involved in the text and compares them. It then assigns a relevance to the document depending on how closely it matches the patterns established by the training." (Autonomy UG at 4). "By maintaining a set of agents that correspond to a user's interests, on-line publishers and service providers can then offer a range of personalized services." (Autonomy WP at 2.) *See* Autonomy Press Release, at 1 ("Agentware 1.1, the first-ever product that delivers personalized information from the Internet by learning the preferences and needs of the user")

	Autonomy Press Release, at 2 ("They can 'live' on the user's PC (client) or on a publisher's Website (server) . . .") Autonomy Press Release, at 2 ("Agentware 1.1 requires a 486DX or microprocessor running Windows 95 or 3.11 . . ." Autonomy Technology Whitepaper, at AUT00068 ("Autonomy's technology offers a breakthrough in managing unstructured digital information, including word process and HTM-based files, email messages, and electronic news feeds.") Autonomy Technology Whitepaper, at AUT00078 ("Autonomy's software enables automatic personalization of Web content as well as flexible management of unstructured information.") Autonomy Agentware User Guide, at AUT00002 ("Autonomy Agentware is the first mass market application of Artificial Intelligence technology for the Internet") Autonomy Agentware User Guide, at AUT00004 ("Autonomy browses the web like a person, reacting to its environment, and bringing back only the relevant pages")
a) transparently monitoring user interactions with data while the user is engaged in normal use of a computer;	Autonomy Press Release, at 1 (Agentware "automatically learns user preferences to deliver personalized information on demand.") Autonomy Press Release, at 2 ("The Agent keeps learning about your user's interests and will adapt accordingly as your interests change") Autonomy Technology Whitepaper, AUT00069 ("As users' needs and interests change, the agents dynamically track those shifts without the need for manual intervention") Autonomy Technology Whitepaper, AUT00070 ("Many of Autonomy's products rely on user interest or employee expertise profiles created implicitly, simply by observing user's actions") Autonomy Technology Whitepaper, AUT00070 ("Autonomy's software applies the pattern-

	matching technology to extract key ideas from the articles a user reads online." Autonomy Technology Whitepaper, AUT00070 ("Because these services are based on a user's actual interests, they do not require him to fill out lengthy questionnaires or rate his likes and dislikes.") Autonomy Technology Whitepaper, AUT00070 ("As an individual reads additional articles online, publishes material on the corporate intranet or submits documents to the knowledge management system, the Autonomy system updates his agents by recalculating interest levels in the different ideas. . . . In this way, the Autonomy system keeps pace with an individual's changing interests. This is in contrast to an explicit preference setting, which users must remember to adjust as their interests evolve") Autonomy Agentware User Guide, at AUT00119 ("The Agents in Autonomy are intelligent because they learn all the time that you use them. Autonomy learns by retraining using samples of good documents. . . . Autonomy bases its assessment of how common phrases are on an initial knowledge of English, and what it learns from you as you use it. For example, if every document in your library is about aeroplanes, Autonomy will start to conclude that the phrase 'aeroplane' is less important than say 'safety systems' in your training text. Autonomy will adapt to the style of English that you use to train it, and the style used in documents that you decide to keep") *See also* **SCHUETZE** at 5:36-40, 11:12-14, 18:11-17, 28:65 – 29:6 **CULLISS** at 3:46-56; 5:18-21; 7:14-20. **MLADENIC**, at 3. **REFUAH** at Abstract; 3:3-11; 5:34-50; 19:20-22. **WASFI** at Abstract, 60.

	MONTEBELLO at 3.
b) updating user-specific data files, wherein the user-specific data files comprise the monitored user interactions with the data and a set of documents associated with the user;	Autonomy Press Release, at 1 ("Simply name your Agent and train it by typing in a sentence or two in plain English. . . . The Agent keeps learning about your user's interests and will adapt accordingly as your interests change.") Autonomy Technology Whitepaper, at AUT00069 ("Autonomy's technology also can create highly specific user profiles by analyzing and abstracting *Concept Agents* from every article a user reads. By maintaining a set of agents that correspond to a user's interests, on-line publishers and service providers can then offer a range of personalized services.") Autonomy Technology Whitepaper, at AUT000069 ("Concept Agents are created by having the DRE (Dynamic Reasoning Engine) process a set of text. This text could be a phrase that is typed specifically to train the agent, or could consist of an existing document or set of documents") Autonomy Technology Whitepaper, at AUT00070 ("Online publishers and Intranet developers can maintain sets of agents representing an individual's interests to offer a number of personalized services.") Autonomy Technology Whitepaper, at AUT00070 ("As a user is served documents, Autonomy's software automatically creates a set of *Concept Agents*.") Autonomy Technology Whitepaper, at AUT00070 ("Many of Autonomy's products rely on user interest or employee expertise profiles created implicitly, simply by observing a user's actions.") *See also* **SCHUETZE** at 10:14-18, 10:32-39, 11:12-17, 17:47 – 18:27, 28:65 – 29:6, 34:34-37 **CULLISS** at 3:13-35; 5:36-48; 7:14-42. **MLADENIC** at 3, 8.

	REFUAH at Abstract; 5:34-50; 6:5-15; 8:31-39; 20:31-37. **WASFI** at 58, 60, 61. **MONTEBELLO** at 3-4.
c) estimating parameters of a learning machine, wherein the parameters define a User Model specific to the user and wherein the parameters are estimated in part from the user-specific data files;	Autonomy Press Release, at 1 ("Autonomy's Agentware use Agents which locate information based on concepts and context, thereby selecting the most relevant information according to the individual's preferences") Autonomy Press Release, at 1 ("Simply name your Agent and train it by typing in a sentence or two in plain English. . . . The Agent can now be sent out to scour the Internet, bringing back a selection of relevant information. The Agent keeps learning about your user's interests and will adapt accordingly as your interests change.") Autonomy Technology Whitepaper, at AUT00069 ("Autonomy's technology can create highly specific user profiles by analyzing and abstracting *Concept Agents* from every article a user reads. By maintaining a set of agents that correspond to a user's interests, online publishers and service providers can then offer a range of personalized services. As users' needs and interests change, the agents dynamically track those shifts without the need for manual intervention.") Autonomy Technology Whitepaper, at AUT00070 ("typical applications maintain a set of multiple *Concept Agents* for each user.") Autonomy Technology Whitepaper, at AUT00070 ("Autonomy's software applies the pattern-matching technology to extract key ideas from the articles a user reads online. As a user is served documents, Autonomy's software automatically creates a set of *Concept Agents*. By weighting the frequency with which certain topics occur, the server can then encode a set of interests into Autonomy *Concept Agents*.") \ Autonomy Technology Whitepaper, AUT00070 ("As an individual reads additional articles online, publishes material on the corporate intranet or submits documents to the knowledge management

	system, the Autonomy system updates his agents by recalculating interest levels in the different ideas. . . . In this way, the Autonomy system keeps pace with an individual's changing interests.") Autonomy Agentware User Guide, at AUT00002 ("Autonomy learns by changing the search criteria of an Agent to reflect your choices of good documents") *See also* **SCHUETZE** at 27:44-64, 27:65-28:14 **CULLISS** at 3:57-65; 4:54 – 5:10. **MLADENIC**, at 9, 10. **REFUAH** at 2:9-35; 6:49-64; 8:30-58; *See generally* 14:21 – 15:45. **WASFI** at 58, 61, 63. **MONTEBELLO** at 3, 4.
d) analyzing a document d to identify properties of the document;	Autonomy Press Release, at 1 ("a user interested in business information could create an Agent, name it 'Traveler', and send it out to look for travel arrangement information based on their own designated personal preferences . . .") Autonomy Technology Whitepaper, at AUT00068 ("the technology can analyze a text and identify the key concepts within the document because it understands how the frequency and relationships of terms correlate with meaning. . . . Autonomy . . . extract[s] a document's digital essence and determine[s] the characteristics that give the text meaning. Once Autonomy's technology has identified and encoded the unique 'signature' of the key concepts, Concept Agents are created to seek out similar ideas in websites, news fees, email archives and other documents." Autonomy Technology Whitepaper, at AUT00069 ("Autonomy's APCM technology can analyze a piece of text and determine the main ideas through its understanding of how the frequency and

	relationships of terms correlates with meanings") Autonomy Technology Whitepaper, at AUT00069 ("the idea, or concept is represented by the pattern of terms and contextual relationships that are most commonly recognized as important in documents that address the concept") Autonomy Technology Whitepaper, at AUT00069 ("*Concept Agents* can be used to automatically sort documents into pre-defined categories. . . .") Autonomy Technology Whitepaper, at AUT00071 (describing sorting of documents into pre-defined categories) Autonomy Technology Whitepaper, at AUT00071 (describing the use of Shannon's Information Theory "which enables Agentware to determine the most important (or informative) concepts within a document.") Autonomy Agentware User Guide, at AUT00002 ("Once Autonomy has identified this 'pattern' in the training text it can compare it to the documents it finds on the Internet. Autonomy does not use keyword searches, but actually identifies the concepts involved in the text and compares them. It then assigns a relevance to the document depending on how closely it matches the pattern established by the training.") Autonomy Agentware User Guide, at AUT00117 ("In the Library Hit List, the documents are ranked in order of relevance to your query, as indicated by the length of the 'bone' shown beside them") *See also* **SCHUETZE** at 3:40-44, 5:59-63, 5:59-63, 10:20-31, 11:42 – 15:19 **CULLISS** at 2:43-46; 5:36-48; 10:47-52. **MLADENIC**, at 4, 12.

	REFUAH at 7:53 – 8:6; 20:31-37; 21:6-30. **WASFI** at 61. **MONTEBELLO** at 3, 4.
e) estimating a probability P(u|d) that an unseen document d is of interest to the user u, wherein the probability P(u|d) is estimated by applying the identified properties of the document to the learning machine having the parameters defined by the User Model; and	Autonomy Press Release, at 1 ("Autonomy's Agentware use Agents which locate information based on concepts and context, thereby selecting the most relevant information according to the individual's preferences") Autonomy Press Release, at 1 ("Simply name your Agent and train it by typing in a sentence or two in plain English. . . . The Agent can now be sent out to scour the Internet, bringing back a selection of relevant information. The Agent keeps learning about your user's interests and will adapt accordingly as your interests change.") Autonomy Press Release, at 1 ("Autonomy Agents are persistent. They can be used again and again . . .") Autonomy Press Release, at 2 ("Agentware 1.1, is based on the Dynamic Reasoning Engine (DRE) . . .") Autonomy Press Release, at 1 ("a user interested in business information could create an Agent, name it 'Traveler', and send it out to look for travel arrangement information based on their own designated personal preferences . . .") Autonomy Technology Whitepaper, at AUT00069 ("Concept agents are created by having the DRE (Dynamic Reasoning Engine) process a set of text. . . . The agent then reviews the source text and calculates the patterns of its most important concepts . . ." Autonomy Technology Whitepaper, at AUT00071 (describing the use of Bayesian analysis as "centered on calculating the probabilistic relationship between multiple variables and determining the extent to which one variable impacts another.")

	Autonomy Agentware User Guide, at AUT00119 ("Autonomy's neural network is able to identify the important words and phrases in your training text, and then apply a weighting based upon how common the phrase is according to its knowledge of language") *See also* **SCHUETZE** at 18:62 – 19:10 **CULLISS** at 2:43-51; 5:36-62. **MLADENIC** at 5, 7, 10, 12, Table 2. **REFUAH** at 3:56 – 4:4; 17:32 – 18:4. **WASFI** at 60, 61. **MONTEBELLO** at 4.
f) using the estimated probability to provide automatic, personalized information services to the user.	Autonomy Press Release, at 1 ("Agentware 1.1, the first-ever product that delivers personalized information from the Internet by learning the preferences and needs of the user") Autonomy Press Release, at 1 ("Autonomy's Agentware use Agents which locate information based on concepts and context, thereby selecting the most relevant information according to the individual's preferences") Autonomy Press Release, at 1 ("Simply name your Agent and train it by typing in a sentence or two in plain English. . . . The Agent can now be sent out to scour the Internet, bringing back a selection of relevant information. The Agent keeps learning about your user's interests and will adapt accordingly as your interests change.") Autonomy Press Release, at 1 ("Autonomy Agents are persistent. They can be used again and again . . .")