B. Because *Wasfi* Does Not Teach Estimating Parameters of a Learning Machine that Define a User Model Specific to the User and which are Estimated From User-Specific Data Files, *Wasfi* Cannot Anticipate Claims 1, 21, 22 and 32.

In the ACP, claims 1, 21, 22 and 32 were rejected under 35 U.S.C. §§ 102(a) and (b) as being anticipated by *Wasfi*. This was an error. In fact, because the present claims recite features not discussed by *Wasfi*, *Wasfi* does not anticipate any of the present claims. *Verdegaal Bros., supra,* 814 F.2d at 631.

Independent claims 1 and 32 each recite: "estimating a probability P(u|d) that an unseen document d is of interest to the user u". The claims further require that this probability be estimated *by applying identified properties of the unseen document to the learning machine*. See element (e) in claims 1 and 32, '040 Patent col. 32, ll. 39-43, and col. 35, ll. 31-35.

Wasfi, on the other hand, suggests pages of a subject web site according to separate content-based and collaborative filters. *Wasfi* at p. 61. The collaborative filtering process is based on a probability, but *not* a probability that is determined by applying any document properties to a user model. Instead, the collaborative filtering process relies on probabilities of a user visiting a next page in a sequence of pages, as determined by conditional probabilities derived from page navigations performed by prior visitors to the subject web site. *Id*. On this point *Wasfi* states: "it is reasonable to advise one user of what was done by others . . . For instance, when there is a high probability of visiting page B given page A, it may indicate that B has an important content." *Id*. Therefore, ProfBuilder "finds pages from the user's current path, which is in this application only his/her current page, and select[s] the top-frequency pages for presentation to the user." *Id*., and see *id*. at p. 63 rt. col. ("In this paper we have proposed a new learning mechanism to learn user preferences from the retrieved pages. It is based on their probabilities, *which are obtained from collecting visiting patterns of past users*." (emphasis added)).

No application of any page properties to any user model is made in order to derive these page probabilities. Instead, *Wasfi's* ProfBuilder system merely takes the current page that a user is at, consults a frequency model of which pages other users visited next, and presents the top-frequency pages for consideration by the current user. See, e.g., *id*. at pp. 61, 63; Nicholas Dec. at para. 15. This is a significantly different procedure than that recited in the claims and so the collaborative filtering process described by *Wasfi* cannot anticipate the present claims.

The content-based filter operates in a very different manner — one that is unrelated to probabilities. In this regard, *Wasfi* describes determining a similarity between a page (represented by vector D_i) and the user (represented by a vector Q_j). In particular,

$$Similarity(D_i, Q_j) = \sum_k w_{ik} * w_{jk}$$

Wasfi at p. 61. As discussed above, this vector scalar product is *not* a probability, nor is it an estimate of probability.[24] Instead, the result is merely a number,[25] specifically an algebraic sum of a series of products of weights, w. The weights, w, are identified as TFIDF measures, *id*. at p. 61, that is, measures of the frequency with which certain words appear in the vectors representing the document and the user. There is nothing probabilistic about such a sum and it has none of the hallmarks of a probability (or an estimate thereof). Nicholas Dec. at para. 16.

To make this point more plain, consider that *Wasfi's* scalar products have no absolute meaning. It is true that when grouped with other similarity measures one can rank pages according to their respective similarity metrics (and so *Wasfi's* ProfBuilder is able to present pages in some ranked order, see *Wasfi*, p. 62, Fig. 2), but this says nothing about the probability that any given page is interesting or not. Probabilities have absolute meaning within a defined range.

Hence, *Wasfi* does not teach estimating a probability P(u|d) that an unseen document d is of interest to the user u *by applying identified properties of the unseen document to the learning machine* as recited in independent claims 1 and 32 and so cannot anticipate the present claims. When discussing probabilities, *Wasfi* is referring to collaborative filtering, which makes predictions solely on the actions of prior visitors to the subject web site and not any user model. When using a user model, as part of a content filter, and applying the properties of documents thereto, *Wasfi* eschews probabilities in favor of similarity metrics that are not probabilities or estimates thereof.[26] Accordingly, *Wasfi* does not anticipate the claims of the '040 Patent.

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[24] As alluded to above, *Wasfi's* similarity metric resembles a cosine value of the vectorized document and user profile. See, e.g., *Yang* at p. 15, eq. 1, describing the conventional similarity measure for two vectors. *Wasfi's* formulation fails to include a denominator term, however, in practice, one often normalizes results, obviating the need for a denominator. *Yang* specifically indicated that such a measure is *not* a probability. *Yang* at p. 16.

[25] The dot product of two vectors is a number, not a vector.

[26] Thus *Wasfi* itself distinguished between use of probabilities when no user model is considered and use of a different measure when such a model is considered. See Nicholas Dec. at para. 17.

C. Because *Wasfi* Does Not Teach a Learning Machine that Attempts to Improve its Predictive Ability, *Wasfi* Cannot Anticipate Claims 1, 21, 22 and 32.

The "learning machine" recited in the claims has been construed as a mathematical function and/or model used to make a prediction, that attempts to improve its predictive ability over time by altering the values/weights given in its variables. Earlier it was shown that this is the broadest reasonable interpretation of the term and so should be the same construction accorded by the USPTO. Wasfi's user profile does not satisfy this criterion and so cannot be deemed equivalent to the recited learning model.

The vector Q_j, which is *Wasfi's* user profile, is a set of weighted keywords from documents the user has visited. *Wasfi* at pp. 58, 61. In other words, *Wasfi* teaches simple memorization of these keywords. Such a user model is not one that *that attempts to improve its predictive ability over time*. Consider a simple case of a user interested in basketball. A model that is constructed from a document that describes "dunking the ball" is of little or no value when trying to classify a document that discusses "the jump shot". The lack of overlapping keywords renders the user model unhelpful at best and perhaps even useless.

The learning machine recited in the claims, on the other hand, "generalizes" (i.e., attempts to improve its predictive ability over time). Generalization is the ability of a machine-learning algorithm to perform accurately on new, unseen examples after training on a finite data set. The core objective of a learner is to generalize from its experience. Such "learning" is absent from *Wasfi*[27] and this is a further reason why *Wasfi* does not anticipate the present claims.

D. Because *Wasfi* Does Not Teach Estimating Parameters of a Learning Machine that Define a User Model Specific to the User and which are Estimated From User-Specific Data Files, *Wasfi* Cannot Anticipate Claims 1, 21, 22 and 32.

As indicated above, *Wasfi's* "learning mechanism" relies on "probabilities, which are obtained from collecting the visiting patterns of past users." *Id*. at p. 63. Such visiting patterns are not "user-specific data files" in the sense recited in claims 1 and 32, because they are activities of web site visitors other than the "user" of interest (i.e., the one for whom interestingness of unseen pages is to be determined). Hence, *Wasfi* cannot anticipate claims 1 and 32, or any of their respective dependent claims.

[27] The reformulation formula for Q_j on p. 58 of *Wasfi* does not compel a different result. Notice that the variable t_{ij} is always a nonnegative number. *Wasfi* at p. 58. Hence, word weights can only ever increase and, as a result, the model will eventually saturate with only highly weighted words. Such a model will not generalize and so does not meet the requirements of the present claims.

It was noted above that the learning mechanism described by *Wasfi* relies on the variable t_{ij}, which represents some form of entropy of a page at the subject web site. The entropy of a page is determined by "collecting the visiting patterns of many users." *Id*. at p. 59. Indeed, this is noted as one of ProfBuilder's weaknesses. "[O]ne problem of its learning mechanism is that it needs large numbers of users, in order to have enough data for reflecting the interdependency between pages." *Id*. at p. 63. Without this prior user data, there is no way to update the user model, Q_j. Indeed, the entire premise of ProfBuilder's predictive ability is rooted in the idea that past actions of prior users is the way to determine when a current user's interests have changed. ProfBuilder is not concerned with or centered on a user model that is made up of parameters estimated from user-specific data files. Instead, just the opposite is true – ProfBuilder is organized around a user model that is determined by the activities of other visitors to the subject web site. *Id*. at pp. 58-59.

To summarize, *Wasfi* describes a learning mechanism that updates parameters of a user model according to web site navigation activities of previous visitors to the subject web site. In contrast, the claims recite a process in which the parameters of a learning machine are estimated from user-specific data files. The two are quite distinct and so *Wasfi* cannot be said to anticipate the present claims.

E. Because *Culliss* does not Cure the Deficiencies of *Wasfi* with Respect to Estimating a Probability that the Document is of Interest to a User by Applying the Identified Properties to a Learning Machine, Claims 11, 22 and 34 Remain Patentable Over the Combination of *Wasfi* and *Culliss*.

It was noted above that *Culliss* does not, indeed cannot, disclose "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." Instead, *Culliss* requires the existence of a query in order to produce any results. Absent the query, the Culliss system is unable to estimate any user interest in a document. See *Culliss* at 5:18-35. Accordingly, even if the teachings of *Culliss* were combined with those of *Wasfi*, such a combination still would not yield the step of "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", inasmuch as neither reference teaches or suggests such estimation. Stated differently, the claims remain patentable over the combination of *Wasfi* and *Culliss*.

IV. RESPONSE TO REJECTIONS BASED ON PRIMARY REFERENCE *REFUAH*

A. *Refuah* is not Prior Art under 35 U.S.C. §102(e).

The Third Party Requester made an erroneous allegation, which the Examiner adopted but did not address when the issue was raised in the Patent Owner's Response filed on July 27, 2011. Response at 25. *Refuah* does not qualify as prior art under 35 USC §102(e). Under 35 USC 102(e), only if the subject U.S. patent's international (i.e., PCT) application parent was filed on or after November 29, 2000 (and its corresponding WIPO publication was in English and designated the United States), is the patent's 102(e) date the international filing date (or an earlier filing date if a priority benefit is properly sought). In all other cases, the subject patent's 102(e) date is the date on which the requirements of 35 USC 371(c) (1), (2) and (4) were satisfied. See 35 U.S.C. 102(e) and MPEP 706.02(a).

Refuah is a U.S. national stage application under 35 USC 371 that is based on an international application filed January 28, 1999, i.e., *before November 29, 2000*. Hence, the 102(e) date for *Refuah* is the date on which the requirements of 35 USC 371(c) (1), (2) and (4) were satisfied. According to the face of the *Refuah* patent, this date was July 28, 2000.

The subject '040 Patent was filed June 20, 2000 (excluding any consideration of its priority claim to December 28, 1999), i.e., *before* the effective 102(e) date of *Refuah*. Accordingly, because all of the present rejections that rely on *Refuah* as a primary reference do so under the guise of 35 USC 102(e), all of those rejections are inadequate as a matter of law and must be withdrawn.

B. Because *Refuah* Does Not Teach Estimating Parameters of a Learning Machine, Claims 1 and 32 and Their Respective Dependent Claims Are Not Anticipated by *Refuah*.

On the face of the *Refuah* patent, nowhere does *Refuah* disclose "learning," "learning machine," "probability," or "estimating a probability."

Refuah describes a method of searching and retrieving information from the Internet, which is personalized to a particular user as identified by a persona and a mood so that format and presentation are adapted according to the user preferences. See *Refuah* at Figs. 1 & 2, and 13:53-57, 16:35-37; Nicholas Dec. at paras. 18-19. Contrary to the conclusions set forth in the

ACP, however, *Refuah* does not teach 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. In particular, at 17:44-46, *Refuah* discusses how a site is evaluated for suitability and/or for qualities which are preferred and/or matched to a particular persona. Examples of such qualities include the number of images in the site, expected download times and/or the number of links from the site. *Refuah* at 17:46-48. Evaluation of such criteria is not an estimation of a probability, P(u|d), as recited in claims 1 and 32. At best, it is perhaps a discussion of a matching process to determine if discrete qualities of a site are the same as those included in a persona. Certainly none of these measured qualities is an estimate of a probability.

In the ACP, the Examiner cited the alleged assertion in the Request where Requester made no reference as to why *Refuah* anticipates a "learning machine" in claim 1. ACP at p. 23; Request at pp. 26-27. Requester appears to contend that "a mood and/or persona [which] may be updated by modifying continuous parameters" as the reason that *Refuah* teaches a learning machine. *Id*. This argument has no foundational basis. The characteristics of mood is temporal where the mood modifies a persona and acts as a temporal change of persona. *Refuah* gave an example where if a user is in a rushed mood, only a line will be displayed for each search result. *Refuah* at 3:20-22. There is no learning about the user as recited in claim 1 that requires "estimating parameters of a learning machine, wherein parameters define a User Model to the user and wherein the parameters are estimated in part from the user-specific data files."

The Examiner elaborated on the claim constructions for "learning machine" and "User Model specific to the user." ACP at p. 23. However, claim 1 recites a "learning machine" (or user model) that is construed as a mathematical model that attempts to estimate and improve the user's interest, which is not taught by *Refuah*. The teaching in *Refuah* centers around the combinational use of persona and/or mood to affect the display or view on the interaction between a user and the Internet. *Refuah* at 2:63-66 and 13:64-66. The objective in the *Refuah* patent is to achieve certain display effects, such as limiting the display of information and affecting the format of a site on a computer display. *Refuah* simply does not teach a learning machine that takes user-specific data files and estimate parameters of a user model.

The phrase "estimating parameters of a learning machine" has been construed to mean "estimating values or weights of the variables of a learning machine." Markman Order at p. 1.

The term "learning machine" has been construed to mean a "mathematical function and/or model used to make a prediction, that attempts to improve its predictive ability over time by altering the values/weights." *Id.* at pp. 1-2. The parameters in *Refuah* are distinguishable from the "parameters of a learning machine." *Rufuah* discloses a positive parameter or a negative parameter, e.g., "subject of interest – chess," or "reject – pornography." *Refuah* at 6:49-53. *Rufuah* further describes the parameters can include weight information as a relative preference of subjects of interests, and functional information on how to evaluate a particular parameter. *Id.* at 6:54-58. The parameters in *Refuah*, however, refer to personal data elements or attributes of persona, which are not the values or weights of the variables of a learning machine (or mathematical function). Thus, *Refuah* does not disclose "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."

Refuah does not teach or suggest "estimating parameters of a user-specific learning machine based at least in part on the documents of interest to the user," as recited in the claims. As described above, the term "learning machine" was determined to mean a "mathematical function and/or model used to make a prediction, that attempts to improve its predictive ability over time by altering the values/weights given to its variables, depending on a variety of knowledge sources, including monitored user interactions with data and a set of documents associated with the user." Markman Order, pp. 2-3. The use of cookies and subject categories in updating a persona and/or mood is not equivalent to estimating probabilities using a learning machine. The personality cookie described by *Refuah* is not and does not provide a "mathematical function and/or model used to make a prediction, that attempts to improve its predictive ability over time by altering the values/weights given to its variables, depending on a variety of knowledge sources, including monitored user interactions with data and a set of documents associated with the user."

Requester further cited "a parameter may be reflexive towards the persona" as teaching estimating parameters of a learning machine. ACP at 23; Request at 26. The word "reflexive" was used just once in *Refuah* as an additional or alternate approach to modify persona and/or a mood based on user activities without any elaboration of what this means. *Refuah* at col. 6:59-62. *Refuah* does not describe how aggressive, moderate, or incremental change based on a user activity in the direction of persona and mood that would be considered as reflexive. Even though a parameter may be changed to be reflexive toward a persona, such brief description in *Refuah* falls short as a mathematical function or model that is used to make a prediction that attempts to improve its predictive ability over time. See Nicholas Dec. at para. 19. If the reflexive is viewed as an addition, the parameters in *Refuah* describe a parameter "subject of interest = chess." *Refuah* at col. 6:49-50. It follows that the reflexive parameter of a persona in *Refuah* would identify the user as either interested or disinterested in chess, which is a characteristic of a binary matching or memorization as somehow characterizing the user's interest in chess, than the claimed invention in estimating parameters of a learning machine.

C. Because *Refuah* Does Not Teach Estimating a Probability That an Unseen Document is of Interest to the User, Claims 1 and 32 and Their Respective Dependent Claims Are Not Anticipated by *Refuah*.

The Examiner is mistaken in adopting the Requester's illogical statement. The Requester stated that "[t]his 'evaluation of suitability' clearly qualifies as 'estimating a probability' that the document is of interest to the user." ACP at p. 24; Request at p. 27. Such reasoning was further compounded when the Requester asserted that "[t]he evaluation of suitability disclosed in *Refuah* also extends to 'unseen' sites." *Id*. This allegation is flawed from many angles.

The teaching of *Refuah* is directed to evaluating a "website" or a "site" instead of "analyzing a document" to identify properties of the document or "estimating a probability" that an unseen document is of interest to the user. A website in *Refuah* is different from a document in the claimed invention. In fact, *Refuah* made this exact argument during prosecution that "Herz describes identifying WWW [web] pages of interest based on their content. (Col. 67, lines 30-35). Hertz does not teach or suggest determining a trait of a site." Prosecution history of *Refuah*, Amendment at p. 23, January 5, 2004. Evaluation[28] of suitability is more general and refers to a site as suitable or not suitable. It is not credible for Requester to claim that evaluation of suitability of a site clearly qualifies as estimating a probability about a document. There is no basis in analogizing or even in equating the two, as they are distinctively different.

Assuming *arguendo* that we continue this line of analysis by looking into what *Refuah* meant by evaluation of a site, the description in *Refuah* fails to provide any credence to the

[28] The word "evaluation" has been defined as "the comparison of actual impacts against strategic plans. It looks at original objectives, at what was accomplished and how it was accomplished. It can be formative, that is taking place during the life of a project or organization, with the intention of improving the strategy or way of functioning of the project or organization. It can also be summative, drawing lessons from a completed project or an organization that is no longer functioning." http://en.wikipedia.org/wiki/Evaluation.

Requester's assertion. *Refuah* describes a matching feature where a site is evaluated for suitability and/or for qualities which are preferred and/or match a particular persona. *Refuah* at 17:44-46. *Refuah* gave an example of what it means by "matching a particular persona," such as the number of images in the site, expected download time, and/or number of links from the site. *Id. Refuah* teaches a binary match in the evaluation of a site, which is distinctively different from estimating a probability.

Requester further argued that "evaluation of suitability" [of a site] clearly qualifies "estimating a probability" because this phrase has been construed as "approximating or roughly calculating a numerical degree of belief or likelihood that an unseen document d is of interest to the user u given the information that is known about the unseen document." ACP at p. 25; Request, OTH-B at p. 23. The evaluation in the suitability of a site in *Refuah* is not based on the content of a document (or a web page), but rather by matching a user's persona and/or mood to determine if a site is suitable or not suitable. *Refuah* at 3:64-4:l, 6:23-26, and 17:44-48. The evaluation of a site in *Refuah* employs a binary matching that the site is suitable for the user or the site is not suitable for the user. Estimating a probability in the claimed invention requires a numerical degree of belief, which is not taught by *Refuah*.

For the reasons discussed above, Patent Owner respectfully requests the Examiner confirm the patentability of claims 1 and 32 over *Refuah*.

Furthermore, *Refuah* does not disclose analyzing a document to identify properties of the document, as recited in step 1d. As discussed above, the *Refuah* patent is directed to evaluating a "website" or a "site" instead of "analyzing a document" to identify properties of the document. During prosecution, *Refuah* affirmatively and unequivocally isolated itself from this claimed limitation in arguing that the subject matter disclosed in *Refuah* concerns determining a trait of a site, rather than identifying web pages of interest based on their content. See *Refuah* prosecution history, Amendment filed January 5, 2004, at p. 23. Therefore, *Refuah* does not teach the claimed limitation "analyzing a document d to identify properties of document," and claims 1 and 32 are patentable over *Refuah*.

Claim 11 depends from claim 1 and therefore is not anticipated by *Refuah* for at least all of the same reasons as claim 1. Claim 11 further recites 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. The ACP relies on *Refuah* for teaching personalization that can affect "many methods" of information retrieval. *Refuah* at 17:22-24. The search engine retrieves matches for a query and the user's persona and mood affect the sorting or filtering of the results. *Id*. at 17:27-36.

While interesting, this is not what is being claimed. Filtering search results according to a persona does not necessarily involve estimating a posterior probability, but instead *Refuah* describes filtering search results based on a site that they originated from according to binary matches with the persona, such as the number images. *Refuah* at 17:44-46. Even if it is somehow considered posterior probability, a point not conceded by any means, it is not directed to a document but rather for a website as described in col. 17 in *Refuah*. Indeed, it appears *Refuah* makes use of a simple comparison. *Refuah* at 17:36-48. No probabilities, prior, posterior or otherwise, are estimated. Hence, this is a further reason why *Refuah* does not anticipate claim 11.

Claim 21 depends from claim 1 and therefore is not anticipated by *Refuah* for at least all of the same reasons as claim 1. Claim 21 further recites sending user interest information derived from the user model to a third party web server. *Refuah* does not teach such subject matter. In particular, the virtual personas described by *Refuah* are not "derived from [a] User Model" that defines parameters of a learning machine, as required by the present claims. Instead, the virtual personas are either defined through a question and answer session, *Refuah* at col. 22:15-18, or are selected from a library of pre-defined personas and modified by individual users, *id*. at 21:40-44, or are compiled through the monitoring of user actions on the Internet. *Id*. at 21:22-24. Accordingly, claim 21 is not anticipated by *Refuah*.

Claim 22 depends from claim 1 and is therefore not anticipated by *Refuah* for at least all of the same reasons as claim 1. Claim 22 further limits claim 1 by reciting that the monitored user interactions include a sequence of interaction times.

Claim 34 depends from claim 32 and is therefore not anticipated by *Refuah* for at least all of the same reasons as claim 32. In addition, claim 34 recites analysis of documents of different media types. The ACP hypothesizes that because websites in 1999 could include multiple media types, *Refuah* inherently provides for such analysis. This speculation finds no support in the cited reference. Nothing in *Refuah* describes how the teachings are applicable to documents of different media types, nor has the ACP established how web pages including multiple types of media are documents of different media types. Without such a determination, the Examiner has failed to make out a *prima facie* case of anticipation and the rejections must be removed. *In re King*, 801 F.2d at 1327, 231 USPQ at 138-39; *In re Wilder*, 429 F.2d at 450, 166 USPQ at 548.

D. Because *Mladenic* Does Not Cure Deficiencies of *Refuah* With Respect to Estimating a Probability That an Unseen Document is of Interest to the User by Applying the Identified Properties of a Learning Machine, Claims 1, 11, 21, 22, 32 and 34 Remain Patentable over the Combination of *Refuah* and *Mladenic*.

With respect to independent claims 1 and 32, it was previously noted that *Refuah* fails to teach or suggest 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. *Mladenic* has a similar deficiency and the detailed reasons for that deficiency are described above. Accordingly, any combination of *Refuah* and *Mladenic* would lack any teaching or suggestion of 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. Accordingly, claims 1, 11, 21, 22, 32 and 34 are patentable over the combination of these references.

V. RESPONSE TO REJECTIONS BASED ON PRIMARY REFERENCE *CULLISS*

On its face, nowhere does *Culliss* disclose "learning," "learning machine," "probability," "estimation," "prediction," "estimate a probability," "model," or "user model."

Culliss describes a personal search system where the system combines personal data items stored about the user with a search query the user has entered to create a combined query. A search result is then returned to the user. *Culliss* does this by accumulating personal data about the user. This personal data will be utilized to personalize the user queries. The degree of personalization is a function of the augmented search query based on additional personal data items related to the query, e.g., adding the word "woman" to the query "shoes" to produce a combined query of "shoes-woman." See Nicholas Dec. at para. 20.

Culliss describes techniques purportedly useful in connection with searches that make use of search engines, specifically a method of organizing information in which the search activity of previous users is monitored and used to organize articles for future users. *Culliss*, Abstract. User data is used to refine search results returned by the search engine, *id*. at col. 1, ll. 48-50, and users can specify their own personal data or it can be inferred from a history of their search requests or article-viewing habits. *Id*. at col. 3, ll. 46-48; Nicholas Dec. at para. 20.

In operation, a cumulative score is kept of the occurrences of certain classified key terms, queries or visited URLs to quantify how strongly someone is associated with a particular item of personal data. When a first user enters a search query, that user's personal data can be considered part of the request and it is stored within or added to an index, either individually or in groupings with other items, such as key terms, categories, or ratings. Once so associated with a query, the personal data can be used to recall different lists of articles in response to new queries from new users. For example, when a new user enters a search request, that search request and the new user's personal data are combined to form groupings containing key term groupings, key term and personal data groupings, category and personal data groupings, rating and personal data groupings, etc. Articles associated with these groupings are then retrieved from the index, and their relevancy scores are used or combined to determine their rankings. *Culliss* at 5:18 – 6:13; Nicholas Dec. at para. 21. Thus, in the *Culliss* system information services which are provided to a user are dependent upon and informed by activities of the prior users.

A. Because *Culliss* Does Not Teach Estimating a Probability That an Unseen Document is of Interest to the User, Claims 1 and 32 and Their Respective Dependent Claims Are Not Anticipated by *Culliss*.

One fallacy in the Requester's allegation, as adopted by the Examiner, is the assertion that: "*Culliss* discloses that, when a user enters a search request, the search request and the user's personal data are combined to form various groupings … Based on these groupings, the system determines how relevant a given document d is to the searching user u … Nothing in *Culliss* requires that these documents (which are analyzed and given relevancy scores) be previously seen by another user." ACP at pp. 31-32; Request at p. 34.

Augmenting a search query based on personal data is an essential component in *Culliss*. More precisely, the *Culliss* patent describes a combined query in which an augmented search system combines personal data (e.g., personal data items) stored about the user with a search query the user has entered to create an augmented query. *Culliss* at col. 5, ll. 18-20, 41-45.

Culliss does not disclose "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." This step is performed without the involvement of a search query. The teaching in *Culliss* is directly contrary to the recited step.

Even if we consider operating *Culliss* without a query, which is something that *Culliss* had not mentioned or envisioned, which we are not conceding, and supplying personal data element of the user as key item (P) to the Index as implied here, this would raise two issues. First, there is no assurance that the unseen document from which a search system attempts to estimate the user interest is in the index in the row corresponding to the key item (P), and in the likely case that the unseen document is not in the relevant place in the Index, this hypothetical theory has no solution. Second, even if by chance the unseen document happens to be in the corresponding row in the index, it would have only previous-user relevancy score (PRS) that is not personal to the user but the result of the activities of the relevant previous users and therefore could not constitute an estimate of the specific user interest in the unseen document as recited in step 1e. See Nicholas Dec. at para. 22.

In *Culliss*, only after a user enters a search query does the personal data in which the system has stored about the user becomes part of the query, and the revised query is used to retrieve personalized search results. The system is, therefore, unable to estimate any user interest in a document absent the user entering a query. As taught in *Culliss*, a user enters a search query, the personal data becomes part of the request and stored within or added to the index, individually or in groupings with other items of data such as key terms, categories, or ratings. *Id.* at col. 5, ll. 18-35.

In addition, *Culliss* describes previous-user relevancy score as a mechanism to associate an article. *Id.* at 3:31-37, 3:46-51. Each article can be associated with one or more key terms. *Id.* at 3:31-33. However, previous-user relevant score measures the relation between a query and articles based on to the aggregated action of multiple users, and thus also does not anticipate estimating a probability that an unseen document d is of interest to the user u.

In determining whether to associate personal data to a particular user, *Culliss* teaches a rudimentary approach with a cumulative score feature. Personal data about a particular user is accumulated with a cumulative score of the number of occurrences of certain classified key terms, queries or visited URLs. *Id.* at 3:57-65. One objective of the cumulative score is to keep count (simple histograms) for each personal data item with a corresponding personal data item score. *Id.* at col. 4, ll. 61-66. When the personal data item score of the user attains a specified threshold, the personal data item is associated with that user. *Id.* at col. 4, l. 65 - col. 5, l. 2. The description of cumulative score in *Culliss* thus does not anticipate estimating a probability that an unseen document d is of interest to the user u.

Culliss fails to anticipate independent claims 1 and 32. For example, claims 1 and 32 recite *estimat[ing] a probability P(u|d) that an unseen document d is of interest to the user*. As demonstrated above, this is a determination that is independent of the information need of the user. *Culliss*, on the other hand, describes grouped relationships that are used as a basis to retrieve articles, and relevancy scores of those retrieved articles that are to determine their respective rankings. The relevancy scores are necessarily relevancies with respect to a query – i.e., with respect to an information need. Nicholas Dec. at para. 22. Hence, they cannot be considered the probabilities recited in claims 1 and 32, which are independent of information-need. Consequently, claims 1 and 32 are not anticipated by *Culliss*.

B. Because *Culliss* Does Not Teach Estimating Parameters of a Learning Machine Specific to the User, Claims 1 and 32 and Their Respective Dependent Claims Are Not Anticipated by *Culliss*.

Requester presented indirect reasoning and asserted key facts that sometimes do not exist in *Culliss*, which the Examiner adopted, resulting in statements that do not make logical sense. Requester argued that "*Culliss* discloses that a user model specific to the user can be estimated in part from the user-specific data files" when in fact *Culliss* does not disclose a "user model". ACP at p. 30; Request at p. 32. Requester then took a logical leap by stating that, "the user can be identified as having the personal data characteristic of being a sports fan and having an interest in finance because there are three queries relating to sports ('sports scores,' 'football,' and 'nba') and five queries containing key words relating to finance (stock quotes,' 'cnnfn,' Junk bonds,' 'stock quotes,' and 'dowjones.')" without explaining why the cited text in *Culliss* anticipates the limitation "a user model specific to the user." *Id.* It appears that Requester has mischaracterized that "PUM has argued in the Pending Litigation that a User Model may be 'specific to the user' even if it serves as a model for other users as well" (citing OTH-C at 2-3), which Patent Owner refutes this characterization. ACP at p. 30; Request at p. 29.

On the limitation of "estimating parameters of learning machine," Requester made a similar type of phantom assertion that "Culliss further discloses estimating parameters of a learning machine" when "learning machine" is nowhere to be found in *Culliss*. ACP at pp. 30-31; Request at p. 33. The term "learning machine" has been construed to mean a mathematical function or model used to make a prediction that attempts to improve its predictive ability over time by altering the values/weights given to its variables. Markman Order at pp. 6-7.

Culliss does not teach a "learning machine," which is recited as "estimating parameters of a learning machine" in step 1c and estimating a probability that an unseen document is of interest to the user by applying the identified properties of the document to the learning machine in step 1e. *Culliss* describes a basic approach in counting the personal data item score to determine if it has reached a certain threshold. Id. at col. 4, l. 65 – col. 5, l. 2.

Culliss describes accumulating data on the user but does not build a user model based on a learning machine, as recited in step 1c "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." Specifically, after every search that the user has executed, the index common to all users is updated, as described by block 30 in Figure 1 of *Culliss*, which does not pertain to anything specific to the user. The altering of values/weights that is described in *Culliss* is of the index which is not specific to the user. If Requester tries to argue that *Culliss* tracks the user's browsing history and uses this history to update the weights of the personal data to best reflect the changing interests of the user, the update in weights of the personal data in *Culliss* is not learning based on "attempts to improve its predictive ability" but rather simply to ensure that the user personal data items are current. Therefore, the *Culliss* patent does not disclose a learning machine that attempts to improve predictive ability over time by altering the values/weights given to its variable.

For at least the foregoing reasons, Patent Owner respectfully requests the Examiner confirm the patentability of claims 1 and 32 over *Culliss*.

Claim 11 depends from claim 1 and therefore is not anticipated by *Culliss* for at least the reasons provided above with regard to claim 1. *Culliss* additionally fails to teach 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. Indeed, *Culliss* fails to describe any type of estimated probability calculation (posterior or otherwise) and only discloses using a user's personal data to retrieve articles related to the user's search request from an index and ranking retrieved articles according to a relevancy score. Id. at col. 5, ll. 40-48. Using personal data of a user to answer a query is not the same as estimating a posterior probability that a document will be of interest to a user given a particular query, as required by claim 11. Hence, claim 11 is not anticipated by *Culliss*.

Claim 22 depends from claim 1 and therefore is patentable over *Culliss* for at least the reasons provided above with regard to claim 1. Claim 22 further requires that the monitored user interactions include a sequence of interaction times. Culliss does not teach or suggest such monitoring. Instead, *Culliss* discloses altering the key term scores or key term total scores of articles "according to whether they were displayed to a user, whether they were selected by a user, how much time users spent with the article, etc." See e.g., id. at col.2, ll. 43-46. Monitoring how long a user spends with an article is not monitoring a sequence of interaction times as required by claim 22.

Claim 34 depends from claim 32 and therefore is patentable over *Culliss* for at least the reasons provided above with regard to claim 32. Further, while *Culliss* may indicate that the Internet can include a variety of different kinds of documents, files, etc., id. at col. 2, ll. 19-25, *Culliss* does not teach how to analyze documents having multiple distinct media types, as claimed. Indeed, nowhere does the ACP indicate where such teachings (of analysis of these different media types, rather than simple acknowledgment of their existence) can be found in the cited reference. Accordingly, claim 34 is not anticipated by Culliss.

C. Because *Mladenic* does not Cure the Deficiencies of *Culliss* with Respect to Estimating a Probability that the Document is of Interest to a User by Applying the Identified Properties to a Learning Machine, Claims 1 and 32 and Their Respective Dependent Claims are Patentable over *Culliss* in View of *Mladenic*.

With respect to independent claims 1 and 32, it was previously noted that *Culliss* fails to teach or suggest "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" as recited in claims 1 and 32. As discussed above, *Mladenic* has a similar deficiency. Mladenic teaches analyzing a currently viewed web page to identify extended representations of hyperlinks on that web page, which extended representations of hyperlinks are used to determine whether the hyperlinks (not the currently viewed web page or any web page(s) pointed to by the hyperlink(s)) are of interest to the user. Even assuming the models UserHL and UserDOC can reasonably be considered implementations of "learning machines" (and this point is not conceded), the models do not (nor does the classifier that operates on the models) approximate or roughly calculate a numerical degree of belief or likelihood that an unseen document is of interest to the user, as required by the claims. Instead the classifier uses the models to "predict if a new hyperlink is a