

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

META PLATFORMS, INC.,
Petitioners

v.

STERLING COMPUTERS CORPORATION,
Patent Owner.

IPR2025-00430

U.S. Patent No. 7,716,217

**PETITION FOR *INTER PARTES* REVIEW
OF U.S. PATENT NO. 7,716,217**

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<i>United Fire Prot. Corp. v. Engineered Corrosion Sols. LLC,</i> IPR2018-00991, Paper 10 (Nov. 15, 2018)	9
<i>Valve Corp. v. Elec. Scripting Prods., Inc.,</i> IPR2019-00062, Paper 11 (Apr. 2, 2019)	8
<i>Videndum Prod. Sols., Inc. v. Rotolight Ltd.,</i> IPR2023-01218, Paper 12 (Vidal Apr. 19, 2024)	8
<i>Williamson v. Citrix Online, LLC,</i> 792 F.3d 1339 (Fed. Cir. 2015)	11

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EXHIBIT LIST

Ex No.	Shorthand	Reference
1001	'217 Patent or Marston	U.S. Patent No. 7,716,217
1002	'217 Patent File History	File History of the '217 Patent
1003	Fox Decl. or Fox	Declaration of Dr. Edward A. Fox in Support of Petition
1004	Fox CV	<i>Curriculum Vitae</i> of Dr. Edward A. Fox
1005	Dumais	U.S. Pat. App. Pub. No. 2007/0016553 A1 to Dumais, et al.
1006	Rose	U.S. Pat. No. 6,202,058 B1 to Rose, et al.
1007	Bieganski	U.S. Pat. No. 6,334,127 to Bieganski, et al.
1008	Lesk	Michael Lesk, <i>Understanding Digital Libraries</i> (Elsevier, 2nd ed. 2004)
1009	Arms	William Y. Arms, <i>Digital Libraries</i> (MIT Press, 1st ed. 1999)
1010	Carroll	John M. Carroll, <i>Human-Computer Interaction in the New Millennium</i> (Pearson Education 2002)
1011	Kuniavsky	Mike Kuniavsky, <i>Observing the User Experience: A Practitioner's Guide to User Research</i> (Elsevier 2003)
1012	Shneiderman	Ben Shneiderman, <i>Designing the User Interface: Strategies for Effective Human-Computer Interaction</i> (Addison Wesley 3rd ed. 1998)
1013	User Goals	Daniel E. Rose and Danny Levinson, <i>Understanding user goals in web search</i> , 13–19 (In Proc. WWW '04, Association for Computing Machinery, May 2004)
1014	Teevan	Jaime Teevan, et al., <i>Personalizing Search via Automated Analysis of Interests and Activities</i> , 449-56 (In Proceedings of SIGIR '05)
1015	Miller	Miller, B. et al., <i>Experiences with GroupLens:</i>

Ex No.	Shorthand	Reference
		<i>Making Usenet Useful Again</i> , 219-33 (In Proceedings of the USENIX 1997 Annual Technical Conference)
1016	Claypool	Mark Claypool, et al., <i>Combining Content-Based and Collaborative Filters in an Online Newspaper</i> , (ACM SIGIR Workshop on Recommender Systems, Aug. 1999)
1017	Goldberg	David Goldberg, et al., <i>Using Collaborative Filtering to Weave an Information Tapestry</i> 35:12, 61-70 (Communications of the ACM, Dec. 1992)
1018	Melville	Prem Melville, et al., <i>Content-Boosted Collaborative Filtering for Improved Recommendations</i> 187-92 (In Proceedings of the Eighteenth National Conference on Artificial Intelligence, AAAI-2002)
1019	Beyond Search	Daniel E. Rose, <i>Beyond Search: The Information Access Research Group at Apple</i> , 85–89 (SIGCHI Bull. 30, 2, April 1998)
1020	MessageWorld	Daniel E. Rose et al., <i>MessageWorld: A New Approach to Facilitating Asynchronous Group Communication</i> , 266-73 (Association for Computing Machinery, In Proceedings of the Fourth International Conference on Information and Knowledge Management (CIKM), December 1995)
1021	Herz	U.S. Patent No. 8,799,461 B2 to Herz, et al.
1022	Kim	S. Kim and E. Fox, <i>Interest-Based User Grouping Model For Collaborative Filtering In Digital Libraries</i> , In Proceedings of the 7th International Conference on Digital Libraries (ICADL, Dec. 2004)
1023	Belkin	Nicholas J. Belkin and W. Bruce Croft, <i>Information Filtering and Information Retrieval: Two Sides of the Same Coin?</i> 29-38, Communications of the ACM, 35:12, (Dec. 1992)
1024	Wittenburg	Kent Wittenburg and Eric Sigman, <i>Integration of Browsing, Searching, and Filtering in an Applet for</i>

Ex No.	Shorthand	Reference
		<i>Web Information Access</i> , 22-27 (In Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems, March 1997)
1025	Jung	Seikyung Jung, et al., <i>Applying Collaborative Filtering for Efficient Document Search</i> , 20-24 (In Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence, September 2004)
1026	Ponte 1	U.S. Patent No. 6,826,559 B1 to Ponte
1027	Ponte 2	U.S. Patent No. 7,047,242 B1 to Ponte
1028	Melton	U.S. Patent No. 9,864,813 B2 to Melton, et al.
1029	Malik	U.S. Pat. App. Pub. No. 2004/0078447 to Malik, et al.
1030	McKeogh	John McKeogh and Chris Exton, <i>Eclipse plug-in to monitor the Programmer Behaviour</i> , In Proceedings of the 2004 OOPSLA Workshop on Eclipse Technology eXchange (Eclipse '04), 93–97 (Association for Computing Machinery, New York, NY October 2004)
1031	Rich	Charles Rich, et al, <i>A Plug-in Architecture for Generating Collaborative Agent Responses</i> , 782–89 (In Proceedings AAMAS '02, Association for Computing Machinery, New York, NY)
1032	Domingue	John Domingue, et al. <i>Magpie: Supporting Browsing and Navigation on the Semantic Web</i> , 191–97 (In Proceedings IUI '04, Association for Computing Machinery, New York, NY, 2004)
1033	Cöster	Rickard Cöster & Martin Svensson, <i>Inverted File Search Algorithms for Collaborative Filtering</i> , 246–52 (In Proceedings SIGIR '02, Association for Computing Machinery, New York, NY, 2002)
1034	Heath	Lenwood S. Heath, et al. 1995. <i>Envision: a User-Centered Database of Computer Science Literature</i> . Commun. ACM 38, 4 (April 1995)

Ex No.	Shorthand	Reference
1035	Nowell	Lucy Terry Nowell, et al., <i>Visualizing search results: some alternatives to query-document similarity</i> 67–75 (In Proc. SIGIR '96, Association for Computing Machinery, New York, NY) (1996)
1036	Saracevic	Tefko Saracevic, <i>A Review of and a Framework for the Thinking on the Notion in Information Science</i> 321-43 (Journal of the Am. Society for Info. Sci., Dec. 1975)
1037	Meta Dkt.	Docket for <i>Sterling Computs. Corp. v. Meta Platforms, Inc. f/k/a Facebook, Inc.</i> , Case No. 1:24-cv-00551 (W.D. Tex. May 22, 2024)
1038	X Dkt.	Docket for <i>Sterling Computs. Corp. v. X Corp. f/k/a Twitter, Inc.</i> , 1:24-cv-00552 (W.D. Tex. May 22, 2024)

LISTING OF CHALLENGED CLAIMS

Reference	Claim Limitations
Claim 1	
1[pre]	A computer-implemented system for determining a relevance score of a piece of electronic content sent from a sender to a user, the relevance score determined with respect to the user, the computer-implemented system comprising:
1[a]	a computer processor; and
1[b]	a computer-readable storage medium storing computer program modules configured to execute on the computer processor, the computer program modules comprising:
1[c]	a monitoring module configured to track actions by a plurality of users associated with an application for managing electronic content;
1[d]	a first relevance measurement module coupled to the monitoring module and configured to determine a first measure of relevance of the piece of electronic content based at least in part on one or more actions of the user on the piece of electronic content;
1[e]	a second relevance measurement module coupled to the monitoring module and configured to:
1[f]	identify at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user, and
1[g]	determine a second measure of relevance of the piece of electronic content as based at least in part on one or more measures derived from the group consisting of: a local importance describing an importance of the sender to the user, a global importance describing an importance of the sender within an organization with which the plurality of users are associated, a content relevance determined responsive to content of the piece of electronic content, and

	one or more actions on the piece of electronic content of the at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user; and
1[h]	a relevance analysis module configured to determine the relevance score of the piece of electronic content sent from the sender to the user, the relevance score being determined based at least in part on the first determined measure of relevance and on the second determined measure of relevance.
Claim 2	
2	The system of claim 1, further comprising: a content presentation module configured to present the piece of electronic content to the user in accordance with the determined relevance score and to present to the user a value describing the determined relevance score.
Claim 3	
3	The system of claim 1, further comprising: a search module configured to search the electronic content in accordance with the determined relevance score.
Claim 5	
5	The system of claim 1, wherein the electronic content comprises at least one of an email, a document, an instant message, and an SMS message.
Claim 6	
6[pre]	A computer program product for determining a relevance score of a piece of electronic content sent from a sender to a user, the relevance score determined with respect to the user, the computer-program product having a computer-readable storage medium having computer program instructions encoded thereon comprising:
6[a]	a monitoring module configured to track actions by a plurality of users associated with an application for managing electronic content;
6[b]	a first relevance measurement module coupled to the monitoring module and configured to determine a first measure of relevance of the piece of electronic content based at least in part on one or more actions of the user on the piece of electronic content;
6[c]	a second relevance measurement module coupled to the monitoring module and configured to:

6[d]	identify at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user, and
6[e]	determine a second measure of relevance of the piece of electronic content based at least in part on one or more measures derived from the group consisting of: a local importance describing an importance of the sender to the user, a global importance describing an importance of the sender within an organization with which the plurality of users are associated, a content relevance determined responsive to content of the piece of electronic content, and one or more actions on the piece of electronic content of the at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user; and
6[f]	a relevance analysis module configured to determine the relevance score of the piece of electronic content sent from the sender to the user, the relevance score being determined based at least in part on the first determined measure of relevance and on the second determined measure of relevance.
Claim 7	
7[pre]	A computer-implemented method for determining a relevance score of a piece of electronic content sent from a sender to a user, the relevance score determined with respect to the user, the computer-implemented method comprising:
7[a]	tracking actions by a plurality of users associated with an application for managing electronic content;
7[b]	identifying at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user,
7[c]	determining a first measure of relevance of the piece of electronic content based at least in part on one or more actions of the user on the piece of electronic content;

7[d]	determining a second measure of relevance of the piece of electronic content based at least in part on one or more measures derived from the group consisting of: a local importance describing an importance of the sender to the user, a global importance describing an importance of the sender within an organization with which the plurality of users are associated, a content relevance determined responsive to content of the piece of electronic content, and one or more actions on the piece of electronic content of the at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user; and
7[e]	determining the relevance score of the piece of electronic content sent from the sender to the user, the relevance score being determined based at least in part on the first determined measure of relevance and on the second determined measure of relevance.
Claim 8	
8	The system of claim 1, wherein identifying at least one other of the plurality of users that is cognate to the user comprises analyzing historical actions of the at least one other of the plurality of users with respect to historical actions of the user.
Claim 9	
9	The system of claim 8, wherein the at least one other of the plurality of users is cognate to the user, and the user is not cognate to the at least one other of the plurality of users.
Claim 13	
13	The computer program product of claim 6, further comprising: a content presentation module configured to present the piece of electronic content to the user in accordance with the determined relevance score and to present to the user a value describing the determined relevance score.
Claim 14	

14	The computer program product of claim 6, further comprising: a search module configured to search the electronic content in accordance with the determined relevance score.
Claim 15	
15	The computer program product of claim 6, wherein the electronic content comprises at least one of an email, a document, an instant message, and an SMS message.
Claim 18	
18	The method of claim 7, further comprising: presenting the piece of electronic content to the user in accordance with the determined relevance score and presenting to the user a value describing the determined relevance score.
Claim 19	
19	The method of claim 7, further comprising: searching the electronic content in accordance with the determined relevance score.
Claim 22	
22	The method of claim 7, wherein identifying at least one other of the plurality of users that is cognate to the user comprises analyzing historical actions of the one other of the plurality of users with respect to historical actions of the user.

I. INTRODUCTION

Meta Platforms, Inc. (“Meta” or “Petitioner”) requests *inter partes* review (“IPR”) of claims 1-3, 5-9, 13-15, 18-19, and 22 (“Challenged Claim(s)”) of U.S. Patent 7,716,217 (“Marston” or “the ’217 patent”; EX-1001).

Petitioner has shown a reasonable likelihood of prevailing as to each Challenged Claim and respectfully requests the Board institute trial.¹

II. GROUNDS FOR STANDING

Petitioner certifies Marston is available for IPR and Petitioner is not barred or estopped from requesting IPR on the grounds herein. On May 22, 2024, Sterling Computers Corp. (“Sterling” or “PO”) sued Meta in the Western District of Texas. EX-1037 and EX-1038. Petitioner files this Petition within one year of service on Meta of PO’s district court complaint.

III. STATEMENT OF PRECISE RELIEF REQUESTED FOR EACH CLAIM CHALLENGED

Petitioner respectfully requests review and cancellation under 35 U.S.C. §311 of the Challenged Claims in view of:

¹ Petitioner submits the declaration of Edward A. Fox (EX-1003), an expert in the field of the ’217 patent. *See* Fox, ¶46 (summary of opinions), ¶¶6-19 (discussing background and qualifications), ¶¶23-25 (materials considered); EX-1004 (CV).

Prior Art	
Dumais (U.S. Pat. Appl. Pub. 2007/0016553A1), filed on June 29, 2005, published on January 18, 2007; prior art under at least 35 U.S.C. §102(e) ² (EX-1005)	
Rose (U.S. Pat. No. 6,202,058), filed on April 25, 1994, issued on March 13, 2001; prior art under at least 35 U.S.C. §102(b) (EX-1006)	
Bieganski (U.S. Pat. No. 6,334,127), filed on July 17, 1998, issued December 25, 2001; prior art under at least 35 U.S.C. §102(b) (EX-1007)	

Ground (all under 35 U.S.C. §103)	Claims	References
1	1-3, 5-9, 13-15, 18-19, 22	Dumais
2	1-3, 5-9, 13-15, 18-19, 22	Rose
3	1-3, 5-9, 13-15, 18-19, 22	Rose, Bieganski

IV. '217 PATENT OVERVIEW

A. Background

At the time of the '217 patent (Marston), numerous techniques existed for evaluating the relevance of electronic content, from movie rating websites to search engines and more. Fox, ¶¶47-50, 54, 56-57, 60-62 (citing EX-1023, 37; EX-1024, 293; and EX-1025, 3-4 for discussion of searching/information retrieval).

² All references to 35 U.S.C. §§102, 103 are to the pre-AIA statutory framework.

Academics, especially in the context of digital libraries or web-based information repositories, studied techniques for evaluating relevance. Fox, ¶¶12, 17, 48-50, 53; EX-1008, xxvii, 213; EX-1009, 2-3, 45, 143-61. By the mid-1990s, a person of skill in the art (“POSITA”) would have known many ways to estimate the relevance of electronic data based on its content, and computers could estimate the relevance of electronic content based on a user’s actions on that content, including both explicit and implicit monitoring.³ *Id.*, ¶¶54-55 (citing EX-1010, 493).

Long before Marston, computers could use “collaborative filtering” to estimate the relevance of electronic data based on inputs from multiple users. *Id.*, ¶¶56-59; EX-1017, 61; EX-1019 (Beyond Search), 87 (discussing Apple research group involving Daniel Rose, co-inventor of EX-1007); EX-1020, 266, 272

³ An “explicit” action on (e.g., related to, addressing, dealing with) content could be a user providing a rating (e.g., 5/10 stars) or indicating that they like (or dislike) certain content using direct feedback. Fox, ¶¶53-55 (citing EX-1010, 493); *see also* EX-1015, 12 (using “implicit measures of user interest” in items for “implicit ratings”); Bieganski, 2:31-39 (discussing implicit/explicit actions). Implicit monitoring includes monitoring how long a user might look at a piece of electronic content or what actions the user takes on that electronic content, to evaluate whether it is relevant to the user. Fox, ¶¶53-55

(discussing Apple’s “MessageWorld” system incorporating “learning from the community” in email/bulletin boards). Indeed, as early as 1992—and certainly by 2002—systems combined both content-based and collaborative-filter-based recommendation systems to estimate the relevance of electronic content. *Id.*, ¶¶56-59, 61; EX-1010, 494 (discussing Tapestry system), 500 (discussing “hybrid systems” that “combine collaborative filtering with content-based recommenders”); *see also* EX-1018 (Melville) (combining “Content-Boosted Collaborative Filtering for Improved Recommendations”).

B. Specification

Marston relates generally to techniques for estimating the relevance of electronic content. EX-1001, 3:34-36. “Given the heavy use of electronic mail, many email users receive hundreds of different emails a day,” much of which is “irrelevant (or more colloquially, is ‘junk’) and serves as a nuisance that the individual must navigate through.” *Id.*, 1:25-30. Sorting through emails to identify those “relevant to the recipient” takes time, and “typical email applications are resigned to providing unintelligent mechanisms (e.g., keyword, sender, recipient, and/or date range searches) for mining through email.” *Id.*, 1:30-44.

Marston’s embodiments “relate to a technique for determining the relative relevances of electronic mail messages” “based on, for example, *user actions* (e.g., what did the user do with that piece of electronic mail), *other user actions* (e.g., what

did other users do with that piece of electronic mail), and/or *administrative settings*.” *Id.*, 3:34-42⁴. Marston teaches “relevance” applies to “content” and “reflect[s] a user’s likely interest in the content,” whereas “importance” refers to an “entity” and “reflect[s] a user’s likely interest in content involving that entity.” *Id.*, 5:53-67.

Relevance and importance can “be determined based on monitoring users’ actions.” *Id.*, 6:1-3. For example, saving or forwarding a message suggests it is more relevant than deleting it, just as routinely reading a manager’s messages indicates the manager is important. *Id.*, 6:3-22. A system can “identify a cognate group of the n other users regarded as most similar,” which “may be defined by similar past user actions and assessments, and/or a direct input by a user.” *Id.*, 14:59-66. Relevance can involve both an “Individual Relevance Component” (“IRC”) for a given user and a “cognate relevance value” that is “based on a weighted average of the IRC’s of the n users considered to be the cognate group for that recipient.” *Id.*, 25:37-26:52.

⁴ All emphasis added, unless indicated otherwise.

C. Prosecution History

The application leading to Marston was filed on January 16, 2007.⁵ EX-1002. The Examiner issued an initial rejection on November 14, 2008 based on Malik (EX-1029). EX-1002, 208-23 (November 14, 2008 Non-Final Rejection). In an Examiner Interview, PO argued Malik did not estimate relevance based on user actions “on a piece of electronic content.” *Id.*, 224-25 (Dec. 15, 2008 Examiner Interview Summary). After PO sought reconsideration, the Examiner issued a Final Rejection based on Malik. *Id.*, 249-62 (May 12, 2009 Final Rejection). PO submitted a Request for Continued Examination and substantially amended the claims. *Id.*, 327-35 (January 15, 2010 Amendment).

The Examiner allowed the claims, but noted Malik taught essentially all limitations of the claims, including (i) a monitoring module to track actions of users; (ii) a relevance analysis module to determine relevance of content to a user, based on (iii) actions of the user on the content, and (iv) relevance determined dependent on one or more actions of other users that received the content. Ex-1002, 519-28 (Feb. 12, 2010 Notice of Allowance), 524-25. Despite acknowledging the prior art

⁵ For purposes of this Petition, Petitioner assumes the '217 patent is entitled to a priority date of January 13, 2006 based on provisional application No. 60/758,828, but reserves the right to challenge priority in other proceedings.

disclosed essentially the entire claim, the Examiner noted, without explanation, that Malik lacked the overall combination of the claimed first/second relevance module used to estimate relevance. *Id.*, 526. But as shown in the unpatentability grounds in this Petition, the use of the claimed first/second relevance measurement modules were taught in the prior art.

V. DISCRETIONARY DENIAL WOULD BE INAPPROPRIATE HERE

A. Status of Prior and Co-Pending Litigation

PO asserted Marston for the first time on May 22, 2024, filing two suits in the Western District of Texas against Meta and X Corp., f/k/a Twitter, Inc., respectively. *Sterling Computers Corp. v. Meta Platforms, Inc. f/k/a Facebook, Inc.*, Case No. 1:24-cv-00551 (W.D. Tex. May 22, 2024) (“Meta lawsuit”) (EX-1037) (docket); *Sterling Computers Corp. v. X Corp. f/k/a Twitter, Inc.*, 1:24-cv-00552 (W.D. Tex. May 22, 2024) (“X lawsuit”) (EX-1038) (docket). X Corp. filed an IPR petition challenging claims of Marston on December 12, 2024, less than two months before Meta filed this Petition. Assuming both IPRs are instituted, Meta expects Final Written Decisions (“FWDs”) in this and X’s IPRs around July 2026 and June 2026, respectively.

The Meta lawsuit is still in its infancy: trial is set for March 1, 2027; PO has served its initial infringement contentions, but Meta has not yet served invalidity contentions; and the parties have not engaged in claim construction. EX-1037. Meta

understands that the X lawsuit's trial is set for April 5, 2027 and X has filed a pending motion to stay. (EX-1038).

B. *General Plastic*

The Board should not discretionarily deny institution under *General Plastic* based on X Corp.'s IPR petition. *General Plastic* factors 1-3 weigh heavily against exercising discretion to deny institution because this is Petitioner's first challenge of the '217 patent. X filed IPR2025-00299 challenging claims 1-22 of Marston on December 12, 2024 (slightly more than one month prior to this Petition). Petitioner and X do not have a substantial relationship, unlike the petitioners in *Valve Corp. v. Elec. Scripting Prods., Inc.*, IPR2019-00062, Paper 11, 9 (Apr. 2, 2019) (precedential). Petitioner and X are defendants in different district court litigations brought by PO; each litigation accuses different products of infringement; and Petitioner has not requested to join X's petition. *Compare* Ex-1038 (docket for *Sterling v. X Corp.*), with Ex-1037 (docket for *Sterling v. Meta*); *see also* *Videndum Prod. Sols., Inc. v. Rotolight Ltd.*, IPR2023-01218, Paper 12 (Vidal Apr. 19, 2024) (vacating and remanding decision extending *General Plastic* to parties lacking a "significant relationship"); *Ford Motor Co. v. Neo Wireless LLC*, IPR2023-00763, Paper 28, 10 (Vidal Mar. 22, 2024) (vacating and remanding decision where patent challengers had "different allegedly infringing products" in "different district court proceedings"). Petitioner and X have not coordinated or collaborated in the filing of

their respective petitions, and the petitions challenge different sets of claims using different grounds. Importantly, Petitioner filed this petition before PO filed a preliminary response to the X petition, eliminating concerns of road-mapping that underlie *General Plastic*. See, e.g., *NetNut Ltd. v. Bright Data Ltd.*, IPR2021-00465, Paper 11, 7-8 (Aug. 12, 2021). *General Plastic* factors 2-3 weigh heavily against exercising discretion to deny institution for the same reasons.

The remaining factors (4-7) also weigh against discretionary denial. Petitioner has diligently worked towards filing this Petition since learning of the asserted prior art. Finally, the Board will not be unduly burdened by addressing this Petition. See *United Fire Prot. Corp. v. Engineered Corrosion Sols. LLC*, IPR2018-00991, Paper 10, 17 (Nov. 15, 2018).

This Petition is not an abusive serial attack, but rather Petitioner's first Petition to challenge a patent on which they were sued. Evaluating this Petition on the merits will serve the Board's mission "to improve patent quality and restore confidence in the presumption of validity that comes with issued patents." *Cuozzo Speed Techs., LLC v. Lee*, 579 U.S. 261, 272 (2016).

C. *Fintiv*

Petitioner expects PO will not raise *Fintiv* because the earliest trial date set by the district court is March 1, 2027 (EX-1037), well after the expected FWD deadline in this IPR (Sept. 3, 2026) and in X's IPR (July 14, 2026).

D. Section 325(d)

The Board should likewise not exercise its discretion under §325(d) to deny institution. *Becton, Dickinson & Co. v. B. Braun Melsungen AG*, IPR2017-01586, Paper 8, 17-18 (Dec. 15, 2017) (precedential); *Advanced Bionics, LLC v. MED-EL Elektromedizinische Geräte GmbH*, IPR2019-01469, Paper 6, 9-11 (Feb. 13, 2020) (precedential). This Petition’s grounds rely on three prior art references, none considered by the Examiner during prosecution of Marston. Thus, Section 325(d) is inapplicable to this Petition’s grounds.

VI. LEVEL OF ORDINARY SKILL

A POSITA would have had a bachelor’s degree in electrical engineering, computer engineering, computer science, or a similar field, and two to three years of experience with systems estimating relevance for various types of content. Fox, ¶¶20-23. More work experience could substitute for education and vice versa. *Id.*

VII. CLAIM CONSTRUCTION

Petitioner does not believe claim construction is needed to demonstrate the Challenged Claims are unpatentable, and Petitioner applies the plain and ordinary meaning of the claim terms. *Nidec Motor Corp. v. Zhongshan Broad Ocean Motor Co.*, 868 F.3d 1013, 1017 (Fed. Cir. 2017). Petitioner presents its understanding of the “module” limitations below.

A. Limitations Implicating Means-Plus-Function (“MPF”)⁶

No claim terms in the Challenged Claims use the term “means,” and there is a rebuttable presumption that they are not MPF. *Williamson v. Citrix Online, LLC*, 792 F.3d 1339, 1348 (Fed. Cir. 2015). The presumption, however, is overcome for all “module” limitations in the Challenged Claims. *See id.*, 1350 (“‘Module’ is a well-known nonce word that can operate as a substitute for ‘means’ in the context of §112, para. 6.”); *see also* MPEP §2181(I)(A) (“The following is a list of non-structural generic placeholders that may invoke 35 U.S.C. 112[, ¶6]:...‘module for.’”). Marston explains a “module” can be “any program, circuitry, logic, and/or functionality implemented in either software and/or hardware,” acknowledging that “any combination of the modules shown therein may run on any type of computer system.” EX-1001, 6:36-38, 6:65-66. Petitioner argues the claims are unpatentable regardless of MPF; however, if the Board finds the claims are MPF, Petitioner identifies structure for each such limitation below. Fox, ¶¶72-82. Petitioner explains in each unpatentability ground how the prior art teaches that structure.

1. “Monitoring Module”

Limitation (Function Underlined)	Corresponding Structure

⁶ Petitioner reserves the right to raise and address indefiniteness, enablement, and/or written description issues for the Challenged Claims in other proceedings.

a monitoring module configured to <u>track actions by a plurality of users associated with an application for managing electronic content; (cls. 1/6)</u>	Software and/or algorithms at EX-1001, 1:49-52, 6:39-45, 7:16-19, 15:51-58, 16:31-57, 27:11-40. At best, the structure for carrying out the function of the “the monitoring module” in Marston is either: (a) “client-side integration” relying on a “plug-in” that “monitor[s] end users actions on the mail content,” or (b) a server-side implementation using a “relational electronic mail server” and/or “relational knowledge server” that “tag[s] content with ‘flags’” to track what happens to content during the life cycle of the content. Fox, ¶¶74-75.
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2. “First Relevance Measurement Module”

Limitation (Function Underlined)	Corresponding Structure
a first relevance measurement module coupled to the monitoring module and configured to <u>determine a first measure of relevance of the piece of electronic content based at least in part on one or more actions of the user on the piece of electronic content; (cls. 1/6)</u>	Software and/or algorithms at EX-1001, 6:39-48, 25:45-49, 27:12-19, 28:63-29:41. At best, the structure of the “First Relevance Measurement Module” in Marston involves algorithms for estimating a user’s “Individual Relevance Component” based on a “plurality of factors,” including “dichotomous” (<i>i.e.</i>, binary, yes/no) and “cardinal” (<i>i.e.</i>, scaled) factors. Fox, ¶¶76-77.

3. “Second Relevance Measurement Module”

Limitation (Functions Underlined)	Corresponding Structure
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a second relevance measurement module coupled to the monitoring module and configured to: <u>identify at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user,</u> and <u>determine a second measure of relevance of the piece of electronic content [as] based at least in part on one or more measures derived from the group consisting of:</u> <u>a local importance describing an importance of the sender to the user,</u> <u>a global importance describing an importance of the sender within an organization with which the plurality of users are associated,</u> <u>a content relevance determined responsive to</u>	For identifying “cognate” users that are recipients of the electronic content, the software and/or algorithms at EX-1001, 6:42-55, 14:45-15:11, 17:4-22, 25:65-26:10, 43:30-37 At best, the structure for carrying out the function of identifying “cognate” users that are recipients of the electronic content of the “second relevance measurement module” in Marston involves routines using “role or group based; collaborative filtering; fingerprinting; cluster models; search-based methods; frequency analysis; and importance value correlation” to evaluate “similar past user actions and assessments, and/or a direct input by a user.” <i>Id.</i>, 14:59-15:11, 43:30-37; Fox, ¶78. For determining a second measure of relevance, the software and/or algorithms at EX-1001, 6:42-55, 14:45-15:11, 25:49-58, 26:11-17, 26:24-30, 27:12-42, 29:50-31:13, 31:21-34:48, 32:42-57, 33:1-20, 33:29-33, 34:29-39, 41:7-25, 42:35-36. The “second measure of relevance” can be met by any of four options in a Markush Group. Fox, ¶79. At best, the structure for carrying out the function of each Markush group of the “second relevance measurement module” in Marston involves: • <u>Local Importance:</u> Determined using (a) the sender’s relative position to the recipient in an “organizational chart” or “inter-company project,” or (b) calculating an “Individual Importance Component” (“IIC”) for a sender based on the user’s actions on messages from that sender. EX-1001, 25:45-49, 27:12-42, 30:4-9, 31:21-32:35; Fox, ¶79. As discussed at 31:21-32:33, the IIC can be determined using a “weighted function” based on “the individual recipient’s actions towards” the sender, as shown below:
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<u>content of the piece of electronic content, and one or more actions on the piece of electronic content of the at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user; (cls. 1/6)</u>	$IIC_{sr} = w_1 \frac{1}{n_s} \sum_{x=1}^{n_s} f^t(\text{del}; \text{no}) + w_2 \frac{1}{m_s} \sum_{x=1}^{m_s} f^t(l_{x1} / L_{x1}) + w_3 \sum_{x=1}^v f^t(R(T_x)) + w_4 f^t(I_{rs}^{\text{assigned}})$ <i>Id.</i> • <u>Global Importance:</u> Determined using (a) an organization chart (29:64-30:3), or (b) calculated based on: (1) a “weighted average of all IIC values” for a sender, (25:55-58, 30:63-31:3, 32:46-47), (2) the importance of electronic mail objects received, (30:25-31, 33:1-20), (3) an assigned value (33:21-28, 34:29-39, 42:35-36); or (4) “transferred post importance,” (33:29-33), as depicted in the formula below: $I_s^g = \alpha^{(k-1)} I_s^g + (1 - \alpha) \left[w_1 f \left(\sum_{i=1}^n f \{ IIC_{sr}^{(k-1)}; I_r^g \} \right) + w_2 f \left(\sum_{j=1}^{m, (k-1)} I_s / N_j; \frac{1}{m} \sum_{j=1}^{m, (k-1)} I_s / N_j \right) + w_3 f({}^o HR_s^t) + w_3 f({}^o HR_s^p) \right]$ Fox, ¶79. • <u>Content:</u> Determined using “spiders” to “identify terms within the content and “statistical techniques” to identify “[k]eywords of high relevance” with content relevance. EX-1001, 41:7-25, 45:13-37; Fox, ¶79. • <u>Actions by Cognate Users:</u> Determined based on a “weighted average of the IRC’s of the n users considered to be the cognate group for that recipient.” EX-1001, 26:11-17; Fox, ¶79. The algorithm for the First Measure Module identifies how to calculate users’ IRC’s.
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4. “Relevance Analysis Module”

Limitation (Function Underlined)	Corresponding Structure
a relevance analysis module configured to <u>determine the relevance score of the piece of electronic content sent from the sender to the user, the relevance score being determined based at least in part on the first determined measure of relevance and on the second determined measure of relevance (cls. 1/6)</u>	Software and/or algorithms at EX-1001, 25:21-26:52, 27:12-19, 29:41-30:35, 35:62-36:6. At best, the structures of the “Relevance Analysis Module” in Marston involves algorithms used to determine the “local relevance value,” which is “a function of the user’s own IRC, the global and cognate relevance scores, and the combined importance relating to that mail.” Fox, ¶80.

5. “Content Presentation Module”

Limitation (Function Underlined)	Corresponding Structure
a content presentation module configured to <u>present the piece of electronic content to the user in accordance with the determined relevance score and to present to the user a value describing the determined relevance score (cls. 2/13)</u>	Software and/or algorithms at EX-1001, 2:41-3:9, 6:55-60, 7:28-50, 24:30-34, 24:60-62, Figs. 5, 19-20. At best, the structure of the “Content Presentation Module” in Marston involves the “mail presentation module.” EX-1001, 6:55-60, 7:28-34; Fox, ¶81. The mail presentation module can be used to generate the various web page interfaces depicted in Figures 9-20. <i>Id.</i>

6. “Search Module”

Limitation (Function Underlined)	Corresponding Structure
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a search module configured to <u>search the electronic content in accordance with the determined relevance score</u> (cls. 3/14)	Software and/or algorithms at EX-1001, 6:60-64, 7:32-34, 7:42-48, 8:9-12. At best, the structure of the “search module 262,” which “provide[s] a user with search capabilities in accordance with the relevance and importance scores determined by the relevance analysis engine 252.” EX-1001, 6:60-64, 7:32-34, 7:42-48, 8:9-12; Fox, ¶82. Search criteria can include “keywords, dates, specific senders.” EX-1001, 16:10-15. Because the claims specify searching electronic content “in accordance with the determined relevance score,” a POSITA would understand Marston’s discussion of “help[ing] rank search results and indicate to the user how likely each piece of content is to be of interest” provides the corresponding structure for the “search module.” Fox, ¶82.
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VIII. DETAILED EXPLANATION OF GROUNDS

A. Ground 1: Obviousness Over Dumais (EX-1005)

1. Dumais

Dumais discloses a data manipulation system that assigns scores of relevance to electronic content, which can be based on both content and users’ interactions with that content. Dumais, Abstract, ¶¶7-8, 23-25. As shown in Figure 1 (below), Dumais discloses a “monitor component” observing user interaction or activity with data items—documents, files, email messages, calendar appointments, or web

pages—that is coupled to a “tag component” assigning or associating weights/scores with “data items” in database(s) to indicate the “importance” of the item:

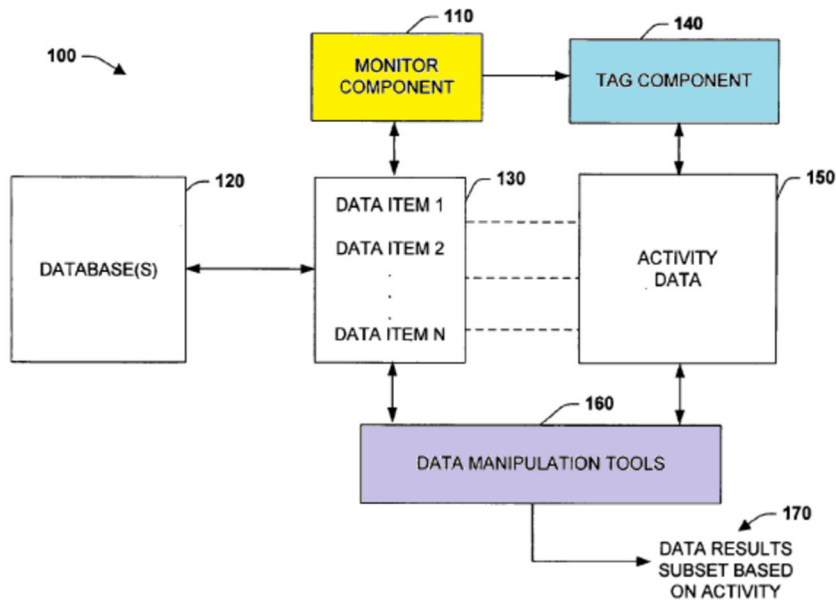


FIG. 1

Id., ¶¶22-23, 31-33, Fig. 1.⁷ Monitored user interactions on a data item can include opening, closing, editing, adding to or deleting from, reading from or writing to, cutting, pasting, forwarding, or replying to a document, as well as the amount of time viewed. *Id.*, ¶¶8, 22.

Dumais teaches the use of a “personalization component” that builds “User Models & Data,” depicted in Figure 5 (below), that reflect users’ interests and can be used to personalize search results according to “determined activity data”:

⁷ For all figures throughout Petition, highlighting/annotations have been added.

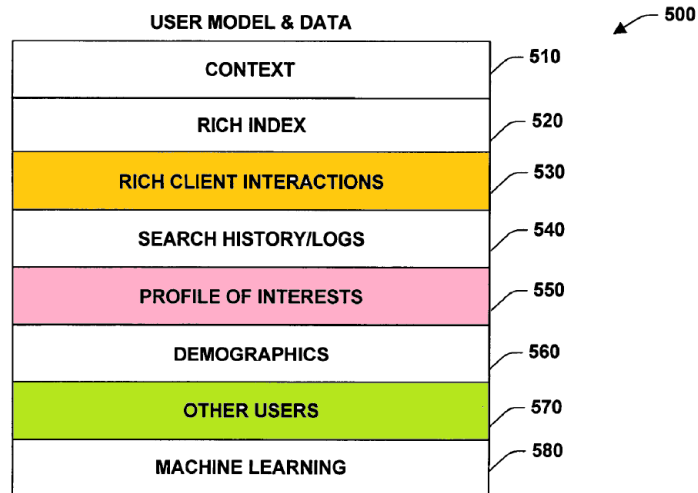


FIG. 5

Id., ¶43, Fig. 5 (highlighting different relevance inputs). The “user model” can be based on “many different sources of information” and created for individuals and/or groups via “collaborative filtering techniques that develop profiles by the analysis of similarities among individuals or groups.” *Id.*, ¶¶43-50, 52. Dumais can identify a subset of users that “belongs to a desired social network of interest for the one user” by observing how users interact. *Id.*, ¶21.

The monitor component and tag component are further connected to Dumais’s “data manipulation tools,” which can “refine” search results by “filtering or ranking” items. *Id.* ¶¶8, 24. Figure 4 (below) shows how a “user model” and a “global database 490 of user statistics” can modify both search queries and results:

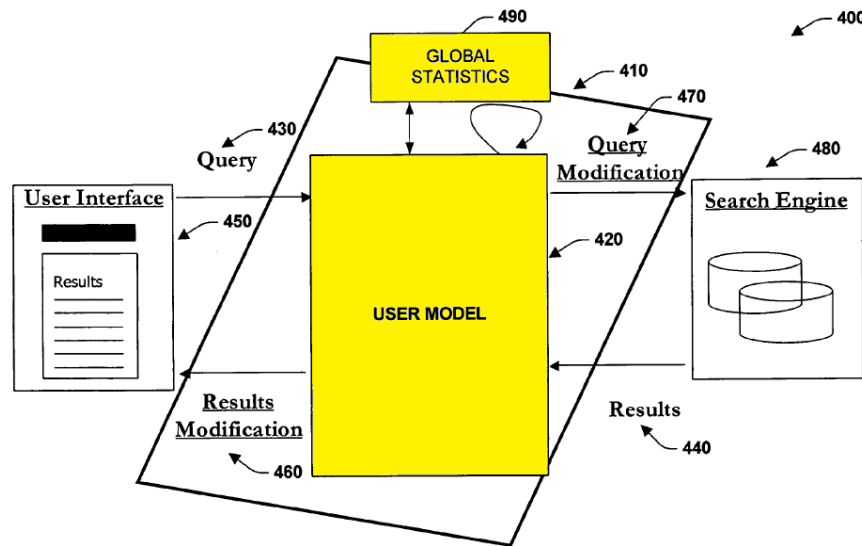


FIG. 4

Id., ¶40, Fig. 4; Fox, ¶85. The user model and global statistics can be “associated with user activity or interaction data...to facilitate data manipulation or processing.” Dumais, ¶40. Dumais’s data manipulation system can also apply content-based scores to data items “based on the similarity of a user’s query to the content of the document,” using “activity data” to identify regions or terms of interest to a user. *Id.*, ¶25. Figure 2 (below) depicts an “exemplary user interface” that uses tagged scores to identify relevant data files for users:

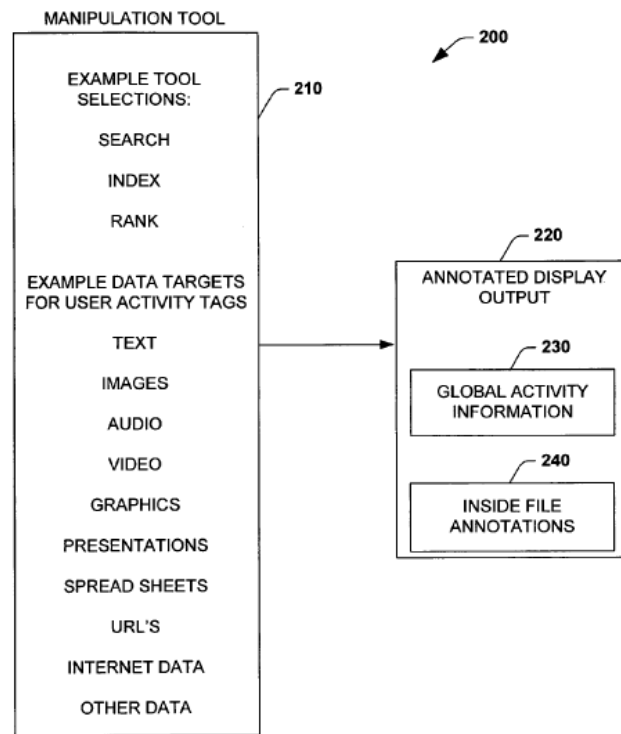


FIG. 2

2. Independent Claims

The '271 Patent (Marston) includes three overlapping independent claims. Fox, ¶¶68-70. Claim 1 is narrower than claims 6 and 7, with claim 6 reciting a “computer program product” and claim 7 reciting a “computer-implemented method (without any MPF “modules”).

a. 1[pre]/6[pre]/7[pre]

If limiting, Dumais teaches 1[pre]/6[pre]/7[pre]. Dumais discloses a “system 100” and describes “computer 812” as an “exemplary environment 810” (“*a computer-implemented system*”). Dumais, ¶¶17, 22, 70, Figs. 1, 4, 8; Fox, ¶¶97-100,

142, 149. Terms used within Dumais—“component,” “system,” “tag,” “monitor,” “model,” “query,” etc.—“refer to a computer-related entity, either hardware, a combination of hardware and software, software, or software in execution.” Dumais, ¶20.

For the reasons discussed below for 1[a] and 1[b], Dumais discloses 6[pre]’s “*computer-program product having a computer-readable storage medium having computer program instructions encoded thereon*” and 7[pre]’s “computer-implemented method.” Dumais, ¶20, 22 (describing a “system 100...to perform various computer-related tasks”), Fig. 8. A POSITA would have understood a “computer implemented system” (1[pre]) teaches a “computer-program product” (6[pre]) and “computer-implemented method” (7[pre]). Fox, ¶¶142, 149.

Dumais’s “monitor component” observes a user’s interactions with databases storing data items (“*pieces of electronic content*”). Dumais, ¶22. “Data items” include “documents, files, email messages, calendar appointments, web pages.” *Id.*, ¶31. Data items can be “forwarded,” “replied to,” or “sent” from one user (“*a sender*”) to another. *Id.*, ¶22. A tag component assigns weights/scores to reflect the user’s interactions with an item. *Id.*, ¶¶22-23, 31; Fox, ¶98. Dumais also stores “user models” that reflect a users’ interests, (Dumais, ¶¶43-50), alongside “global statistics 490,” both of which “can be associated with user activity or interaction data...to facilitate data manipulation,” (*id.*, ¶40).

Noting “other forms of data manipulation” can be used, Dumais provides an example of manipulating user searching, including by personalizing search queries or results. *Id.*, ¶40; *see also id.*, ¶¶41-42, Fig. 4. Modification of search results typically includes “re-ranking and/or selection from a larger set of alternatives,” including “consideration or weighting from determined activity data.” *Id.*, ¶41. Dumais’s ranking of content entails a “ranking score” (“*a relevance score*”). *See, e.g., id.*, cl. 17 (“providing a ranking score used for retrieval”); Fox, ¶99. Rankings are “personalized” to users (“*determined with respect to the user*”). Dumais, ¶41. Several inputs can affect Dumais’s rankings, including (1) “tags and data items,” (*Id.*, ¶¶24, 41); (2) “content-based scores” that “give more weight” to terms with which the user has interacted (*id.*, ¶25); and (3) a “user model” updated using the “global database” of user statistics (*id.*, ¶40, Fig. 4).

b. 1[a]

Dumais’s components include “a processor” (“*a computer processor*”). *Id.*, ¶20, 70 (“exemplary environment” includes “processing unit” that “can be any of various available processors”), Fig. 8 (below); Fox, ¶¶101-02.

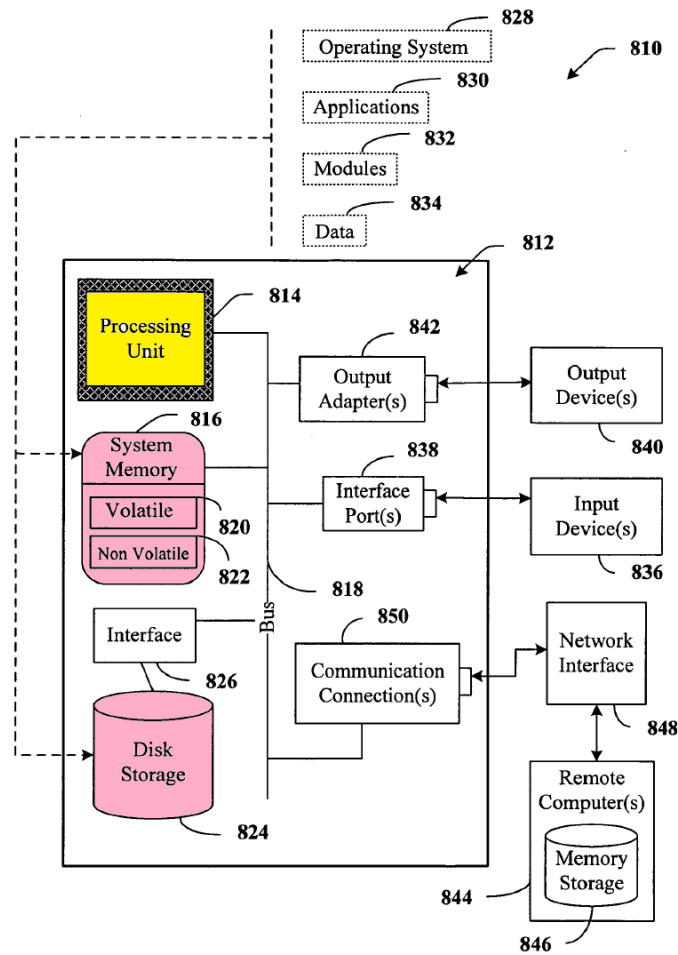


FIG. 8

c. 1[b]

Dumais teaches 1[b]. As discussed with 1[a], Dumais's components run on a "processing unit" (*processor*). Further, these components "execute from various computer readable media having various data structures stored thereon" (*computer-readable storage medium*) and "may communicate via local and/or remote processes." Dumais, ¶20. Figure 8 (above) depicts an "exemplary environment" for the data manipulation system where "applications," "modules," and "data" are stored

in system memory and disk storage (*storing computer program modules configured to execute on the computer processor*). *Id.*, ¶¶20 (discussing “program modules” and “program data” stored in “system memory” or “disk storage”), 70, 72-74; Fox, ¶¶103-04.

d. 1[c]/6[a]/7[a]

Dumais teaches 1[c]/6[a]/7[a], under MPF or non-MPF.⁸ Dumais’s monitor component 110 (*monitoring module*) tracks “when the data items 130 are interacted with by users” (*track actions by a plurality of users*). Dumais, ¶22, Fig. 1 (below).

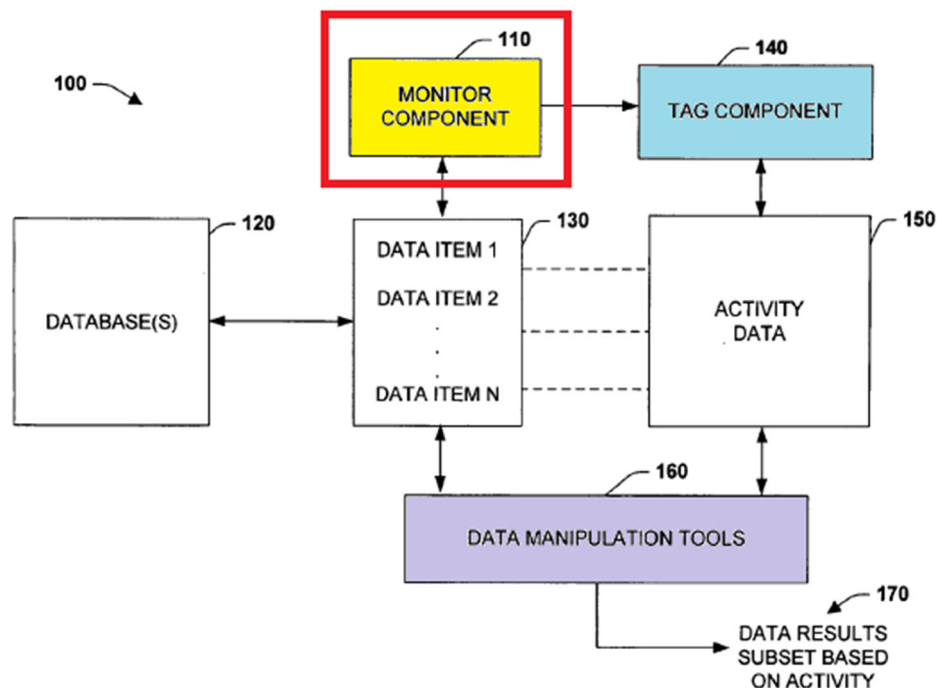


FIG. 1

⁸ Claim 7 does not recite “modules” or implicate MPF analysis.

Dumais's "monitor component" monitors many kinds of user actions on a data item (opening, closing, editing, forwarding, replying to, etc.). *Id.*, ¶¶19, 22 ("Monitoring can...determine when the data items 130 are interacted with by *users*"), 38. Moreover, Dumais discloses a "global database 490 of user statistics." *Id.*, ¶40. Dumais discloses "collaborative filtering techniques," (*supra* §VIII.A.1), that evaluate similarities of users "based on the content and/or [their] usage of items," confirming it tracks usage data for multiple users. *Id.*, ¶52; Fox, ¶¶105-06. Dumais uses "data acquisition components" (e.g., cell phone, microphone, GPS, calendars, desktop activity, website interaction, etc.) to record/log user event data. Dumais, ¶54. Monitored data activities further include how long a user interacts with a data item. *Id.*, ¶23. That activity or interaction is "subsequently tagged to a data item," so the system can track user activity. *Id.*, ¶¶19, 23; Fox, ¶¶105-07.

Dumais teaches a "data processing" and "information retrieval" system that ranks content to identify "a smaller or more manageable set of items" (*an application for managing electronic content*). Dumais, ¶¶8, 10-13, 23 (discussing monitoring user actions "within an application"), 31. Dumais's data manipulation system can be implemented in "substantially any manner that supports personalized query and results processing," such "as a server, a server farm, *within client application(s)*, or more generalized to include a web service(s) or other *automated application(s)*" (*users associated with an application for managing electronic content*). *Id.*, ¶54.

A POSITA would have understood Dumais's "monitor component" teaches the structure of the "monitoring module," including because Dumais (1) contemplates that monitoring can be performed on a client, just like a client-side "plug-in" monitoring end users' actions on mail content (*id.*, ¶¶20, 46, 52, 54, 56, 78, Fig. 9), and (2) discloses a server that can "tag content with flags," i.e., the "tags" applied to data items by the "tag component" based on monitored actions, as discussed below in 1[d]/6[b]/7[b], (*id.*, ¶¶8, 20, 23, 56, 78). Fox, ¶¶106, 108-09; EX-1030, 93-94 (discussing the "Eclipse" plug-in); EX-1031, Abstract, 785-87; EX-1032, 193. Dumais explicitly contemplates emails and email applications with searching functionality, *i.e.*, conventional email. *Id.*, ¶¶1, 31, 58, 65 (discussing integrating a user's "e-mail system or other message system"); Fox, ¶110. If Dumais does not explicitly teach a conventional email system, a POSITA would have found it obvious to integrate such a system with Dumais's searching and ranking system to personalize email and search results. EX-1001, 1:33-63 (discussing "traditional email"), 2:17 (discussing Fig. 1A's "traditional prior art email system"), 16:31-39 (referring to "conventional email systems"), 47:9-10; Fox, ¶111.

e. 1[d]/6[b]/7[b]

Dumais teaches 1[d]/6[b]/7[b], under MPF or non-MPF. In Dumais, "activity or interaction[s] can be monitored and subsequently tagged to a data item." Dumais, ¶19. Based on users' monitored actions, Dumais's "tag component 140" then

assigns, or “tags,” that data item with a score or weight (*first measure of relevance of the piece of electronic content*) “according to the type and intensity of the activity” (*based at least in part on one or more actions of the user on the piece of electronic content*). *Id.*, ¶¶7, 23. “Weights or scores” are variable and “can reflect the amount or pattern of the user’s interaction with a given piece of data or application” (i.e., the “type and intensity of the activity”).” *Id.*, ¶¶7-8, 23. “Tags and data items” can be used with “data manipulation tools” to “employ user activity information derived from the tags to augment...information access (e.g., searching, filtering or ranking of items)[.]” *Id.*, ¶24.

A POSITA would have understood Dumais’s “tag component” teaches the structure of the “*first relevance measurement module*” because the tag component assigns “weights or scores” based on monitored user activity (*id.*, ¶¶7, 23), which mirrors Marston’s discussion of “Individual Relevance Components.” *See, e.g.*, EX-1001, 25:45-49; Fox, ¶¶113-14. Dumais’s tags can be based on both dichotomous (opened email, replied, etc. (Dumais, ¶38)) and scaled factors (tracking how often a user interacts with a data item, (*id.*, ¶¶7-8, 23, 31); *cf.* EX-1001, 28:63-29:40 (considering if user opens/replies to mail, alongside “how many extra times” users perform actions). Fox, ¶¶114-16.

For example, “minimal file usage” (e.g., “opened one time within a year,” “very light perusal”) could be assigned a lowed weight indicating “lower importance

of the file to the user,” whereas “extensive editing of the file” may be assigned a higher weight. Dumais, ¶¶8, 23, 39. “Determined weight information” is illustrated as “Activity Data 150” in Figure 1:

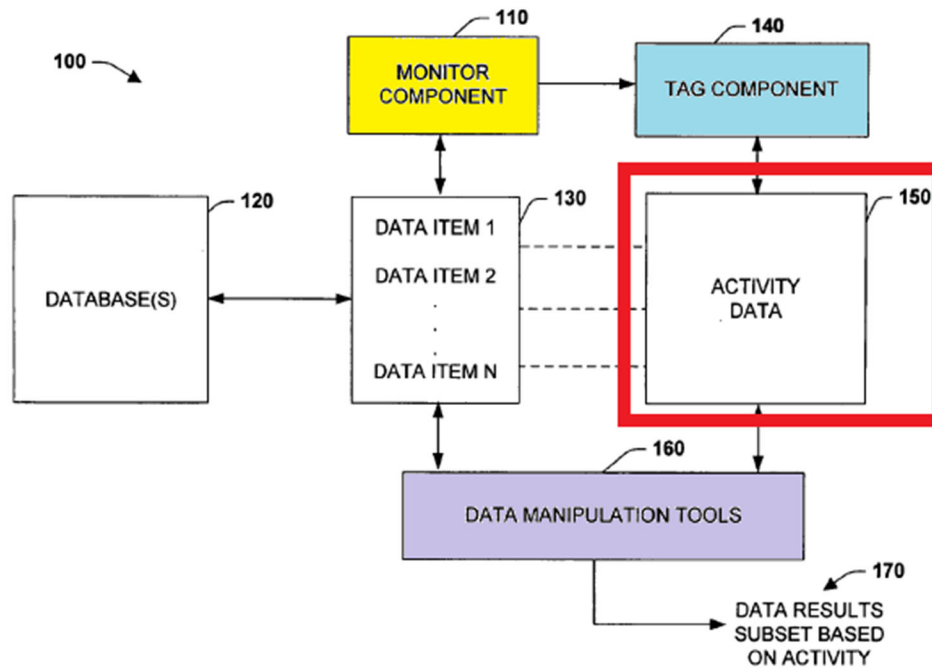
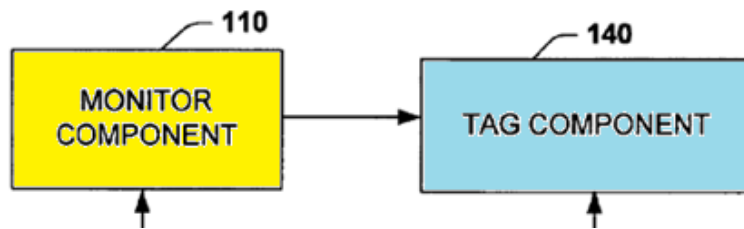


FIG. 1

Dumais associates scores/weights with data items to indicate the user’s “past usage or interactions” with it. *Id.*, ¶¶8, 23, 35, 39, Fig. 2. Figure 1 (below, excerpted) shows that the “tag component” (*first relevance measurement module*, blue) is connected

to and communicates with (*coupled to*)⁹ the monitoring component (*monitoring module*, yellow):



Id., Fig. 1, ¶20 (“The components may communicate via local and/or remote processes...(e.g., data from one component interacting with another component in a local system, distributed system, and/or across a network such as the Internet...).”). Together, the tag component and monitor component calculate the “weight and score.” *See* 1[a]-1[b]; *id.*, ¶¶8, 23; Fox, ¶116.

f. 1[e]/6[c]/7[c]

Dumais teaches 1[e]/6[c]/7[c], under non-MPF or MPF, as discussed below in 1[f]/6[d]/7[d] and 1[g]/6[e]/7[e]. Dumais teaches a “personalization component 410” (*second relevance measurement module*) that includes a “user model” “based on user activity,” as well as processing components for “using the model to influence search results.” Dumais, ¶¶40-41, Fig. 4; *see also* 1[f]/6[d]/7[d]-1[g]/6[e]/7[e]

⁹ The ’217 patent never restricts how modules are “coupled.” *See generally* EX-1001.

(below). Personalization component 410 uses a “global database” of “user statistics” to update user models. Dumais, ¶40.

A POSITA would have been motivated to use “personalization component 410” in combination with (*coupled to*) tag component 140 and monitor component 110, because Dumais discusses that the user model can be used with “determined activity data” to personalize search results. *Id.*, ¶¶40, 43; *see also id.*, ¶¶40 (“[T]he user model 420 and/or global statistics 490 can be associated with user activity or interaction data...to facilitate data manipulation or processing.”), 43, 53, 79, Fig. 5. Dumais teaches that the user model can be used for “data manipulation,” (*id.*, ¶40), such that a POSITA would understand the “personalization component” to be located within the “Data Manipulation Tools,” connected to (*coupled to*) the monitor/tag components in Figure 1:

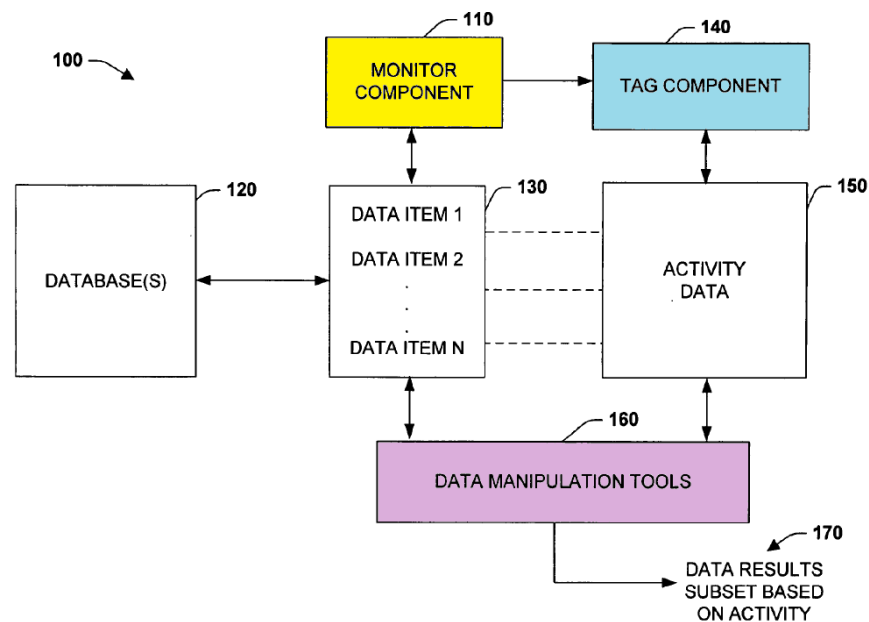


FIG. 1

Id., 22, 40, 43, Fig. 1; Fox, ¶¶118-19.

g. 1[f]/6[d]/7[d]

Dumais teaches 1[f]/6[d]/7[d], under MPF or non-MPF. Dumais discloses identifying other recipients of electronic content that are “cognate” to the user because the personalization component builds “user models,” in part, using “collaborative filtering techniques” that analyze “similarities among...groups of individuals...based on the content *and/or usage of items*.” Dumais, ¶52; *see also id.*, ¶22 (“Monitoring can...determine when the data items 130 are interacted with *by users*.”), Fig. 5 (depicting “Other Users” data in “User Model & Data”); Fox, ¶120. Dumais discusses “observing that one user interacts with a subset of other users over a network” to “determine[] or infer[] that this subset of users belongs to a *desired social network of interest*[.]” Dumais, ¶21. A POSITA would have understood these disclosures teach identifying a “cognate” group of users for a user, as used in Marston. Fox, ¶120; EX-1001, 14:59-15:11.

Dumais teaches that “data files” can include emails (and other documents sent to a recipient), and Dumais contains robust disclosures discussing emails and integrating with a user’s “e-mail system.” Dumais ¶¶31, 36, 56, 65; Fox, ¶121. Thus, when considering other users’ “usage of items” in the context of email, especially in the context of collaborative filtering, a POSITA would have understood Dumais contemplates users receiving and interacting with the same email, including

identifying all of those receiving an email message based on inclusion in the TO or CC fields. Fox, ¶121.

Dumais further teaches the structure for this function of the second relevance measurement module. Indeed, “collaborative filtering” and “group based” analyses—both taught by Dumais to build “Other User” information within user models—are two of the ways Marston teaches to estimate “similar past user actions and assessments” of users. EX-1001, 14:59-15:11, 43:30-37; Fox, ¶122.

h. 1[g]/6[e]/7[e]

Dumais teaches 1[g]/6[e]/7[e], under MPF or non-MPF. Dumais’s personalization engine builds “user models” from a “variety of sources” (containing a *second measure of relevance of the piece of electronic content*) which generally map to the limitations of 1[g]/6[e]/7[e] (*based at least in part on one or more measures derived from the group*). Dumais, ¶43; Fox, ¶¶123-28. Dumais relies on the relevance values from the user model to personalize and rank content.

Dumais teaches “*local importance describing an importance of the sender to the user*” because “Rich Client Interactions” data (shown in Figure 5’s “User Model & Data”) includes monitoring “client interactions” like a user’s “recent or frequent contacts.” Dumais, ¶¶43-46; cf. EX-1001, 13:53-67 (discussing estimating the importance of a user’s contacts), 19:25-33. Dumais’s “data items” can include email, and it monitors when items are “forwarded, replied to, [or] sent to” others.

Dumais, ¶¶22, 31. Dumais contemplates evaluating the “rate and frequency of email...from the author of a message *at a user’s focus of attention*,” estimated based on that user’s activity. *Id.*, ¶64. For MPF, a POSITA would have understood Dumais teaches the structure of the “second relevance measurement module” for “local importance” because evaluating the user’s “recent or frequent contacts” is based on a user’s actions on that sender’s messages (which inform the user’s “focus of attention”). *Id.*, ¶43; Fox, ¶124.

Dumais teaches “*a global importance describing an importance of the sender within an organization with which the plurality of users are associated*”, describing a sender’s importance within an organization, because “client interactions” can include the user’s “relationships in an organizational chart.” Dumais, ¶46. For MPF, a POSITA would have understood Dumais’s organizational chart teaches the structure of the “second relevance measurement module” for “global importance.” EX-1001, 29:64-30:3 (using organizational chart to identify global importance); Fox, ¶125.

Dumais teaches “*a content relevance determined responsive to content of the piece of electronic content*” by discussing an example where it assigns “content-based scores” to documents “based on the similarity of a user’s query to the content of the document.” Dumais, ¶25. Dumais’s personalization component can modify search results using statistical similarity matching or category matching, both of

which personalize search results by evaluating a user's interests and content. *Id.*, ¶¶42, 52. Moreover, Figure 5's "User Model & Data" can include an "index of content previously encountered." *Id.*, ¶¶43, 45. For MPF, a POSITA would have understood Dumais teaches the structure of the "second relevance measurement module" for "content relevance" by mirroring Marston's teachings about using "statistical techniques" to evaluate content. *Id.*, ¶42; *see also* EX-1001, 41:7-25 ("statistical techniques"), 45:13-37; Fox, ¶126.

Finally, Dumais teaches "*one or more actions on the piece of electronic content of the at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user.*" As discussed for 1[f]/6[d]/7[d], Dumais employs collaborative filtering techniques that update the relevance of messages based on actions of other users on that same message. Dumais, ¶¶52, 55. A POSITA would have understood that Dumais monitors the actions of other users, as discussed in 1[c]/6[a]/7[a]. *Id.*, ¶¶19, 22, 38, 48, Fig. 5 (showing "Other Users" data); Fox, ¶¶127, 105-11. Dumais teaches that "several algorithms" can implement collaborative filtering, including "techniques based on correlation coefficients, vector-based similarity calculations, and statistical Bayesian methods." *Id.*, ¶55; *see also id.*, ¶¶53 (discussing "statistical/mathematical models and processes for modeling users and determining preferences"), 41 ("modification of results...can include a consideration or weighting from determined activity data").

For MPF, a POSITA would have understood that Dumais renders obvious the structure of the “second relevance measurement module” for actions of cognate users, including because (1) it can use “correlation coefficients” to perform a “weighted average” of data from cognate users, and (2) a weighted average is a simple and well known “statistical/mathematical” technique. Fox, ¶127.

While only a single “second relevance score” from this Markush group is needed, Dumais renders all four obvious. Fox, ¶¶123-28.

i. $1[h]/6[f]/7[f]$

Dumais teaches $1[h]/6[f]/7[f]$, under non-MPF or MPF.

Although “other forms of data manipulation can be performed,” Dumais uses personalized searching to explain how it recommends content. Dumais, ¶40. Dumais’s “personalization component 410” contains “processing components” (*relevance analysis module*) that use “user models” to personalize searches by modifying either search queries or results, as shown in Figure 4:

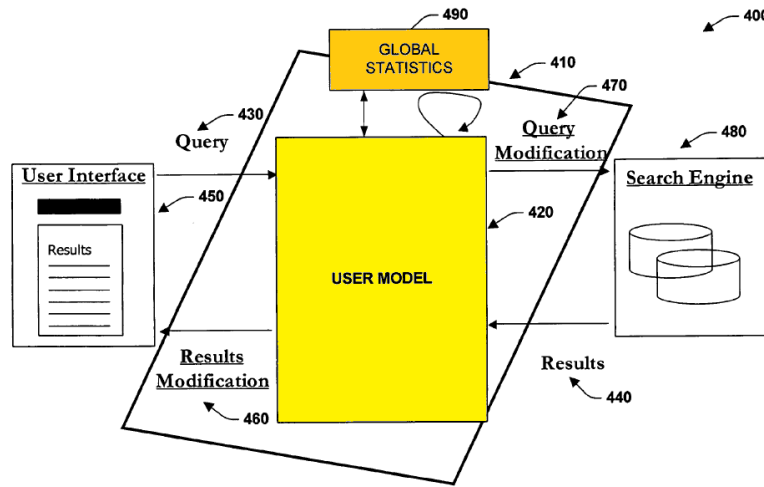


FIG. 4

Id., ¶40 (“processing components (e.g., retrieval algorithms modified in accordance with the user model) for using the model to influence search results by modifying a query 430 and/or modifying results 440 returned from a search.”); *see also id.*, ¶¶41-42, 50, Fig. 4. Dumais teaches that modification of search results typically includes “re-ranking and/or selection from a larger set of alternatives,” including “consideration or weighting from determined activity data.” Dumais, ¶41. A POSITA would have understood that this ranking of content requires a “ranking score” (*a relevance score*). *See, e.g., id.*, cl. 17 (“ranking score used for retrieval”); Fox, ¶¶99, 129.

User models “can be based on many different sources of information” to personalize results for a user. Dumais, ¶50. In addition to the user model, Dumais maintains a “global database” of user statistics, where “the user model 420 and/or global statistics 490 can be associated with *user activity or interaction data...*to

facilitate data manipulation.” *Id.*, ¶40. As discussed for 1[d]/6[b]/7[b], this activity/interest data is stored in “tags” on data items (*the first determined measure of relevance*) that “indicate at least one user’s interaction with the data items.” *Id.*, ¶19. Thus, Dumais teaches combining information from user models (informed by a global database of user statistics) (containing the *second determined measure(s) of relevance*, see 1[f]/6[d]/7[d]-1[g]/6[e]/7[e]), and determined activity data (*i.e.*, “tags” on data items based on monitored interactions, see 1[d]/6[b]/7[b]) (*the relevance score being determined based at least in part on the first determined measure of relevance and on the second determined measure of relevance*). The ultimate ranking is determined by (1) considering or weighting from “determined activity data” (within or derived from “tags” on data items), and (2) data from the user model (“Rich Client Interactions,” “Other Users,” etc.).

Rankings of search results can be accomplished using “statistical similarity match[ing]” or “category matching,” which compare “user interests and content” to identify relevant results. *Id.*, ¶42. For example, several inputs can affect Dumais’s rankings, including (1) “tags and data items” (*id.*, ¶¶24, 41 (“determined activity data”)); (2) “content-based scores” that “give more weight” to terms the user has interacted with (*id.*, ¶¶25, 33); and (3) a “user model” updated using a “global database 490 of user statistics,” which contains information specific to a user relating to “recent or frequent contacts,” an “organizational chart,” and “other users” (*id.*,

¶¶40, 45-46, Fig. 5). *See also id.*, ¶¶36 (“Searches can be crafted in a plurality of ways and can include combinations of content searching, activity-based searching, and or combinations thereof”), 40, 46, Figs. 4-5; Fox, ¶¶129-32. For example, Dumais’s “content-based score” can be assigned to documents based on a user’s query (which can be modified based on the user model). Dumais, ¶¶25, 41. When ranking documents in response to the user’s search, the results will use tags (derived from monitored user actions) to “give more weight to terms that appear in documents or sections of a document that have been edited or the user has spent lots of time reading.” *Id.*, ¶¶24-25. Thus, this “content-based score” is based on both (a) information from a user’s “user model” and (b) determined or “tagged” activity data based on monitored user interactions with content. *Id.*, ¶¶25, 41; Fox, ¶¶131-32.

A POSITA would have understood the personalization component’s processing components disclose the structure of the “relevance analysis module.” *Cf.*, EX-1001, 26:46-52. As discussed in 1[c]/6[a]/7[a] above, “tags and data items” and “determined activity data” reflect the relevance of an item to the user, mirroring the “individual relevance components” discussed in Marston. Dumais, ¶31 (“[A] viewer allows a user to retrieve items based on functions of one or more tags.”). Similarly, Dumais discloses developing local/global and cognate relevance scores for data items, including email, as discussed in 1[e]/6[c]/7[c]-1[g]/6[e]/7[e] above.

A POSITA would have understood Dumais's discussion of "statistical similarity match[ing]" or "category matching" refers to functions of the various relevance measures discussed for claim 1[d]/6[b]/7[b] and 1[e]/6[c]/7[c]-1[g]/6[e]/7[e]. Dumais, ¶42; Fox, ¶133.

3. Claims 2/13/18.

Dumais teaches claim 2/13/18's additional limitation under MPF or non-MPF. Dumais teaches a "user interface display" or "user interface" (*content presentation module*) that can display search results with "highlighting," "graphics," and annotations on items indicating user activity. Dumais, ¶¶35-36, 40, 58, Fig. 4. Dumais personalizes search results, including by ranking content for display (*present the piece of electronic content to the user in accordance with the determined relevance score*). *Id.*, ¶¶40-43.

As discussed above for 1[d]/6[b]/7[b], activity data can "identify regions or terms of interest" where content-based scores are used to "[d]ifferentially present (via highlighting or other techniques) items or regions of items of interest." *Id.*, ¶¶25-30, Fig. 2. For example, Dumais discusses presenting emails that have been highlighted "in one color" to indicate items having "a higher activity score" (*a value describing the determined relevance score*). *Id.*, ¶36; Fox, ¶¶134-35, 165, 168; See EX-1034, 52-53; EX-1035, 67-75.

If PO argues this claim requires a literal number representing the value of the relevance score, a POSITA would have found it obvious to “differentially present” content by displaying a score or rank next to it. Dumais, ¶¶25-30; Fox, ¶¶136-37. Dumais already calculates a ranking score to “re-rank” content, so displaying the score would be obvious. *See* Dumais, ¶41; Fox, ¶135. Indeed, before Marston, search engines often provided search results alongside a ranking (*a value describing the determined relevance score*). Fox, ¶136.

A POSITA would have understood Dumais teaches the structure of the “content presentation module.” Dumais repeatedly discusses being used with e-mail and integrating its data manipulation tools with a user’s “e-mail system.” Dumais, ¶¶1, 36, 65. Dumais discusses changing how emails are displayed on a “user interface display,” (*id.*, ¶36), mirroring Marston’s discussion of a “mail presentation module” generating interfaces for e-mail. EX-1001, 6:55-60, 7:28-34; Fox, ¶¶136-37.

4. Claims 3/14/19.

Dumais teaches claim 3/14/19’s additional limitation under MPF or non-MPF. Dumais discloses an exemplary system for personalizing search results. Dumais, ¶40. As with 1[e]/6[c]/7[c]-1[g]/6[e]/7[e], the “personalization component” has “processing components (e.g., retrieval algorithms modified in accordance with the user model)” for search engines to modify search queries or results. *Id.*, ¶40. As

depicted in Figure 4 (below), Dumais contemplates that “search engines 480” can conduct searches (*a search module configured to search the electronic content*). A POSITA would understand that search engines, for efficiency or otherwise, often employ shortcuts re-using previously determined relevance scores. Fox, ¶138.

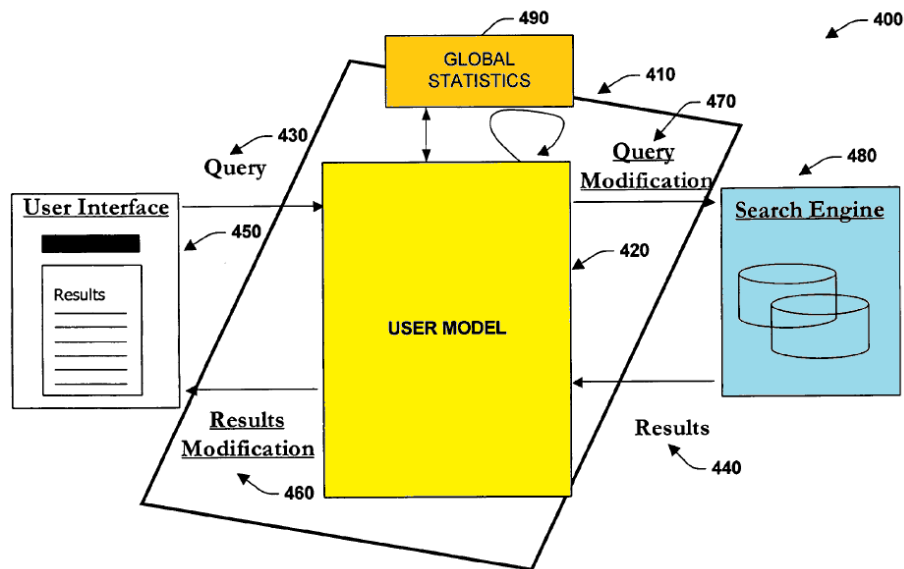


FIG. 4

Dumais teaches modifying search results, which “usually includes some form of re-ranking and/or selection from a larger set of alternatives” (*search...in accordance with the determined relevance score*). *Id.*, ¶41. Dumais contemplates that search queries can also be modified to personalize searching. *Id.*, ¶¶40-41.

A POSITA would have understood Dumais teaches the structure of the “search module.” Like Marston, which helps “rank search results and indicate to the user how likely each piece of content is to be of interest,” Dumais re-ranks search results to personalize them for a user. EX-1001, 8:9-12; Dumais, ¶41; Fox, ¶139.

5. Claims 5/15.

Dumais teaches claim 5/15's additional limitations. Dumais discloses that “[t]he systems and methods described herein support a plurality of data processing applications,” including “processing data items such as **documents**, files, [and] **email messages**,” among other data (*the electronic content comprises at least one of an email, a document, an instant message, and an SMS message*). Dumais, ¶31, 43-45 (“documents, web pages, email, Instant Messages”), Fig. 5; Fox, ¶141.

6. Claim 8/22

Dumais teaches claim 8/22's additional limitations. As discussed above for 1[f]/6[d]/7[d], Dumais teaches identifying “cognate” users. Dumais teaches using “collaborative filtering techniques” to develop profiles based on an “analysis of similarities among individuals or groups of individuals,” where “[s]imilarity computations can be based on the content and/or **usage of items**” (*analyzing historical actions of the at least one other of the plurality of users with respect to historical actions of the user*). Dumais, ¶52. Dumais further discloses that identifying a cognate user comprises analyzing the historical actions of those other users. *Id.*, ¶55 (“[c]ollaborative filtering is applied...to process **previous user activities** from a group of users that may indicate preferences for a given user”); *see also id.*, Abstract, Fig. 5 (storing “Other Users” data). Dumais also teaches coordinating users’ “location history” with their actions on items, confirming

Dumais stores users' historical actions. *Id.*, ¶¶31 (tags represent user's "location history" when accessing items), 44 (history of interactions), 47, 50 ("history or log of locations"), cl. 3 ("history of times" user has accessed item). Fox, ¶¶155-56.

7. Claim 9.

Dumais renders claim 9's additional limitations obvious.

Dumais contemplates searching across different periods of time. Dumais, ¶51. While one user's search may consider the past thirty days, another user's search could consider only the past three, resulting in different cognate relationships for their respective searches. Fox, ¶¶157-58.

Dumais also teaches using "collaborative filtering" to derive user models, analyzing "similarities among individuals or groups of individuals...based on the content and/or usage of items." Dumais, ¶52. A POSITA would have been understood that collaborative filtering often involves asymmetric relationships, including because practical scalability issues often require prioritizing users/factors being evaluated (*wherein the at least one other of the plurality of users is cognate to the user, and the user is not cognate to the at least one other of the plurality of users*). Fox, ¶¶159-64 (explaining scalability issues, in practice, often lead to asymmetry); EX-1033, 246-47, 250-51.

B. Ground 2: Obviousness Over Rose (EX-1006)

1. Rose

Rose teaches a “system for ranking the relevance of information that is accessed via a computer.” Rose, 1:8-10. Ranking is estimated based on a “likely degree of relevance to [a] user’s interests,” and “data regarding correlations of interests between users.” *Id.*, 2:26-27, 2:35-38. For example, a combined data relevance score may be based on “an attribute of the message...with other data relating to correlations of indications provided by users who have retrieved the message.” *Id.*, 6:5-11, 8:38-40 (discussing that the “present invention” considers “not only [] *the user’s own interests*, but also *feedback from the community*” in determining relevance score of messages).

Rose teaches that “one factor” of relevance considers a user’s actions on electronic content “when they retrieve items of information.” *Id.*, Abstract, 6:51-59. Rose monitors users’ explicit ratings (actions) on electronic content. *Id.*, 5:32-34 (user may “provide an indication of degree of interest for each message which has been retrieved.”). For example, Figure 4 (below) shows “thumbs-up”/“thumbs-down” icons allowing users to rate content:

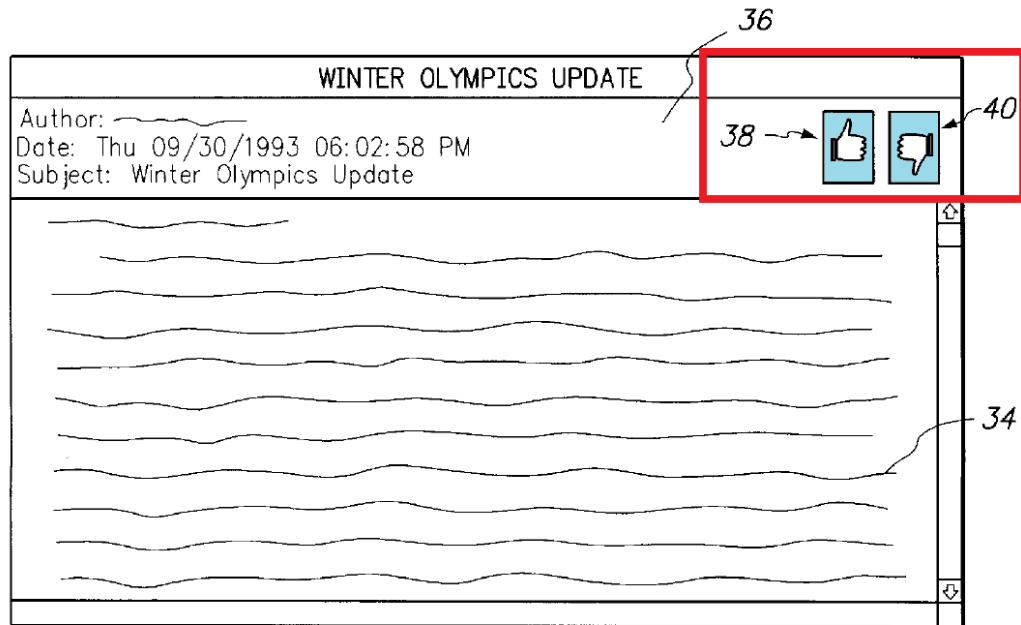


FIG. 4

Each user has a “profile of interests.” *Id.*, 2:28. User responses are “forwarded to the server” and “used to update the user profile.”¹⁰ *Id.*, 5:18-23, Fig. 4, Fig. 6 (depicting user responses). Rose teaches that icons can be more granular, allowing users to provide more-complex feedback. *Id.*, 5:28-31. “[E]ach time a message is retrieved, feedback information regarding the user’s degree of interest [can be used to]...maintain an up-to-date profile for the user.” *Id.*, 5:44-46.

¹⁰ User Profiles have long been used to track user-specific information and customize users’ experiences. Fox, ¶51-52; EX-1011, 130, 403-05; EX-1012, 146; EX-1013, 1, 14-16 (discussing logs to build user-specific data); EX-1014, 449 (discussing personalized searches using user profiles).

When a user “indicates” interest in electronic content, the system updates their profile (and, therefore, what is “relevant”) based on that feedback. *Id.*, 6:38-43 (“[I]f the user indicates interest in a document, all of the significant terms in that document can be given increased weight in the user’s profile”), 6:51-59; *see also* Fox, ¶89 (explaining that increasing the weight of terms in a document increases that document’s relevance to a user). A user’s profile “comprises a vector, based upon the user’s indications...in previously retrieved documents,” shown in Figure 5B:

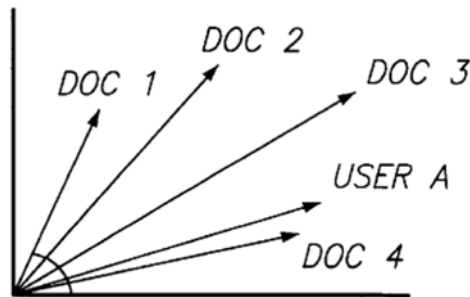
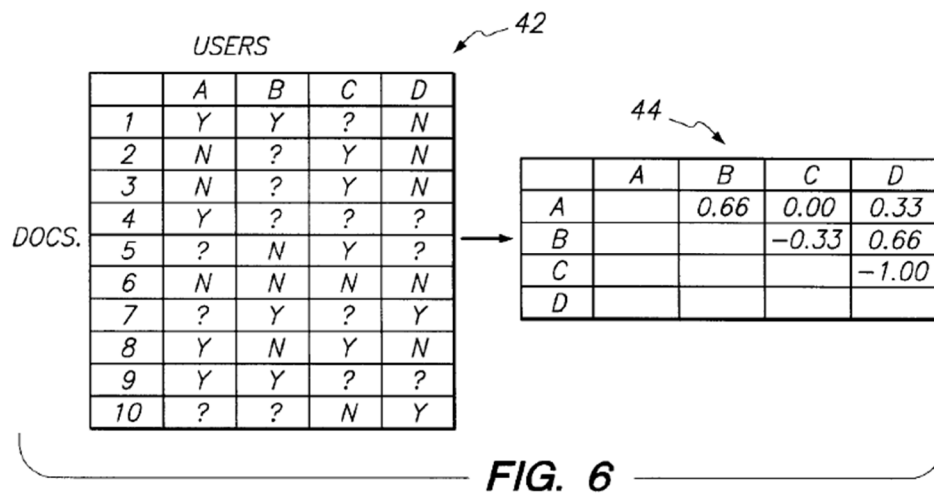


FIG. 5B

Rose, 6:36-38. Relevance for a user is estimated based on the “similarity” of the document’s/user’s “profile vector.” *Id.*, 6:51-53. The smaller the angle between the document vector and the user profile vector, the higher the item will be ranked. *Id.* This ranking system also applies to non-document information by using content data “based upon other attributes that are relevant,” such as a “movie database” where the “content vector” considers “the type of movie, such as action or drama, the actors, its viewer category rating, and the like.” *Id.*, 6:21-26. In another example, “event times can be used in the ranking equation, where older items might get lower

scores.” *Id.*, 8:13-16 (“[A] score might rise as the deadline approach[es], then fall when it [] passe[s].”).

Rose teaches a “second factor” of relevance considers correlations of indications provided by other users. *Id.*, 6:59-7:3. Rose determines a value representing “user correlation” based on “indications provided by users who have retrieved the message” (*actions*). *Id.*, 6:5-11. For example, Figure 6 (below) shows a table (left) listing ratings of documents by users, followed by a “correlation matrix” table (right) reflecting the “degree of correlation between the various users’ interests in commonly retrieved messages” (based on their “indications”).



Id., Fig. 6, 6:5-11, 6:59-7:3.

Finally, Rose teaches that the ultimate “score” for electronic content can be combined from each of these “factors.” *Id.*, 2:38-41 (combining a “value indicative

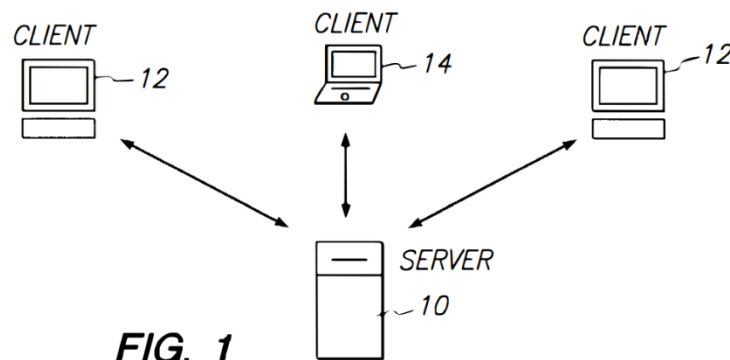
of the [document's] content] with another value defining “user correlation” to produce a “ranking score for a document.”), 6:50-53, 8:38-40.

The “content” of electronic content is evaluated vis-à-vis the user's indications on that content, and a second value indicating “user correlation” is evaluated vis-à-vis indications of other users for “commonly retrieved messages.” *Id.*, 2:39-40, 6:66. Rose also teaches that “multiple regression analysis can be utilized to combine the various factors.” *Id.*, 7:39-43, 2:41-45. Thus, Rose teaches obtaining a combined relevance score based on (1) feedback from a user and (2) feedback from “cognate” users of the same piece of electronic content.

2. Independent Claims

a. 1[pre]/6[pre]/7[pre]

If limiting, Rose teaches 1[pre]/6[pre]/7[pre]. Fox, ¶¶171-73. Rose uses “multiple personal computers that are connected via a network” (*computer-implemented system*). Rose, 3:17-21, Fig. 1 (below).



As discussed below in 1[a] and 1[b], Rose discloses 6[pre]’s “*computer-program product having a computer-readable storage medium having computer program instructions encoded thereon*” and 7[pre]’s “computer-implemented method.” Rose, 3:14-18 (teaching use of “multiple personal computers...connected via a network” 3:20-21, 3:45-57 (discussing that “a database of information is stored at a server computer,” where the server “can be any suitable...computer having sufficient storage capacity to accommodate all of the items of information to be presented to users”). A POSITA would have understood a “computer implemented system” (1[pre]) teaches a “computer-program product” (6[pre]) and “computer-implemented method” (7[pre]). Fox, ¶¶206-08, 215.

Rose teaches a “client-server arrangement,” where a server computer stores a database of information interacting with client computers. Rose, 3:45-62. Rose contemplates being part of an “electronic mail system” and that “message[s]” can be “a memorandum or note that is addressed from one user of an electronic mail system to another” (*a piece of electronic content sent from a sender to a user*). *Id.*, 3:36-42, cl. 12; Fox, ¶172.

Rose’s teachings relate to “ranking the relevance of information that is accessed via a computer” (*determining a relevance score of a piece of electronic content*). Rose, 1:6-10; Fox, ¶173. Rose provides that each user has a “profile of interests” for ranking “messages in an electronic mail network...according to their

likely degree of relevance” (*relevance score determined with respect to the user*). Rose, 2:25-34. Rose’s server evaluates the relevance of received messages based on: (1) the user’s “likely interest in a particular piece of information,” and (2) a “correlation with the indications provided by other users.” *Id.*, 6:51-7:6.

b. 1[a]

Rose teaches 1[a]. Rose states that the “present invention” arises “in a system having multiple personal computers that are connected via a network” (*computer processor*). *Id.*, 3:14-18, 3:20-21 (“[T]he invention can find utility in any situation which provides for computer access to information.”). A POSITA would have understood that a multi-computer system includes multiple computer processors. Fox, ¶174.

c. 1[b]

Rose teaches 1[b]. Considering 1[a], a POSITA would have understood that Rose’s multi-computer system includes storage mediums containing programs that execute on a computer processor (*computer-readable storage medium*). Rose, 3:45-57 (“database of information” stored at “server computer,” which “can be any suitable...computer having sufficient storage capacity to accommodate all of the items of information to be presented to users.”), 3:57-59 (“client computers can be suitable desktop computers 12 or portable computers 14...having the ability to access the server”); Fox, ¶¶175-76. As discussed in the limitations below, Rose’s

storage mediums contain the claimed computer program modules (*storing computer program modules configured to execute on the computer processor*).

d. 1[c]/6[a]/7[a]

Rose teaches 1[c]/6[a]/7[a], under MPF and non-MPF. Rose's invention manages electronic content through a ranking system that monitors user actions (and actions of other users) to estimate relevance. Rose, 2:46-57, 5:43-46, 6:44-46, 7:7-10, 7:35-50. Rose teaches that client computers in a client-server architecture can use any "suitable communication program that enables the user to access messages stored at the server machine," including a client-side "electronic mail system" (*monitoring module*). *Id.*, 3:63-66.

Rose provides examples of interfaces for client-side electronic mail systems that can monitor actions of users (*configured to track actions by a plurality of users*). Figure 4 depicts an interface with "two icons which permit the user to indicate his or her interest in [a] particular message," where indications are "forwarded to the server 10, where it is used to update the user[']s profile." *Id.*, 5:8-23, 5:56-60 ("each time a user sees a movie, he or she can record his or her reaction to it," which "is used to update the user's profile for the movie database, as well as provide information to rank that movie for viewing by other users whose interests in movies are similar or opposed"), Fig. 4.

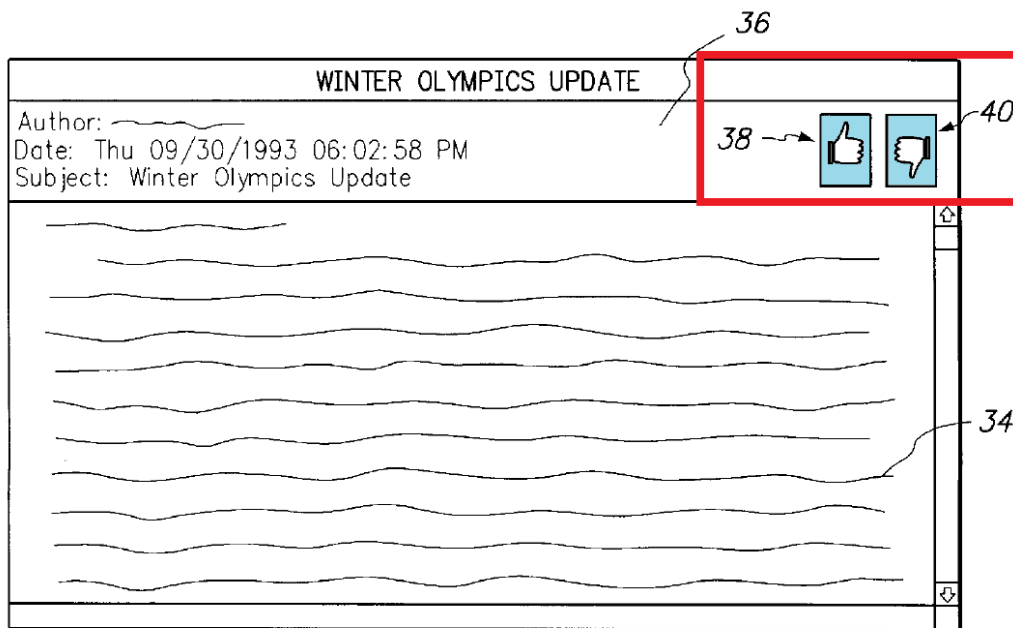


FIG. 4

Figure 7 shows another interface where movie recommendations are ranked according to a “recommendation score.” *Id.*, 5:50-64, Fig. 7.

Your Messages from "Movie Recommendation"	
Score	Title
☐	Jagged Edge
☐	Sea of Love
☐	D.O.A.
☐	The Eye of the Needle
☐	Dave
☐	Sleepless in Seattle
☐	Lost in America
☐	Mephisto
☐	Melvin and Howard
☐	Heat and Dust
☐	One Against the Wind
☐	Flashdance
☐	Duel
☐	In the Line of Fire
☐	Boxing Helena
☐	Indecent Proposal
☐	A River Runs Through It
☐	Cliffhanger
☐	Joe Versus the Volcano
☐	Not Without My Daughter
☐	Fat Man and Little Boy
☐	Runaway Train
☐	Ordeal by Innocence
☐	Cujo
☐	THX 1138
☐	The River
☐	Black Rain

FIG. 7

These interfaces track “not only on the user’s own interests, but also feedback from the community.” *Id.*, 8:38-40; Fox, ¶178. A POSITA would understand that Rose’s teaching on movies apply equally to email systems. Fox, ¶¶89 n.5, 178-79.

Rose also teaches that each user has a “user profile” stored in a database on the server, which they can only access by authorizing themselves using a “suitable communication program” at a client computer (*users associated with an application for managing electronic content*). Rose, 3:63-4:5, 4:13-20; Fox, ¶179.

A POSITA would have understood that Rose renders obvious the structure of a “monitoring module.” For example, Rose contemplates the use of an “electronic

mail system” and generally operates on “messages in an electronic mail network,” confirming it uses email. *See, e.g.,* Rose, 2:25-34, cl. 12. Given that Rose teaches that users can use any “suitable communication program” enabling the user to access messages on the server, a POSITA would have considered it obvious to use plug-ins for that client-side electronic mail system (*e.g.,* running in a browser, etc.) to monitor a user’s interactions with mail. *Id.*, 1:13-49, 2:29-34, 2:50-57, 3:63-66, 4:38-44, cl. 12; EX-1001, 16:31-39; Fox, ¶¶75, 180; *see also* EX-1030, 93-94; EX-1031, Abstract, 785-87; EX-1032, 193. Indeed, by the time of Marston, plug-ins were a common way to add functionality to email applications. *Id.*

e. 1[d]/6[b]/7[b]

Rose teaches 1[d]/6[b]/7[b] under MPF or non-MPF. As Rose discusses, users can use their client-side email systems (*monitoring module*) to rate electronic content (*based at least in part on one or more actions of the user on the piece of electronic content*). Rose, 2:48-50, 5:15-37. When they do, ratings from the user’s client device are sent to a server, which contains programming (*first relevance measurement module*) “used to update the user profile” (containing a *first measure of relevance of the piece of electronic content*) that is “used to rank the messages stored within the system.” *Id.*, 4:33-35, 5:21-23. Rose details how the server’s programming (*a first relevance measurement module*) uses a network to send messages to and receive

feedback from (*coupled to*) the client-side email system (*monitoring module*). *Id.*, 3:51-62, 4:11-20, 5:1-23.

When the user rates electronic content, the system updates weights for “significant terms in that document” in the user’s profile, which then increases (or decreases) the relevance of that document for that user. *Id.*, 6:36-43; Fox, ¶¶181-83. Similarly, Figure 5B shows that “*a score of a document’s relevance*” (another *first measure of relevance*) “can be indicated by the cosine of the angle between the document’s vector and the user’s profile vector.” Rose, 6:54-57.

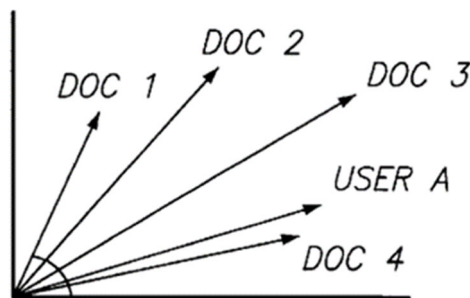


FIG. 5B

Moreover, Rose’s server’s programming renders obvious the structure of a “first relevance measurement module.” For example, the “score of a document’s relevance” just discussed is based on numerous factors that inform relevance, as in Marston. *Id.*, 6:54-57. While using simple numbers for illustrative purpose, Rose explains that a document’s vector “would likely have hundreds or thousands of dimensions, depending upon the number of terms that are monitored.” *Id.*, 6:26-35. Rose provides examples of “dichotomous” factors (“thumbs up,” “thumbs down,”),

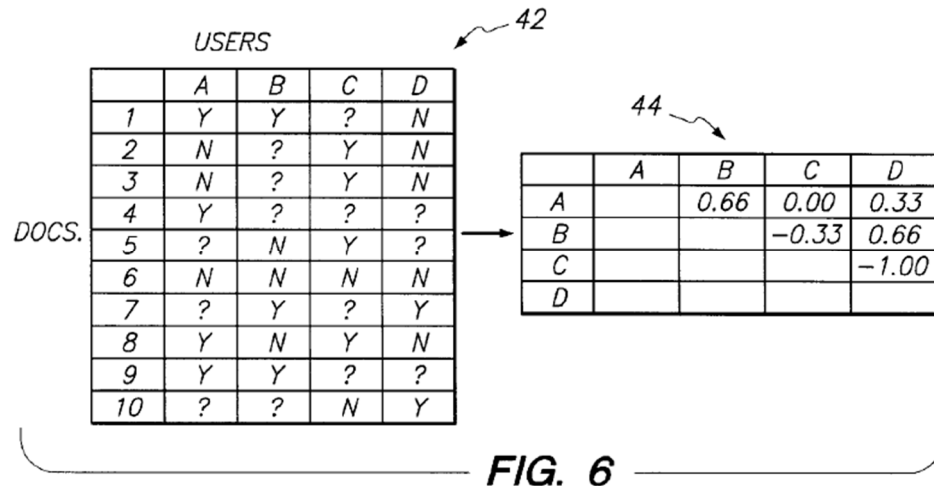
but it also teaches that “cardinal” factors can be considered, such as “the number of times” a term appears in a document or allowing users “finer resolution...by providing additional options for the user.” *Id.*, 5:24-28. A POSITA would thus have understood Rose teaches the structure of a “first relevance measurement module.” Fox, ¶184.

f. 1[e]/6[c]/7[c]

Rose teaches 1[e]/6[c]/7[c], under MPF or non-MPF. In addition to considering relevance based on a user’s actions, as discussed in 1[d]/6[b]/7[b], different programming on Rose’s server (*second relevance measurement module*) manages a “feedback table 42” used to develop a “correlation matrix R” that identifies “[a] second factor in the prediction of a user’s interest in information [that] is based upon a correlation with indications provided by other users.” Rose, 6:59-7:6. As discussed for 1[c]/6[a]/7[a], the server—where the correlation matrix resides—can communicate with (i.e., is *coupled to*) client-side email systems (*monitoring modules*), which track “not only on the user’s own interests, but also feedback from the community.” *Id.*, 8:38-40; Fox, ¶¶178, 185. Each time a user indicates interest in a retrieved document, the indication can be stored and used in the correlation matrix. Rose, 6:59-7:6. A POSITA would have understood Rose’s correlation matrix provides the structure for the “second relevance measurement module,” as discussed in 1[f]/6[d]/7[d]-1[g]/6[e]/7[e] below.

g. 1[f]/6[d]/7[d]

Rose teaches 1[f]/6[d]/7[d], under MPF or non-MPF. According to Figure 6 (below), each time a user indicates interest in a retrieved document, the result can be stored Rose's feedback table 42.



From the leftmost table, Rose generates a “correlation matrix” (right), “whose entries indicate the *degree of correlation* between the various users’ interests in *commonly retrieved messages*.” *Id.*, 6:64-66; Fox, ¶186. Given Rose contemplates email, a POSITA would have understood that users of “commonly retrieved messages” can be recipients of the same email message (*plurality of users that is a recipient of the piece of electronic content*). Fox, ¶¶180, 186.

Rose uses this correlation to identify “users whose interests...are similar or opposed” or “users having similar feedback responses” (*identify at least one other of the plurality of users...that is cognate to the user*). Rose, 5:57-60, 6:61-7:1, 7:39-51; Fox, ¶¶186-87. Further, Rose employs “regression methods...to *identify* the most

important attributes that are used as predictors, e.g., salient terms in a document and *users having similar feedback responses.*” Rose, 7:39-51; Fox, ¶¶187-89.

If Rose does not explicitly identify a group of users based on this correlation, a POSITA would have found it obvious to group users based on Rose’s correlations, to improve results and reduce the workload when processing recommendations. EX-1001, 6:26-29; Fox, ¶188 (explaining that scaling issues would encourage a POSITA to select a subset of users for comparison); *see also* Rose, 6:26-29 (explaining that electronic content “would likely have hundreds or thousands of dimensions”); EX-1022, 533, 541 (noting scalability concerns with collaborative filtering); EX-1033, 247, 249 (discussing “stop conditions” for processing large numbers of users/factors).

Rose’s correlation matrix renders obvious the structure of the second relevance measurement module for 1[f]/6[d]. Rose updates profiles of “users whose interests in movies are similar or opposed” and identifies “users having similar feedback responses” based on correlation matrix values. Rose, 5:57-61; 7:35-50. A POSITA would have understood that Rose mirrors Marston’s use of a correlation matrix (below) to identify cognate users.

	<u>Correlations</u>				
	User A	User B	User C	User D	User E
User A	1	0.042675	-0.35891	0.754378	-0.28248
User B	0.042675	1	0.301382	0.154122	0.122467
User C	-0.35891	0.301382	1	-0.0957	-0.31789
User D	0.754378	0.154122	-0.0957	1	-0.43545
User E	-0.28248	0.122467	-0.31789	-0.43545	1

EX-1001, 46:7-15; *see also id.*, 14:64-66 (using “importance value correlation” to evaluate “similar past user actions and assessments, and/or a direct input by a user”), 35:36-38 (“[A] cognate group of *n* users is identified, whose IICs *correlate most closely* with that user.”), 43:30-37, 46:35-44 (“Another way to determine cognate users relates to *correlating* importance values.”); *see also* Fox, ¶189.

h. 1[g]/6[e]/7[e]

Rose teaches the last option for 1[g]/6[e]/7[e]’s *Markush* group.

As discussed for 1[f]/6[d]/7[d], Rose’s correlation matrix stores a “degree of correlation” based on “indications” (*one or more actions on the piece of electronic content*) provided by other users on “commonly retrieved messages” (*at least one other of the plurality of users that is a recipient of the piece of electronic content*). Rose, 6:59-66; Fox, ¶¶192-93, 186-90. Rose uses the correlation matrix to identify “users whose interests...are similar or opposed” and “users having similar feedback responses” (*cognate to the user*). Rose, 5:57-60; 7:39-51.

A POSITA would have understood that Rose’s correlation matrix renders obvious the structure of the second relevance measurement module for 1[g]/6[e].

Fox, ¶189. The user “indications” for calculating degrees of correlation are monitored and tracked for all users, as discussed in 1[c]/6[c]/7[c]. *See, e.g.*, Rose, 2:46-50 (“The user correlation data is obtained through feedback information provided by users when they retrieve items of information.”); 5:8-23, 5:56-60 (user ratings inform “other users whose interests...are similar or opposed.”). Moreover, Rose like Marston, contemplates calculating a weighted average of user indications from correlated users. *Id.*, 7:35-50; EX-1001, 26:11-17, 43:30-37, 46:7-15; Fox, ¶¶187, 189.

i. 1[h]/6[f]/7[f]

Rose teaches 1[h]/6[f]/7[f] under MPF or non-MPF. As discussed in 1[pre]/6[pre]/7[pre], Rose involves messages (*e.g.*, emails) (*piece of electronic content*) sent between users (*sent from the sender to the user*). As discussed in 1[d]/6[a]/7[a], programming on Rose’s server stores users’ “user profiles” indicating the *first measure of relevance*—when a user “indicates interest in a document, all of the significant terms in that document can be given increased weight in the user’s profile.” Rose, 6:36-43. Rose compares user profiles to document profiles to determine a “score of a document’s relevance” (another *first measure of relevance*). *Id.*, 6:54-57. Similarly, as discussed in 1[f]/6[d]/7[d]-1[g]/6[e]/7[e], Rose’s correlation matrix stores correlation scores (a *second measure of relevance*) based on the actions of correlated users who received the same messages. *Id.*, 6:64-66.

Rose teaches that “a combination of attribute-based and correlation-based prediction is employed to rank the relevance of each item of information. For example, a *weighted sum of scores* that are obtained from each of the content and correlation predictors can be used to determine a final ranking score” (*the relevance score being determined based at least in part on the first determined measure of relevance and on the second determined measure of relevance*). *Id.*, 7:35-40. Similarly, Rose contemplates the use of “regression methods are employed to identify the most important attributes that are used as predictors, e.g., salient terms in a document and users having similar feedback responses, and how much each one should be weighted.” *Id.*, 7:44-47, 7:51-62 (discussing “evolutionary programming techniques” to analyze data/correlations until identifying “the data which can best be used to predict a given user's likely degree of interest in a message.”).

A POSITA would have understood that programming on Rose’s server renders obvious the structure of the “relevance analysis module.” Rose monitors and tracks “indications” for *all* users to calculate degrees of correlation, as discussed in 1[c]/6[a]/7[a] and 1[f]/6[d]/7[d]. Rose, like Marston, discloses calculating a final relevance score based on (1) a relevance score based on that user’s actions, and (2) cognate relevance scores. *Id.*, 7:35-40, 7:44-47.

3. Claims 2/13/18.

Rose teaches claim 2/13/18's additional limitations, under MPF or non-MPF. Rose depicts exemplary "interfaces" (*content presentation module*) that presents ranked messages to a user (*present the piece of electronic content to the user in accordance with the determined relevance score*). *Id.*, Fig. 3. Rose's interface shows a score column displaying the "relative ranking score of each message" (*present to the user a value describing the determined relevance score*). *Id.*, 4:50-53, Figs. 3, 7, cl. 8.

Your Messages		
Score	Date	Author
28	Fri 06/25...	~
30	Thu 09/30...	~
	Thu 08/05...	~
	Thu 06/24...	~
	Thu 07/22...	~

FIG. 3

If PO argues this claim requires display of a literal number as the relevance score, that would have been obvious to a POSITA. Fox, ¶198 (citing EX-1034, 52-53; EX-1035, 67-75 (acknowledging users want to see rankings for documents); and EX-1022, 539). Displaying a numbered rank of sorted items was common at the time of Marston, and Rose already discusses calculating a "final ranking score," (Rose,

7:35-40), such that it would have been obvious to a POSITA to *display* that score. Fox, ¶¶198-99.

A POSITA would have understood that Rose’s interface renders obvious the structure of the content presentation module for claims 2/13. Fox., ¶200. Rose contemplates being used with “electronic mail systems” (*see* 1[pre]/6[pre]/7[pre]), mirroring Marston’s discussion of a “mail presentation module.” Just as Marston discusses various web page interfaces, so, too, does Rose. Rose, Figs. 3, 4, 7.

4. Claim 3/14/19.

Rose teaches claim 3/14/19’s additional limitations, under MPF or non-MPF. Rose states that “[t]he present invention can be employed in various kinds of information access systems, such as electronic mail, bulletin board, *text search* and others.” *Id.*, 3:26-28, cl. 26. Rose’s “relevance predicting technique[s] of the present invention” can be used to filter messages sent to users in email systems or to personalize results obtained through a “text retrieval service” (*search module configured to search the electronic content in accordance with the determined relevance score*). *Id.*, 2:51-55; Fox, ¶201.

A POSITA would have understood that these “search” functions in Rose render obvious the structure of claim 3/14’s “search module.” For example, documents in Rose can be “displayed in order of rank.” Rose, 2:33-34. A POSITA would have understood Rose teaches using the “relevance predicting technique of

the present invention” in the context of search results, (*id.*, 2:51-55), to display search results according to their ranked order. Fox, ¶¶202-03.

5. Claims 5/15.

Rose teaches claim 5/15’s additional limitations. For example, Rose discusses that electronic content includes “messages in an electronic mail network, or documents within a particular bulletin board category” (*wherein the electronic content comprises at least one of an email, a document, an instant message, and an SMS message*). Rose, 2:28-34, 3:38-43 (discussing that “message” “refer[s] to each item of information that is provided by and accessible to users”), 3:26-33, cls. 12 & 24; Fox, ¶¶204-05.

6. Claims 8/22.

Rose teaches claim 8/22’s additional limitations. As discussed above for 1[c]/6[a]/7[a], 1[d]/6[b]/7[b], Rose develops “user profiles” based on “feedback” or “indications” provided by users on electronic content (*analyzing historical actions of the at least one other of the plurality of users with respect to historical actions of the user*), which can be used to identify correlated users via Rose’s correlation matrix (*identifying at least one other of the plurality of users that is cognate to the user*). Rose, 2:28-34; 5:21-23, 5:43-46, 5:55-61, cl. 1. When Rose identifies cognate users, it does so based on their “indication[s] of interest” or “feedback,” which are historical actions. *See* 1[f]/6[d]/7[d].

7. Claim 9.

Rose teaches claim 9's additional limitations. As discussed for 1[f], Rose generates a correlation matrix displaying the “degree of correlation” between users based on prior indications of interest. Rose, 6:61-69.

Although Rose, for Figure 6, discusses an “example” of the correlation matrix that is “symmetric” (*id.*, 7:1-6), a POSITA would have understood that a correlation matrix can be asymmetric (*wherein the at least one other of the plurality of users is cognate to the user, and the user is not cognate to the at least one other of the plurality of users*). Fox, ¶¶223-24, 153-58. Rose discusses that “[i]n practice, of course, the vectors for information content would likely have hundreds or thousands of dimensions.” Rose, 6:26-30. A POSITA would have understood that when computing a correlation matrix using thousands of dimensions for each user/document, shortcuts or post-processing would often lead to a non-symmetric matrix. Fox, ¶¶223-24, 153-58. For example, for a given user A, the top N similar users might be all that have a non-zero value, and might include user B; on the other hand, the top N similar users that have provided indications consistent with user B might not include user A—this asymmetry is a function of not considering every variable/user during every comparison. *Id.* Therefore, a POSITA would have understood Rose's “example” to be just one way to organize the correlation matrix

and would have found it obvious that Rose's correlation matrix would be asymmetric. *Id.*

C. Ground 3: Obviousness Over Rose In Combination with Bieganski (EX-1007)

If Rose alone does not render the Challenged Claims obvious, the Rose-Bieganski combination does.

1. Bieganski

Bieganski teaches an electronic processing system that generates a “[s]erendipity-weighted recommendation output” specific to a user based on “user item preference data and community item popularity data.” Bieganski, Abstract. Bieganski recommends content by considering both “user item preference data and community item popularity data” to produce a “filtered recommendation output set.” *Id.*, 3:30-44. “Preference data” can include both “explicit” (e.g., “values that a user has supplied directly”) and “implicit” values (e.g., “values that have been inferred by observing actions that the user has taken”). *Id.*, 2:31-42.

Bieganski Figure 2 (below) illustrates an embodiment that generates recommendations “based on user item preference data, population preference data..., and a serendipity control function” (*id.*, 5:51-58):

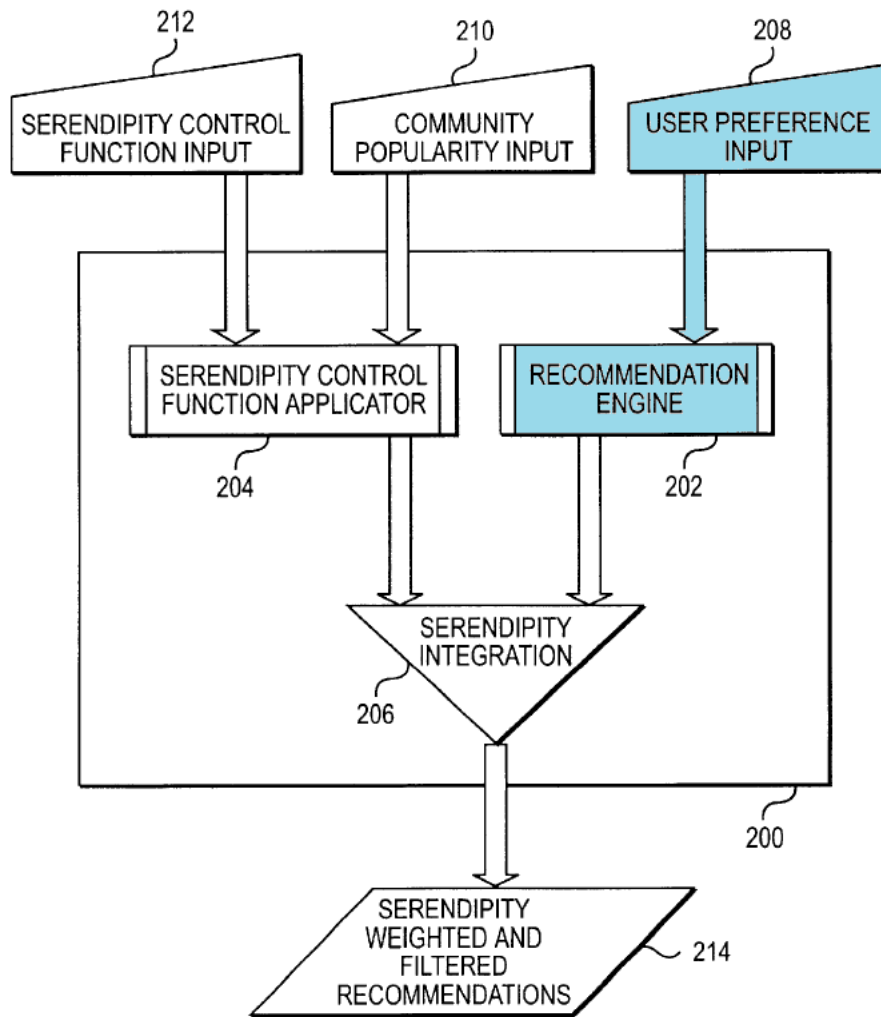


FIG. 2

Bieganski teaches that the recommendation engine “predicts a user’s preference for each item in the dataset, without regard to serendipity.” *Id.*, 6:1-3. The recommendation engine “builds and maintains an interest profile for each user.” *Id.*, 6:3-4.

Bieganski teaches that the recommendation engine can use “many different techniques for generating personalized recommendations from user interest

profiles.” *Id.*, 6:6-9. One such technique is “automated collaborative filtering,” where users are grouped into “affinity groups” or “neighborhoods” based on “shared interests.” *Id.*, 6:27-36. To form a neighborhood for a user, the recommendation engine “finds the set of people in the preference data who have the profiles most similar to the profile of a user.” *Id.*, 6:31-34, 6:37-39 (noting there are “many different methods to form affinity groups”), 6:44-52 (incorporating by reference “examples of neighborhood formation algorithms”). For example, “[s]imilarity between two profiles may be measured by counting the items that are shared by the two profiles.” *Id.*, 6:34-36.

Bieganski discusses forming affinity groups of users “based on user preference data.” *Id.*, 6:39-7:65. “To form a neighborhood, the recommendation engine selects the set of users from the user population who have the profiles most similar to the customer's profile.” *Id.*, 7:9-11. Neighborhood formation is limited by (i) minimum neighbor similarity, and (ii) maximum neighborhood size. *Id.*, 7:16-27, 7:57-65. A POSITA would have understood that these neighborhoods would not necessarily be symmetrical, since a maximum neighborhood size means that “only the best neighbors” will be included. *Id.*; Fox, ¶¶96, 153-58, 269; EX-1033, 247, 249 (discussing “heuristic stop conditions” that limit factors/users examined for scalability).

2. Motivation to Combine

If PO argues or the Board finds Rose does not teach identifying “cognate” users, a POSITA would have been motivated to combine Rose with Bieganski, which explains how to organize users into “sets” (i.e., “neighborhoods”) based on shared interests. Fox, ¶232. A POSITA would have understood Bieganski teaches identifying “cognate” users whose actions inform a second measure of relevance of a piece of electronic content. Fox, ¶¶232-36.

Both Rose and Bieganski are contemporaneous prior art:

	Filed	Issued
Rose	April 25, 1994	March 13, 2001
Bieganski	July 17, 1998	Dec. 25, 2001

Rose, Cover Page; Bieganski, Cover Page; Fox, ¶233. Both Rose and Bieganski are directed to ranking the relevance of information on a computer. Rose, 1:6-10; Bieganski, 1:35-44; Fox, ¶233. Both Rose and Bieganski teach using their systems with search engines. Rose, 1:35-40, 2:51-57, 3:26-28, cl. 26; Bieganski, 16:29-46, 17:59-18:6; Fox, ¶233.

Both Rose and Bieganski base recommendations, in part, on users’ actions. Rose, 2:48-50, 6:51-7:6; Bieganski, 2:31-42 (discussing user “preference data” based on “preference values that a user has supplied directly” or “inferred by observing actions that the user has taken”); Fox, ¶234. Both Rose and Bieganski

provide examples of users providing ratings on movies. Rose, 5:53-64; Bieganski, 1:38-44; Fox, ¶234. And both Rose and Bieganski discuss storing “user profiles” based upon users’ actions on electronic content. Rose, 5:21-23; 6:36-46; Bieganski, 6:1-6; Fox, ¶234. Rose contemplates that it can be used with “[o]ther approaches which take into account both the attribute-based information and user correlation information.” Rose, 7:35-8:19; *see also* Bieganski, 6:1-54 (explaining that Bieganski’s teachings can be used with “many different methods” for forming affinity groups). Collaborative filtering was a well-known technique that a POSITA would have found obvious to apply when seeking to improve recommendations. Fox, ¶235; *see also* EX-1016, 1-2; EX-1018, 4.

Both Rose and Bieganski take advantage of the “community” of users to estimate the relevance of electronic content. Rose, 8:23-40 (“the relevance score of a particular message takes into account not only on the user’s own interests, but also feedback from the community.”); Bieganski, 1:57-60 (“[C]ollaborative filtering allows that user community to share the preferences anonymously in a large scale manner.”). For example, both Rose and Bieganski teach methods that consider, in addition to a user’s actions on content, feedback from “similar” users who have interacted with that same content. Rose, 5:58-60 (rankings consider “other users whose interests...are similar”), 6:6-11 (“correlations of indications provided by users who have retrieved the message”); Bieganski, 1:60-63 (choosing neighbors

“based on how similar their interests and expectations are to the user’s.”), 6:27-36 (“Similarity” measured by “the items that are shared by the two profiles.”); Fox, ¶235.

Rose considers and weights actions of other users based on how “correlated” they are with the user for whom the system is recommending content. Rose, 6:59-7:50. As taught in Rose, the more correlated a user, the greater the weight their opinions will have (and vice-versa). *Id.*, 7:26-34. A POSITA would have been motivated to improve upon Rose’s “correlation” of users by grouping them into neighborhoods, as discussed in Bieganski. Bieganski, 5:26-29; Fox, ¶236. Although Rose weights users according to their correlation—minimizing the influence of inputs from non-correlated users and increasing the import of inputs from correlated users—these results could still be problematic if the system relies on input from poorly suited users. Fox, ¶236 (“a large number of low-correlated users providing input could still skew recommendations”). Bieganski explains:

It is important to limit membership in the neighborhood to those neighbors who can contribute positively to a personalized recommendation for the customer. Since user preference data can often contain information for large numbers of users, it is also important to limit the number of users that are selected as neighbors.

Bieganski, 7:11-16. Thus, Bieganski supplies a motivation for a POSITA to group users into “neighborhoods” to improve recommendations. Fox, ¶236. Bieganski

accomplishes these goals by building a neighborhood using a “minimum neighbor similarity” and “maximum neighborhood size,” “ensur[ing] that all members of a neighbor have a minimum number of items in common” and that “only the best neighbors” are considered. Bieganski, 7:8-27.

A POSITA would have had a reasonable expectation of success in modifying Rose according to Bieganski’s known teachings, both to improve Rose’s recommendations and streamline processing across users. Fox, ¶237. Bieganski itself provides a motivation to combine collaborative filtering with recommendations. Bieganski, 7:11-16. Rose and Bieganski disclose similar systems that consider actions of a user and actions of correlated users/neighbors (Rose, 6:51-7:6; Bieganski, 6:1-36), such that a POSITA would have known how to make this modification with predictable results. This would be a simple modification for a POSITA because recommendations would largely be performed as Rose contemplates, with the additional step of adding well-known collaborative filtering techniques to group correlated users into “neighborhoods.” Fox, ¶237. Rose’s “correlation scores” would inform the “minimum neighbor similarity” and “maximum neighborhood size” factors from Bieganski, ensuring users have a sufficient “minimum neighbor similarity” and identifying the top X users for inclusion. Fox, ¶237. Thus, a POSITA would have been motivated to use, and had a reasonable expectation of success in using, the teachings from Bieganski to identify

“neighborhoods” of users, thereby improving the accuracy of Rose’s recommendations.

3. Independent Claims

a. 1[pre]/6[pre]/7[pre]-1[d]/6[b]/7[b]

As discussed under Ground 2, Rose teaches 1[pre]/6[pre]/7[pre]-1[d]/6[b]/7[b]. Fox, ¶¶238-42, 255-57, 262-64.

b. 1[e]/6[c]/7[c]

As discussed under Ground 2, Rose teaches 1[e]/6[c]/7[c]. Moreover, a POSITA would have modified Rose’s second relevance module based on Bieganski’s teachings, as discussed for 1[f]/6[d]/7[d]-1[g]/6[e]/7e], below. Fox, ¶234.

c. 1[f]/6[d]/7[d]

As discussed under Ground 2, Rose teaches 1[f]/6[d]/7[d]. For example, Rose teaches that users’ “indication[s] of interest” on electronic content inform the relevance of that content for “other users whose interests...are similar.” Rose, 2:46-50, 5:58-60, 6:6-11 (ranking messages based on “indications provided by users who have retrieved the message”), 6:59-7:50, cl. 1 (“determining a measure of correlation between the particular user’s interests and those of other users who have accessed said item of information”). Thus, Rose already considers input from other “cognate” users who have received the same electronic content.

If Rose alone does not meet 1[f]/6[d]/7[d], a POSITA would have been motivated to modify Rose based on Bieganski's teachings to improve predictions by organizing users into neighborhoods based on their prior indications (*identify at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user*). Fox, ¶¶244-48; *see also* EX-1001, 14:59-15:11 (discussing identifying "cognate" users); Rose, 8:37-40; Bieganski, 6:31-36.

Bieganski teaches using "automated collaborative filtering" to evaluate the relevance of content by looking at feedback from "matching users who have shared interests" that have been sorted into "affinity groups" or "neighborhoods." Bieganski, 6:27-36. A "neighborhood" can be formed by identifying "the set of people...who have the profiles most similar to the profile of a user," where "similarity" is "measured by *counting the items that are shared by the two profiles*" (*plurality of users that is a recipient of the piece of electronic content*). *Id.*, 6:30-36. As with Rose alone, a POSITA would have understood "items that are shared" refers to content rated (and therefore, received) by both users. *Id.*; Fox, ¶246.

Bieganski teaches that a neighborhood can be constructed dynamically, in response to a user considering a piece of electronic content. Bieganski, 7:6-39 (providing example of identifying users in a "neighborhood" based on a user's selection of items). Bieganski identifies two parameters—(i) minimum neighbor similarity and (ii) maximum neighborhood size—that allow an administrator to

optimize recommendations by specifying how neighborhoods are formed. *Id.*, 7:16-27, 7:57-65.

With Bieganski's teachings of "neighborhoods," a POSITA would have understood it would have been desirable to improve Rose's teachings of identifying correlated users by relying on an optimized "neighborhood" of correlated users. Fox, ¶¶247-48. From there, Rose already teaches using "a combination of attribute-based and correlation-based prediction" to rank electronic content. Rose, 7:35-42, 6:42-47 (using "[m]ultiple regression analysis" to "identify...salient terms in a document *and users having similar feedback responses.*" *Id.*, 6:42-47.

d. 1[g]/6[e]/7[e]

As discussed under Ground 2, Rose teaches 1[g]/6[e]/7[e]; the Rose-Bieganski combination also teaches them.

As discussed for 1[f]/6[d]/7[d], the Rose-Bieganski combination teaches that users can be organized into "neighborhoods." And as with Ground 2 for 1[g]/6[e]/7[e], Rose identifies the relevance of content based on "indications" (*actions on the piece of electronic content*) provided by the user and their neighbors. Rose relies on each user's profile "based upon the feedback information received each time the user accesses the system," (*see* 1[c]/6[a]/7[a]), to evaluate the relevance of documents. Rose, 6:36-46 (explaining that user's feedback increases weight of "significant terms in that document" in that user's profile), 6:59-63, 7:43-

47 (using “regression methods” to evaluate relevance based on “salient terms in a document and users having similar feedback responses”). Given user correlations are based on user’s indications (*actions*), a POSITA would have understood the “user correlation information” to be “a second measure of relevance of the piece of electronic content as based at least in part on” “one or more actions on the piece of electronic content of the at least one other of the plurality of users that is a recipient of the piece of electronic content and that is cognate to the user.” Fox, ¶¶249-50.

e. 1[h]/6[f]/7[f]

Although the Rose-Bieganski combination relies on Bieganski’s teachings to improve recommendations by identifying “neighborhoods” of users with similar interests, the combination teaches 1[h]/6[f]/7[f] for the same reasons that Rose alone teaches 1[h]/6[f]/7[f], as discussed in Ground 2. Fox, ¶¶251, 261, 267.

4. Claims 2/13/18.

As discussed under Ground 2, Rose teaches claim 2/13/18’s additional limitations.

5. Claims 3/14/19.

As discussed under Ground 2/13/18, Rose teaches claim 3/14/19’s additional limitations. Moreover, Bieganski, like Rose, teaches using its system in the context of a search engine. Bieganski, 16:29-46, 17:59-18:6; Fox, ¶¶233, 253.

6. Claims 5/15.

As discussed under Ground 2, Rose teaches claim 5/15's additional limitations.

7. Claims 8/22.

The Rose-Bieganski combination teaches claim 8/22's additional limitations. Both Rose and Bieganski identify "cognate" users based on their historical actions. *See* 1[f]/6[d]/7[d] in Ground 3; Rose, 2:46-50, 5:58-61, 6:6-11 (ranking messages based on "indications provided by users who have retrieved the message"), 6:59-7:50, cl. 1 (determining "measure of correlation between the particular user's interests and those of other users who have accessed said item of information"); Bieganski, 6:30-36 (measuring similarity by "counting the items that are shared by the two profiles"); Fox, ¶268.

8. Claim 9.

As discussed under Ground 2, Rose teaches claim 9's additional limitations. Moreover, when combining the teachings of Rose with Bieganski to group users into "neighborhoods," a POSITA would have recognized Bieganski teaches "cognate" groups that are not symmetrical. Fox, ¶269; *see also* 1[f]/6[d]/7[d] in Ground 3. For example, Bieganski teaches limiting "neighborhoods" by (i) minimum neighbor similarity, and (ii) maximum neighborhood size. Bieganski, 7:16-27, 7:57-65. Because neighborhoods are limited with a "maximum" size, a POSITA would have

understood neighborhoods would be asymmetrical because the most similar users for one user may not mirror those of another. *Id.*; Fox, ¶¶269, 153-58.

IX. Conclusion

Inter Partes Review of the challenged claims is respectfully requested.

X. Mandatory Notices

A. Real Party in Interest

Petitioner identifies itself, as the real party in interest.

B. Related Matters

To the best of Petitioner's knowledge, the '217 patent (Marston) has been involved in the following district court litigation:

- *Sterling Computs. Corp. v. Meta Platforms, Inc. f/k/a Facebook, Inc.*, 1-24-cv-00551 (W.D. Tex.)
- *Sterling Computs. Corp. v. X Corp. f/k/a Twitter, Inc.*, 1-24-cv-00552 (W.D. Tex.)

C. Notice of Counsel and Service Information

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D. Service Information

Please address all correspondence to lead and back-up counsel at the addresses shown above. Petitioner consents to electronic service by e-mail.

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Date: January 31, 2025

CERTIFICATE OF WORD COUNT UNDER 37 CFR §42.24(d)

Pursuant to 37 C.F.R. §42.24(a), Petitioner hereby certifies that portions of the above-captioned Petition for *Inter Partes* Review of U.S. Patent 7,716,217, in accordance with and reliance on the word count provided by the word-processing system used to prepare this Petition, that the number of words in this paper is 13,963. Pursuant to 37 C.F.R. §42.24(a), this word count is in compliance and excludes the table of contents, table of authorities, mandatory notices under §42.8, certificate of service, certificate of word count, appendix of exhibits, and any claim listing. This word count was prepared using Microsoft Word.

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CERTIFICATE OF SERVICE

The undersigned hereby certifies that true copies of the Petition for *Inter Partes* Review of U.S. Patent No. 7,716,217 and supporting materials (Exhibits and Power of Attorney) were served via overnight delivery on the Patent Owner at the correspondence address of record as listed on PAIR:

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