IN THE UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF TEXAS
MARSHALL DIVISION

FELLOWSHIP FILTERING TECHNOLOGIES, LLC, ***Plaintiff,*** **v.** **ADOBE SYSTEMS, INC,** ***Defendant.***	**Civil Action No._________** **JURY TRIAL DEMANDED**

COMPLAINT FOR PATENT INFRINGEMENT

Plaintiff Fellowship Filtering Technologies, LLC ("Fellowship Filtering" or "Plaintiff"), by and through its attorneys, brings this action and makes the following allegations of patent infringement relating to U.S. Patent No. 5,884,282 ("the '282 patent"). Defendant Adobe Systems, Inc. ("Adobe" or "Defendant") infringes Fellowship Filtering's '282 patent in violation of the patent Laws of the United States of America, 35 U.S.C. § 1 *et seq*.

INTRODUCTION

1. In a relentless effort to expand its product base and profit from the sale of infringing computer-based recommendation technologies, Adobe has undertaken to copy the technologies and inventions of Gary Robinson, the inventor or the '282 patent and a co-owner of Fellowship Filtering.

2. Mr. Robinson is a mathematician and inventor of computer-based recommendation engine technologies that enable the recommending of products and/or content based on novel algorithms that calculate the preferences based on the similarity and dissimilarity of users of a website.

3. Mr. Robinson studied mathematics at Bard College and New York University's Courant Institute of Mathematical Sciences. He is the recipient of the National Science

Foundation – SBIR award.

4. Mr. Robinson is the named inventor on over 20 United States Patents. Google, Inc. ("Google"),[1] Amazon.com, Inc. ("Amazon"),[2] International Business Machines Corporation ("IBM"),[3] and Intel Corporation ("Intel") have acquired Mr. Robinson's patents.

<u>ROBINSON'S LANDMARK ELECTRONIC MAIL INVENTIONS</u>

5. The Robinson Method, named after Gary Robinson, is a Bayesian statistical approach that uses a text-classifier, rule-based method for determining the relevancy of an email message. Numerous leading SPAM filtering technologies utilize the Robinson Method.[4]

6. Robinson's contributions to the field of electronic mail filtering are recognized as landmark technologies.

> Robinson Fisher Method: With the Robinson Fisher method, Gary Robinson developed a more sophisticated way to ensure sensitivity for both recommendations and rejections. Consequently, the Robinson Fisher approach replaced the Geometric Means proposal. To formulate two null hypotheses one must assume ideal conditions, i.e. that token frequencies are pairwise independent, not uniformly distributed, and that the description consists of a random set of tokens. We then calculate a score

Günther Hölbling, Personalized Means of Interacting with Multimedia Content 119 (2011).

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[1] U.S. Patent Nos. 7,966,632; 8,290,964; and 8,762,394.

[2] U.S. Patent Nos. 6,266,649; 7,113,917; 7,433,832; 7,478,054; 7,664,669; 7,778,890; 7,908,183; 7,921,042; 7,945,475; 8,001,003; 8,024,222; 8,108,255; 8,140391; and 8,180,689.

[3] U.S. Patent Nos. 6,356,879; 6,931,397; 7,006,990; 7,080,064; 7,099,859; 7,389,285; 7,885,962; 8,700,448; and 8,825,681.

[4] Ricardo Villamarín-Salomón & José Carlos Brustoloni, *Bayesian Bot Detection Based on DNS Traffic Similarity,* in SAC'09: ACM Symposium on Applied Computing 2040—41 (2009); Masahiro Uemura & Toshihiro Tabata, *Design and Evaluation of a Bayesian-filter-based Image Spam Filtering Method*, in Proceedings of the 2008 International Conference on Information Security and Assurance 46-51 (2008) ("the Robinson Method"); Marco Antonio Barreno, Technical Report No. UCB/EECS-2008-63, Evaluating the Security of Machine Learning Algorithms 45 (2008); Manabu Iwanaga et al., *Evaluation of Anti-Spam Methods Combining Bayesian Filtering and Strong Challenge and Response,* in Proceedings of CNIS'03 (Communication, Network, and Information Security) 214—19 (2003); Blaine Nelson, Technical Report No. UCB-EECS-2010-140, Behavior of Machine Learning Algorithms in Adversarial Environments 62-67 (2010); Gordon V. Cormack & Mona Mojdeh, *Autonomous Personal Filtering Improves Global Spam Filter Performance*, in Proceedings of the 6th Conference on Email and Anti-Spam 2 (2009).

7. Mr. Robinson has published academic articles on statistical approaches to identifying content. A 2003 article in Linux Journal described these mathematical approaches for identifying unsolicited bulk email. Mr. Robinson's approach is notable because it assigned scores to both "spam" and "ham" and used an algorithm to guess intelligently whether an incoming email was spam. This approach was incorporated in products such as SpamAssassin, which used a Bayesian statistical approach using a text-classifier rule to distinguish "spam" and "ham" messages.[5]

8. Mr. Robinson's inventions relating to filtering technologies have been widely adopted by spam filters including Spam Assassin[6] (PC Magazine's Editor's Choice for spam filtering), SpamSieve[7] (MacWorld's Software of the Year), and SpamBayes[8] (PC Worlds Editor's Choice for spam filtering).

ROBINSON'S DEVELOPMENT OF CONTENT FILTERING SYSTEMS

9. Prior to developing groundbreaking electronic mail filtering technologies, Mr. Robinson used his insights to develop the automated content filtering technologies that are used

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[5] Gary Robinson, *A Statistical Approach to the Spam Problem*, LINUX JOURNAL 107 (2003).
[6] *SpamAssassin Pro*, in PC MAGAZINE February 25, 2003 at 82 (awarding SpamAssassin Pro its editors' choice award); *The SpamAssassin Project: Train SpamAssassin's Bayesian Classifier*, http://spamassassin.apache.org/full/3.2.x/doc/sa-learn.html ("Gary Robinson's f(x) and combining algorithms, as used in SpamAssassin"); *Credits - The Perl Programming Language - Algorithms*, http://cpansearch.perl.org/src/JMASON/Mail-SpamAssassin-3.2.5/CREDITS ("The Bayesian-style text classifier used by SpamAssassin's BAYES rules is based on an approach outlined by Gary Robinson. Thanks, Gary!").
[7] David Progue, *From the Deck of David Progue: The Follow-Up Edition*, N.Y. TIMES, April 5, 2006, http://www.nytimes.com/2006/04/05/technology/06POGUE-EMAIL.html ("Spam Sieve is just incredibly, amazingly accurate; my in box is clean, baby, clean!").
[8] Tom Spring, *Spam Slayer: 2003 Spam Awards*, PCWORLD MAGAZINE, December 15, 2003, at 36 ("What makes the program unique is that SpamBayes doesn't use predetermined spam definitions. Rather, it constantly evolves by scanning your in-box to build custom definitions."); MARCO ANTONIO BARRENO, Technical Report No. UCB/EECS-2008-63, EVALUATING THE SECURITY OF MACHINE LEARNING ALGORITHMS 45 (2008) ("SpamBayes classifies using token scores based on a simple model of spam status proposes by Robinson . . . . SpamBayes Tokenizes the header and body of each email before constructing token spam scores. Robinson's method assumes that each token's presence of absence in an email affects that email's spam status independently from other tokens.").

today by Adobe and many of the world's largest corporations without attribution or compensation.

10. In the late 1980's, Mr. Robinson developed a system for collecting preference information and providing recommendations. His company, 212-ROMANCE, was an automated, voice-based dating service that used a passive data collection process to determine likely romantic matches. Mr. Robinson's contributions to the field of content filtering were pioneering.


Boston Business Journal

Few people in the technology industry can say they once ran a successful dating service. Even fewer can say that the dating service led to the creation of a technology used by everyone from the digital music industry to the largest corporations in the world.

But Gary Robinson, chief executive of Bangor-based Transpose LLC, can say that.

Matthew French, *Romantic Beginnings Have Worldwide Effect*, BOSTON BUS. J., May 20, 2002.

11. In the mid-1990s, Mr. Robinson recognized that the growing adoption of the internet and increased computational power enabled collection and processing of data relating to customer and user preferences that, with proper data analytics processes, could provide accurate recommendations of products and content.

12. Mr. Robinson further recognized that the growth of the internet led to unique problems involving information overload that filtering techniques using specific new collaborative filtering technologies could solve.

13. At the time, existing recommendation technologies, discussed in the '282 patent, failed to teach a robust and accurate process for providing recommendations. A key insight of Mr. Robinson was that the input of buying habits and/or ratings information from multiple users over the internet allowed similarity values among users to be calculated based on identifying subgroups of similar users.

14. Mr. Robinson invented an automated collaborative filtering ("ACF") system that received and stored data based on internet users' purchasing history, preferences, and/or buying

history. When a new user accessed the ACF system through a website (in one embodiment), the ACF system recommended further content (*e.g.*, products) based on the similarity values for the first user as compared with other users that previously provided preference data to the ACF system.

15. Mr. Robinson worked to develop novel systems and processes designed to provide accurate content and product recommendations using data stored, collected, and computed on specific computer-based systems. Mr. Robinson's insights led to the patent application resulting in the '282 patent.

16. The patent-in-suit - the '282 patent - is a pioneering patent in the field of data analytics. The '282 patent uses novel algorithmic approaches to provide accurate recommendations of products and content using data analysis specific to a computer system.

> good. The creative license for statistical filtering really belongs to hackers like Paul Graham, Gary Robinson, and Bill Yerazunis and the rest of the community that has invented many of these approaches. Some companies have claimed the technology as their own, which gives people the idea that any other solutions are nonstandard, when it's really borrowed technology.

JONATHAN A. ZDZIARSKI, ENDING SPAM: BAYESIAN CONTENT FILTERING AND THE ART OF STATISTICAL LANGUAGE CLASSIFICATION 269 (2005).

17. The '282 patent has been cited by over 262 United States patents as prior art before the United States Patent and Trademark Office. Companies whose patents cite the '282 patent include:

- Open Text S.A.
- Accenture Global Services GMBH
- YellowPages.com LLC
- Nielsen Holdings N.V.
- International Business Machines Corporation
- Koninklijke Philips N.V.
- Google, Inc.
- Amazon.com, Inc.
- Microsoft Technology Licensing LLC
- Arbor Networks, Inc.
- Johnson & Johnson Consumer Companies

- S.C. Johnson & Son Inc.
- Sony Electronics, Inc.
- Infosys Ltd.
- Parasoft Corporation
- AT&T Intellectual Property LLP
- Dish Network LLC
- eBay, Inc.
- Rovi Corporation
- CBS Interactive, Inc.
- American Express Company
- Hewlett-Packard Company
- Xerox Corp.
- Capital One Financial Corporation
- JDA Software Group, Inc.
- State University of New York
- Robert Bosch Healthcare System, Inc.
- Netflix, Inc.
- Intel Corporation
- Tribune Media Company
- Ingenio, LLC
- Recommend, Inc.
- Dassault Systemes S.A.
- Pandora Media, Inc.
- Pace plc
- Regents of the University of California
- Facebook, Inc.
- Numera, Inc.

18. The claims in the ‘282 patent are directed at solving a problem that did not arise in prior art systems, *i.e.* generating preference data from large data sets. In prior art systems, the sample size of users was typically small, and thus the need for a process that takes into account unusual similarities was not at issue. There is no question pre-electronic recommendation systems are significantly different from computer and/or internet-based recommendation systems. The speed, quantity, and variety of rating information markedly differ from the objectives and data available to recommendation systems existing before modern, computer and/or internet-based systems. Differences between the analog versions of preference systems and the invention disclosed in the ‘282 patent diverge significantly.

19. The use of ratings data and probability values to make recommendations over a computer network was not a longstanding or fundamental economic practice at the time of the invention disclosed in the '282 patent. Nor at the time was the use of ratings data and probability values to make recommendations a fundamental principle in ubiquitous use on the internet or computers in general.

20. The '282 patent discloses how interactions with the internet are manipulated to yield a desired result—a result that overrides the routine and conventional sequence of events ordinarily triggered by requesting content or a product that is relevant to a user of a website.

21. And the use of probability values in collaborative filtering (as in the '282 patent) to control for generally popular content and/or products is important and offers something more than a collaborative filtering system that fails to control for the general popularity of content and/or products. Data scientists at Hulu, LLC (operator of a streaming video website) described the importance of accounting for general popularity of a given item:

> Just because a recommendation system can accurately predict user behavior does not mean it produces a show that you want to recommend to an active user. For example, "Family Guy" is a very popular show on Hulu, and thus most users have watched at least some episodes from this show. These users do not need us to recommend this show to them — the show is popular enough that users will decide whether or not to watch it by themselves. Thus, novelty is also an important metric to evaluate recommendations.[9]

22. Ten years after Gary Robinson conceived of the inventions in the '282 patent, a 2005 White Paper from Oracle, entitled "The Art of Personalization," described the use of collaborative filtering to provide recommendations as "new technology" and a "breakthrough:"

> Collaborative filtering is relatively ***new technology that can deliver better results***. Just go to the leading Web sites that offer "recommendations" and you notice the value. After purchasing a book on *Learning to Golf*, you later return to the Web site and find other books on *Greatest Golf Courses* and *Golf Tips from the Pros*. These recommendations seem relevant, timely, and yet sometimes simplistic. Often you'll see other *Learn to…* books and videos,

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[9] Liang Xiang, Hua Zheng & Hang Li, *Hulu's Recommendation Engine*, HULU TECH BLOG, Sept. 19, 2011, http://tech.hulu.com/blog/2011/09/19/recommendation-system/ (emphasis added).

> like *Learn to Ski*, *Learn to Play Tennis*, and *Learn to Sew*. Compared to past manual attempts at personalization and "e-expectations," this is a ***breakthrough***.[10]

PARTIES

23. Plaintiff Fellowship Filtering is a McKinney, Texas based company committed to advancing the current state of technology in the field of predictive analytics systems. In addition to the ongoing efforts of Mr. Robinson, Fellowship Filtering employs a McKinney, Texas resident as a Technology Analyst. Fellowship Filtering is a Texas limited liability company with its principal place of business at 6851 Virginia Parkway, Suite 214, McKinney, Texas.

24. Fellowship Filtering is a small, Texas-based company. Fellowship Filtering depends on patent protection to effectively license its innovative technologies and build its business.

25. On information at belief, Adobe Systems Incorporated is a Delaware corporation with its principal place of business at 345 Park Avenue, San Jose, CA 95110. Adobe may be served through its registered agent Corporation Service Company d/b/a CSC, 211 E. 7th Street, Suite 620, Austin, TX 78701.

26. According to Adobe's website, infringing products are offered for sale and sold

[10] CHARLES BERGER, ORACLE WHITE PAPER: THE ART OF PERSONALIZATION 4 (August 2005) (emphasis added).

throughout the United States and Canada, including in this District, through various channels.

27. Adobe's infringing products use the same technology that is disclosed in the '282 patent. Adobe offers its infringing products through its distribution channel, which includes numerous distribution points in Texas. Further, Adobe advertises its infringing products throughout the Eastern District of Texas.

JURISDICTION AND VENUE

28. This action arises under the patent laws of the United States, Title 35 of the United States Code. Accordingly, this Court has exclusive subject matter jurisdiction over this action under 28 U.S.C. §§ 1331 and 1338(a).

29. Upon information and belief, this Court has personal jurisdiction over Adobe for at least the following reasons: (i) Adobe has committed acts of patent infringement and willful patent infringement in this District and elsewhere in Texas and the United States; (ii) Adobe knowingly and intentionally places their products, including the accused products, into the stream of commerce within this District and can reasonably be expected to be hailed into court here; and (iii) Adobe has purposefully availed itself of the benefits of doing business in the State of Texas and the exercise of jurisdiction over Defendants would not offend traditional notions of fair play and substantial justice.

30. Venue is proper in this District under 28 U.S.C. §§ 1391 (b)-(c) and 1400(b) because Defendant is subject to personal jurisdiction in this District, has transacted business in this district, and has committed acts of patent infringement in this district.

HISTORY OF FILTERING TECHNOLOGY

31. Advances in computational power and the explosive growth of the internet have led to the development of data analytics systems for accurately recommending content and products to internet users. The '282 patent teaches a specific type of automated collaborative filtering ("Automated CF" or "ACF") for recommending products and content to users of the internet.

32. Although content and product recommendations on websites are commonplace today, at the time the inventions disclosed in the '282 patent were conceived, an advanced system for recommending products and content automatically by weighting and analyzing multiple users' product ratings, purchase history, and/or actions of website users was a novel invention.

33. The claims in the '282 patent describe a solution that is necessarily rooted in computer technology to overcome a problem specifically arising in the realm of computer networks.

> Today increasing numbers of people are turning to computational *recommender systems*. ***Emerging in response to the technological possibilities and human needs created by the World Wide Web***, these systems aim to mediate, support, or automate the everyday process of sharing recommendations.[11]

34. The Tapestry system, developed in 1992, introduced the idea (and terminology) of collaborative filtering.[12] Tapestry was developed at Xerox's Palo Alto Research Center for electronic mail filtering and was based on the idea of exploiting explicit feedback (ratings and annotations) of other users. Tapestry stored the contents of messages, along with metadata about authors, readers, and responders. It allowed any user to store annotations about messages, such as "useful survey" or "Gary should see this!" Tapestry users could form queries that combined basic textual information (*e.g.*, contains the phrase "recommender systems") with semantic metadata queries (*e.g.*, written by Gary OR replied to by Joe) and annotation queries (*e.g.*, marked as "excellent" by Chris).

35. The development of the first collaborative filtering system was directly motivated by the need to sort electronic content transmitted over the internet (*e.g.*, electronic messages posted

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[11] Loren Terveen & Will Hill, *Beyond Recommender Systems: Helping People Help Each Other*, in HCI IN THE NEW MILLENNIUM 2 (Jack Carroll, ed., Addison-Wesley, 2001) (emphasis added).
[12] David Goldberg, David Nichols, Brian M. Oki, & Douglas Terry, *Using Collaborative Filtering to Weave an Information Tapestry*, COMMUNICATIONS OF THE ACM 35 No. 12, 61–70 (1992) (One of the first uses of the term "collaborative filtering" can be found in this paper.).

to newsgroups). "The motivation for Tapestry comes from the increasing use of electronic mail, which is resulting in users being inundated by a huge stream of incoming documents."[13]

36. Although widely adopted today, in the 1990's, collaborative filtering was a groundbreaking technology offering significant benefits over existing recommendation systems that were content based ("Content-based filtering"). Content-based filtering made recommendations based on the content of a document. The creators of Tapestry described this break from prior systems:

> Collaborative filtering is ***novel because it involves the relationship between two or more documents***, namely a message and its reply, or a document and its annotations. Unlike current filtering systems, Tapestry filters cannot be computed by simply examining a document when it arrives, but rather require (potentially) repeatedly issuing queries over the entire database of previously received documents. This is because sometime after a document arrives, a human (say Smith) may read that document and decide it is interesting. At the time he replies to it (or annotates it), you want your filter to trigger and send you the original document.[14]

37. Though Tapestry was a novel filtering system at the time, Tapestry illustrates limitations present in systems contemporaneous to the '282 patent. Tapestry lacked the ability to recommend content automatically based on similarities between users. Instead, the Tapestry system worked by recommending content based on predefined filters set by a second user.[15] For example, if a user wanted to prioritize messages relating to "Bakersfield, California" the system would return all messages that had previously been "tagged" by prior users as relating to "Bakersfield, California." The below images show that the Tapestry system prioritizes content based on a user requesting content that was previously tagged by another user.

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[13] *Id*.
[14] *Id*. at 61 (emphasis added).
[15] The Tapestry system was similar in many ways to Mr. Robinson's earlier 1980's matching system utilized in the Relationship Matching Service.

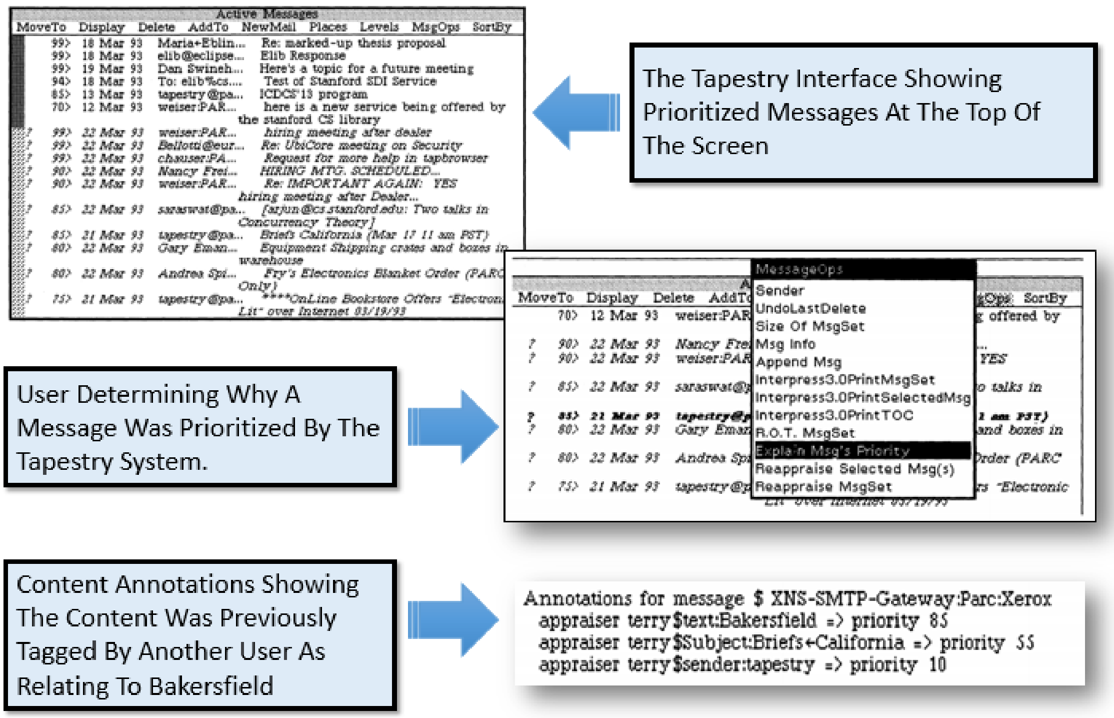

Fig. 1 (images of the Tapestry System (explanation added in blue)).[16]

38. GroupLens was another early collaborative filtering system contemporaneous to the '282 patent. Started in 1994 by researchers at the Massachusetts Institute of Technology and later the University of Minnesota, the GroupLens system implemented a collaborative filtering system for rating Usenet newsgroup articles.[17] To make personalized predictions identifying the most useful Usenet articles to a user, the GroupLens system asked each user to enter a 1 to 5 rating after reading an article. GroupLens collected the ratings data in a database and compared these ratings to find users who shared similar tastes. Users of GroupLens would then be provided a predictive rating for unread Usenet articles. The predictive rating was based on other users who shared similar taste with the user.

[16] Douglas B. Terry, *A Tour Through Tapestry*, in PROCEEDINGS OF THE CONFERENCE ON ORGANIZATIONAL COMPUTING SYSTEMS 21-30 (Simon Kaplan ed. 2003).
[17] Paul Resnick et al., *GroupLens: An Open Architecture for Collaborative Filtering of Netnews*, in PROCEEDINGS OF ACM 1994 CONFERENCE ON COMPUTER SUPPORTED COOPERATIVE WORK 175—86 (1994).

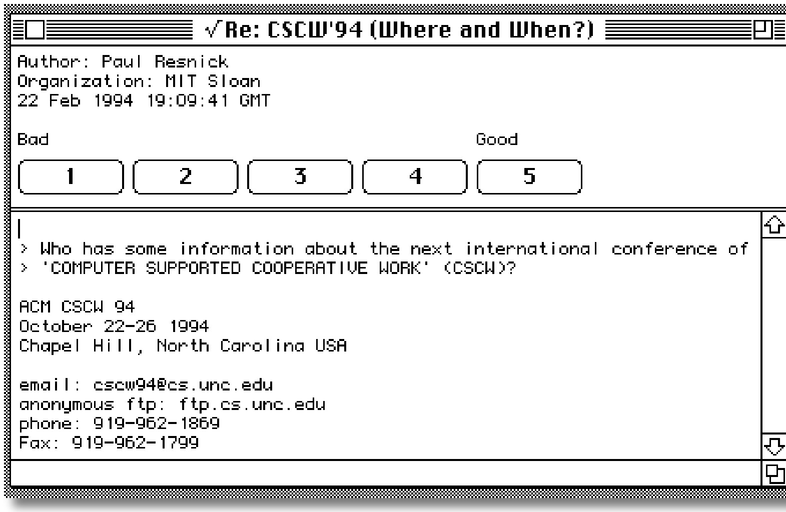

Fig. 2 (showing the user interface for GroupLens and the ability to rate articles 1-5).[18]

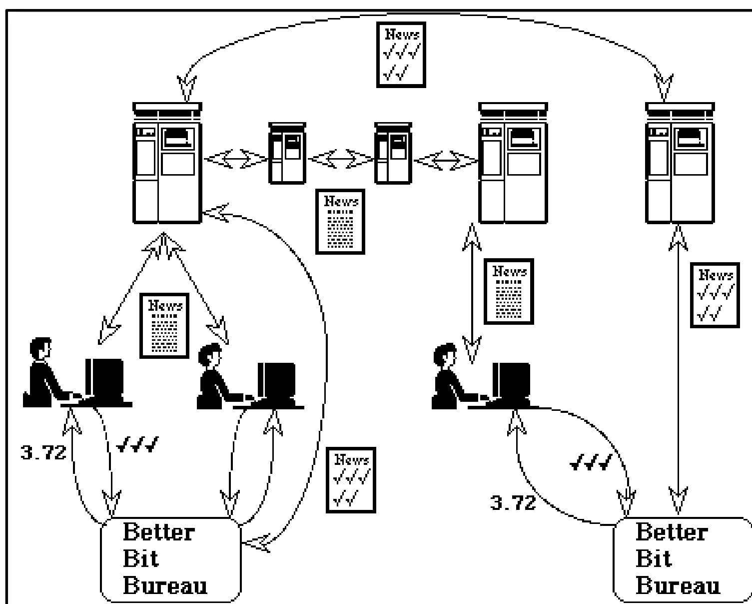

Fig. 3 (showing the architecture of the GroupLens system).[19]

39. GroupLens illustrates limitations in automated filtering systems contemporaneous to the '282 patent. The GroupLens system used the Pearson correlation to calculate similarities between users and use the similarities to generate predictive ratings. The Pearson correlation coefficient is calculated by comparing ratings for all items rated by both the target user and the

[18] *Id*. at Fig. 3.
[19] *Id*. at Fig. 2.

neighbor (*e.g.*, correlated items). The equation below gives the formula for the Pearson correlation between user "u" and neighbor "n," where CRu,n. denotes the set of correlated items between u and n.

$$userSim(u,n) = \frac{\sum_{i \subset \mathrm{CR}_{u,n}} (r_{ui} - \bar{r}_u)(r_{ni} - \bar{r}_n)}{\sqrt{\sum_{i \subset \mathrm{CR}_{u,n}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \subset \mathrm{CR}_{u,n}} (r_{ni} - \bar{r}_n)^2}}$$

40. The Pearson correlation and systems contemporaneous to the '282 patent failed to incorporate agreement about content in the population as a whole. For instance, the system failed to account for the fact that two users' agreement about a universally loved movie was less important than agreement on a controversial or unpopular movie. The Pearson correlation failed to capture distinctions relating to an item's general popularity. Thus, GroupLens made predictions based on data that showed similarities (arising from a piece of content being generally popular) but GroupLens' recommendations were not statistically significant.

41. John Hey's patents (U.S. Pat. Nos. 4,996,642 and 4,870,579), which are cited on the face of the '282 patent, describe a system for recommending items based on ratings of the items. Like GroupLens and other systems contemporaneous to the '282 patent, Hey's system for recommending products based on user ratings failed to account for statistically significant similarities between certain users; the recommendations were merely the product of an item or piece of content being generally popular. This prevented the Hey system from offering accurate predictions and recommendations of items and content. The teachings in the Hey patents were later incorporated into a software product called LikeMinds.

42. Similarly, the Ringo music recommendation system, discussed by Upendra Shardanand and Pattie Maes, and cited on the face of the '282 patent, used Pearson's correlation measure to provide content and product recommendations. Like other systems contemporaneous to the '282 patent, Shardanand and Maes's system failed to take into account the statistically

significant similarities between certain users.[20] Information showing unusual similarity in preferences for particular users was unutilized. Furthermore, these prior art systems did not provide recommendations with statistically meaningful confidence levels as the number of items that both the user and a respective recommending user provided ratings for increased.

43. Collaborative filtering arose to solve problems faced by digital content providers in the internet era as described by Adobe's Global Alliance Manager, Jamie Brighton:

> The catalyst for the evolution of personalization has been competition through, a product of the Internet's explosive growth. This growth provided consumers with so many options for e-commerce that it created a market in desperate need of a process by which consumers could develop a personal connection with a brand or digital storefront in a sea of rapidly evolving competitors.[21]

44. At the time the inventions disclosed in the '282 patent were conceived, the internet and the state of technology generally was vastly different from 2015, or even the state of the internet 10 years ago. For example, Facebook.com, YouTube.com, Wikipedia.com, and LinkedIn.com were years from being launched.[22]

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[20] Upendra Shardanand & Pattie Maes, *Social Information Filtering: Algorithms for Automating Word of Mouth*, in PROCEEDINGS OF CHI '95 CONFERENCE ON HUMAN FACTORS IN COMPUTING SYSTEMS 210—17 (1995).

[21] Jamie Brighton, *Changes in Personalization and What's Coming Next*, ADOBE DIGITAL MARKETING BLOG, October 21, 2014, http://blogs.adobe.com/digitalmarketing/personalization/personalization-past-present-future/.

[22] Rob Waugh, *Before They Ruled The Internet: 'Ancient' Home Pages for Amazon, Google and 'The Facebook' Show Much Web Giants Have Changed*, DAILY MAIL, January 19, 2012, http://www.dailymail.co.uk/sciencetech/article-2088445; TONY SEBA, WINNERS TAKE ALL – THE 9 FUNDAMENTAL RULES OF HIGH TECH STRATEGY 137 (2006); GEORGE A BARNETT, ENCYCLOPEDIA OF SOCIAL NETWORKS 947 (2011).

The above images show major internet properties contemporaneous (and later) to the inventions conceived in the '282 patent, including: Google.com (September 1998), Yahoo.com (March 1995), Amazon.com (1995), Myspace.com (August 2003).[23]

45. Academics such as Daniela M. Witten of the University of Washington describe the development of collaborative filtering systems as directed to solving problems arising out of so called Big Data (a term for modern networked computers that capture considerable volumes of data).

> Collaborative filtering is one example of a statistical method that has been newly-developed in the context of Big Data, in order to answer a question that didn't arise with Small Data. Collaborative filtering systems are used by companies like Amazon to suggest to a customer items that he or she might

[23] *Id.*

> want to purchase, based on his or her past purchase history as well as purchases made by other customers.[24]

46. Collaborative filtering systems, such as the system taught in the '282 patent were directed to solving a problem unique to the internet using uniquely computer based technologies.

> Computers and the web allow us to advance beyond simple word-of-mouth. Instead of limiting ourselves to tens or hundreds of individuals the Internet allows us to consider the opinions of thousands. The speed of computers allows us to process these opinions in real time and determine not only what a much larger community thinks of an item, but also develop a truly personalized view of that item using the opinions most appropriate for a given user or group of users.

J. Ben Schafer, Dan Frankowski, Jon Herlocker & Shilad Sen, *Collaborative Filtering Recommender Systems*, in THE ADAPTIVE WEB: METHODS AND STRATEGIES OF WEB PERSONALIZATION 292 (Peter Brusilovsky *et al*. eds., 2007).

47. On information and belief, contemporaneous to, and following Mr. Robinson's conception of the inventions disclosed in the '282 patent, academics and businesses headquartered in Texas actively entered the field of collaborative filtering. Computer researchers at the University of Texas at Austin founded the Intelligent Data Exploration and Analysis Laboratory and the Machine Learning Research Group. The University of Texas at Dallas operates the Institute of Data Analytics, a center for research on data analysis, which also collaborates with private industry. Baylor University in Waco, Texas is the home of the Electronic Commerce Center, which focuses on integrating technology and electronic data into e-commerce.

48. Texas based companies incorporated collaborative filtering technologies into numerous products and many of these same companies cited the '282 patent in their own patents. Texas based businesses that developed products incorporating collaborative filtering included: VideosDotCom, Inc. of McKinney, Texas; i2 Technologies US, Inc. of Dallas, Texas; Vignette Corporation of Austin, Texas; Texas Shopper Network, Inc. of Houston, Texas; Arrowsmith Technologies, Inc. of Austin, Texas; and HP Enterprise Services, LLC of Plano, Texas. The '282

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[24] Nicholas Bashour, *The Big Data Blog, Part II: Daniela Witten*, AAAS NEWS, March 17, 2014, http://www.aaas.org/news/big-data-blog-part-ii-daniela-witten.

patent is cited by at least 60 patents that were either initially assigned to or are currently assigned to entities headquartered in Texas. These companies include i2 Technologies, Vignette Corporation, AT&T, Hewlett-Packard Development Company, and Blockbuster LLC.

MR. ROBINSON'S INVENTION

49. Executives at leading technology companies have described the value of accurate product and content recommendations as critical, lasting, and prominent. Jamie Brighton, Global Alliance Manager at Adobe, stated accurate recommendation techniques were "a light switch for innovators and marketers alike, as well as a warning. A warning that personalization was rapidly becoming the ultimate avenue for creating lasting partnerships with a digital consumer base, and that ignoring this technology simply wouldn't be an option forever."[25]

50. Personalized product and content recommendations that utilize the capabilities of the internet and advances in processing power are of significant value to corporations ranging from Baynote to IBM.

> Personalized product recommendations work for a simple reason—a majority of people like them. Study after study has confirmed the value of personalized product recommendations, as well as personalized email, in increasing sales and average order value. Given the proven payback, many online merchants have recommendations technology prominently on their radar screens.[26]

> Highly relevant product recommendations lead to increased revenue. Providing relevant product recommendations not only offers a valued service, but also enables the discovery of products visitors might not know are offered.[27]

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[25] Jamie Brighton, *Changes in Personalization and What's Coming Next*, ADOBE DIGITAL MARKETING BLOG, October 21, 2014, http://blogs.adobe.com/digitalmarketing/personalization/personalization-past-present-future/.

[26] *IBM Software Thought Leadership White Paper: Building Lift and Loyalty with Personalized Product Recommendations* 4 (2012), *available at* http://www-01.ibm.com/common/ssi/cgi-bin/ssialias?infotype=SA&subtype=WH&htmlfid=ZZW03062USEN.

[27] *IBM Software Data Sheet, IBM Product Recommendations* 1 (2012), *available at* http://public.dhe.ibm.com/common/ssi/ecm/zz/en/zzd03046usen/ZZD03046USEN.PDF.

51. Numerous companies have confirmed the value of providing accurate product recommendations. "By showing the visitor the content they are looking for, you increase conversion rates and reduce bounce rates."[28] Companies such as HP, RichRelevance, and Adobe confirm the importance of collaborative filtering technologies to generating accurate recommendations.

> With these concerns in mind, RichRelevance based the enRICH platform on multiple recommendation strategies, ranging from simple categorical top sellers, to collaborative filtering algorithms . . . . After deploying the enRICH platform, retail customers report improvements across a range of KPIs, including increased conversion, revenue, and repeat visits.[29]

> In its simplest form, collaborative filtering really works when data from multiple sources comes together and is sorted into categories. ***It is a must these days*** for any e-commerce site striving to deliver a basic level of website personalization.[30]

> Personalized services are becoming increasingly indispensable on the Web, ranging from providing search results to product recommendation. Examples of such systems include recommending products at Amazon.com, DVDs at Netflix, News by Google etc. The central technique used in these systems is collaborative filtering (CF) which aims at predicting the preference of items for a particular user based on the items previously rated by all users.[31]

> The truth is indisputable—optimization increases conversion, so every digital property needs optimization. This singular truth is transforming the practice of marketing. Now, marketers must tap into the constant stream of web activity and customer data to gain insight into what visitors and customers want to see and experience. They must immediately act on that insight and

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[28] *Cognitor: Content Guidance And Recommendations* 2, COGNITOR WEBSITE, April 15, 2015, http://www.cognitor.com/brochures/enterprise.pdf

[29] *Rich Relevance*, *Speak <geek> [sic] Technical Brief* 6 (2009), *available at* http://www.richrelevance.com/wp-content/uploads/2011/01/Speak-Geek2_EnsembleLearning_RichRelevance.pdf.

[30] Dan Darnell, *Collaborative Filtering and Its Importance to Personalized Recommendations in eCommerce*, BAYNOTE BLOG, April 18, 2013, http://www.baynote.com/2013/04/how-collaborative-filtering-impacts-product-recommendations/ (emphasis added).

[31] Rong Pang et al., *One-Class Collaborative Filtering*, in IEEE INTERNATIONAL CONFERENCE ON DATA MINING (ICDM 2008) 502—11 (2008) (Mr. Pang at the time was employed by Hewlett Packard.).

> deliver highly relevant, personalized content throughout the customer life cycle.[32]
>
> Dynamic, relevant content is proven to increase engagement and conversions by as much as 6 times when compared to static content.[33]

U.S. PATENT NO. 5,885,282

52. Fellowship Filtering is the owner by assignment of the ‘282 patent. The’282 patent is entitled "Automated Collaborative Filtering System." The ‘282 patent issued on March 16, 1999, based on a patent application filed on April 9, 1998, and claims priority to a provisional application filed on April 30, 1996. A true and correct copy of the ‘282 patent is attached as Exhibit A.

53. The claims in the ‘282 patent are directed at a unique computing solution that addresses a problem particular to computer networks – the recommendation of items or content based on prior user actions.

54. Recommending content over a computer network presented new and extraordinary issues over the techniques and systems known in the art at the time. Prior art recommendation systems had a number of drawbacks. Such systems “fail to take into account the probability that a random user will provide a given rating. Thus, information showing unusual similarity in preferences for particular users is not utilized.” ‘282 patent, cols. 1:67-2:4.

55. The recommendation technologies claimed in the ‘282 patent were aimed at solving problems specific to the internet. “The catalyst for the evolution of personalization has been competition though, a product of the Internet’s explosive growth. This growth provided consumers with so many options for e-commerce that it created a market in desperate need of a

[32] *Adobe Target Premium Overview* 1 (2014), *available at* http://www.adobe.com/content/dam/Adobe/en/solutions/testing-targeting/pdfs/target-premium-overview-ue.pdf

[33] *BaynoteOne Product Recommendations* 1 (204), *available at* http://www.baynote.com/wp-content/uploads/2012/04/BaynoteONE-Solution-Brief-Personalized-Product-Recommendations.pdf

process by which consumers could develop a personal connection with a brand or digital storefront in a sea of rapidly evolving competitors." [34]

56. The technology "[c]ollaborative filtering is a relatively young algorithmic approach" and thus was not a convention business practice.[35]

57. One or more claims in the '282 patent recite a "similarity calculation." This element of the '282 patent is one of the "inventive concepts" of the '282 patent. The use of a similarity calculation is an "inventive concept" allowing computer servers configured to operate websites to more efficiently and accurately recommend content and products to website users.

58. The '282 patent does not preempt every way of "providing recommendations using a computer system," as systems for doing so existed before this invention, and systems exist now that allow website operators to provide recommendations without infringing the claims of the '282 patent.

59. The '282 patent claims do not preempt the field or preclude the use of other effective recommendation technologies. The '282 patent claims include inventive elements such as the use of probability calculations, randomized transformed ratings data, and/or similarity values to generate preference data over a computer network. The elements in the '282 claims greatly limit the breadth of the '282 patent's claims. These limitations are not necessary or obvious tools for achieving the generation of user preference data and/or recommendations, and they ensure that the claims do not preempt the field of recommendation systems and/or collaborative filtering.

60. Other techniques for collaborative filtering that are not included within the scope of the '282 patent's claims include, but are not limited to, the prior art discussed in the '282 patent:

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[34] Jamie Brighton, *Changes in Personalization and What's Coming Next*, ADOBE DIGITAL MARKETING BLOG, October 21, 2014, http://blogs.adobe.com/digitalmarketing/personalization/personalization-past-present-future/.

[35] Yehuda Koren, *Tutorial on Recent Progress in Collaborative Filtering*, in PROCEEDINGS OF THE 2008 ACM CONFERENCE ON RECOMMENDER SYSTEMS (RECSYS '08) 333-334 (2008).

- U.S. Patent No. 4,870,579 to Hey teaches providing recommendations to a user based on a user selected from a group of users, the reactions of the selected user to items sampled by one or more users in the group but not sampled by the selected user.
- U.S. Patent No. 4,996,642 to Hey teaches providing recommendations to a user based on other items previously sampled by that user and on the availability of the item. Further, the recommendations were represented by a scalar rating for each item.
- U.S. Patent No. 5,452,410 to Magidson teaches apparatus and methods for achieving statistical analysis of categorical and continuous outcomes and for displaying the results of such analyses.
- Upendra Shardanand, "Social Information Filtering for Music Recommendation" Sep. 1994, pp. 1-93, Massachusetts Institute of Technology, Thesis. This system attempted to provide recommendations to a user based on ratings for items provided by the user as compared with other users.

61. The ‘282 patent claims do not preempt the field of recommendation systems. Technologies falling outside the scope of the ‘282 patent may include, but are not limited to, the following: (1) filtering relying solely on content-based techniques, (2) collaborative filtering using only a standard *Pearson r* correlation coefficient, (3) collaborative filtering relying on the Mean Squared Difference, and (4) community-based recommendation systems.

62. In contrast to the ‘282 patent, the patents at issue in *I/P Engine Inc. v. AOL Inc.*, claimed all instances of recommendation systems where content and collaborative filtering was used. Judge Mayer, in his Federal Circuit concurring opinion wrote, “the scope of the claimed invention is staggering, potentially covering a significant portion of all online advertising.” *I/P Engine, Inc. v. AOL Inc.*, 576 F. App'x 982, 995 (Fed. Cir. 2014). Further, despite the asserted patents (U.S. Patent Nos. 6,314,420 and 6,775,664 (“I/P Engine Patents”)) claiming a priority date of 1998 (*Id*. at 997) and a specification 50% shorter than that of the ‘282 patent, the I/P Engine Patents’ broad claims were upheld by the Patent and Trademark Office in two reexamination proceedings, by a jury following a 12 day trial, and by United States District Judge Raymond Alvin Jackson following significant post-trial briefing. In contrast, the provisional application to

which the ‘282 patent claims priority precedes the I/P Engine Patents’ priority date by two years and contains significantly narrower claims.

63. The ‘282 claims are not directed to any “method of organizing human activity,” “fundamental economic practice long prevalent in our system of commerce,” nor “a building block of the modern economy.” Instead, the ‘282 patent’s claims are limited to the realm of systems utilized in “calculating similarity values” and “recommending products and content” over a “computer network.”

64. The ‘282 patent’s claims are not directed at the broad concept or idea of “recommending items.” Instead, the claims are directed to particular, narrow methods and systems for "providing recommendations by transforming user data," using technologies unique to the internet age. The inventive concept in the ‘282 claims is a technological one rather than an entrepreneurial one – the development of systems and methods used to calculate content and/or product recommendations that are statistically significant, thus improving the accuracy of the content and/or product recommendations.

65. The ‘282 patent does not take a well-known or established business method or process and “apply it to a general purpose computer.” Instead, the specific system and processes described in the ‘282 patent have no direct corollary to a business process that predates the advent of the internet.

66. The ’282 patent’s claims are directed toward a solution rooted in computer technology and uses technology unique to computers and networks to overcome a problem specifically arising in the realm of making product and content recommendations over a computer network. For example, the ‘282 patent’s claims are directed toward generating recommendations using data collected in a database from users over the internet — a result that overrides the routine and conventional sequence for providing recommendations known in the art at the time the inventions disclosed in the ‘282 patent were conceived.

67. The ‘282 patent’s claims are not directed at a mere mathematical relationship or formula as the ‘282 patent's claims teach specific systems and methods for providing

recommendations of content and products over a computer network using both data from prior users of a website as well as information created by the systems and methods described in the ‘282 patent’s claims.

68. The ‘282 patent’s claims cannot be performed by a human, in mind, or by pen and paper. The claims as a whole are directed to generating user preference data using a connection to the internet to gather data from users, a database to store user data, and a computer processor to conduct complex statistical calculations. These limitations establish that the ‘282 patent’s claims are not an abstract idea, because they cannot be performed by a human, in the human mind, or by pen and paper.

69. Further, the ‘282 patent disclosure requires a computer to generate content and/or product recommendations. For example, in block 90, the method disclosed in the ‘282 patent computes whether the similarity value is sufficient to generate preference data. The result of the steps described in the ‘282 patent is a computer server using processing power to conduct complex calculations over large data sets and creating new data used by the system to improve the quality of recommendations.

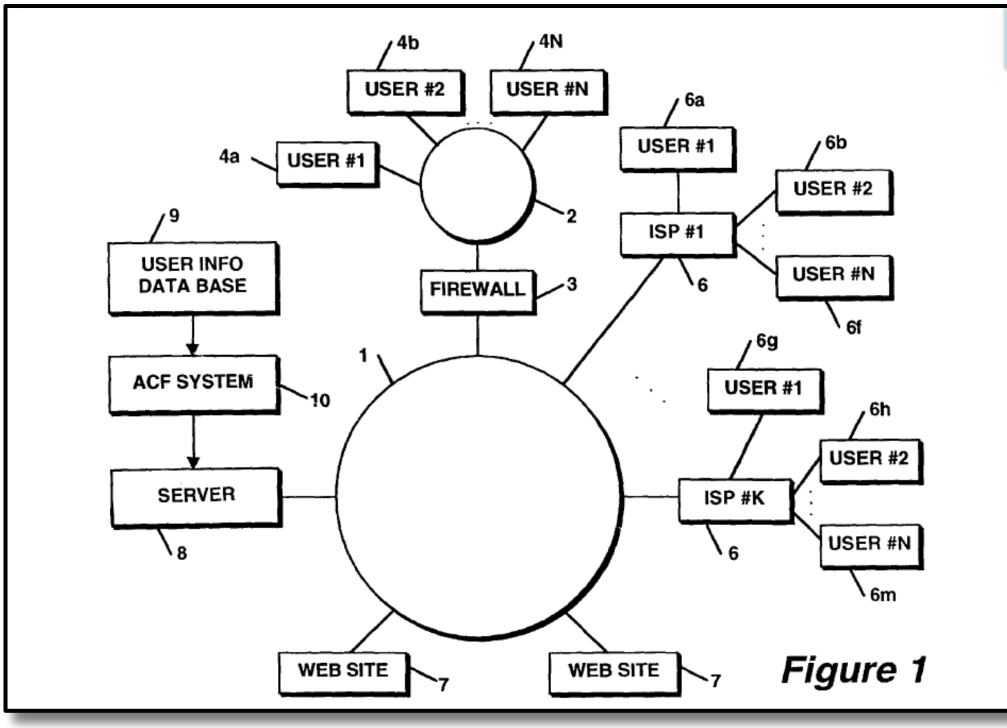

Fig. 4 (showing the implementation of the ‘282 patent system arose from receiving user data over the internet including through a website).[36]

70. The use of probability calculations to generate user preference data is not a conventional, routine activity in which humans engage.

71. The prior art cited on the face of the ‘282 patent further shows the invention claimed in the ‘282 patent is not a patent ineligible abstract idea. The invention described in the ‘282 patent's claims is narrower than much of the cited prior art, and therefore, is not an abstract idea. For example, U.S. Pat. Nos. 4,996,642 to Hey describes systems and methods that attempted to provide recommendations to a user based on ratings for items provided by the user as compared with other users. The ‘282 patent’s claims require additional limitations and thus the ‘282 patent's claims are directed toward significantly more than an abstract idea and the '282 patent's claims do not preempt the field of recommendation engines or even collaborative filtering.

72. The claimed invention in the ‘282 patent’s claims is rooted in computer technology and overcame a problem specifically arising in the realm of computer networks. The ‘282 patent’s

[36] ‘282 patent, fig. 1.

claims require the use of a computer system.

73. The use of a computer system plays a significant part in performing the claims of the '282 patent. For example, the use of a computer processor to generate user preference data utilizing data stored in a computer database is integral to the success of the system, and can only be performed using a computer system. The use of a computer system to process user data stored in a database does far more than improve the efficiency of the process; the computer system is integral to accomplishing the generating of recommendation data.

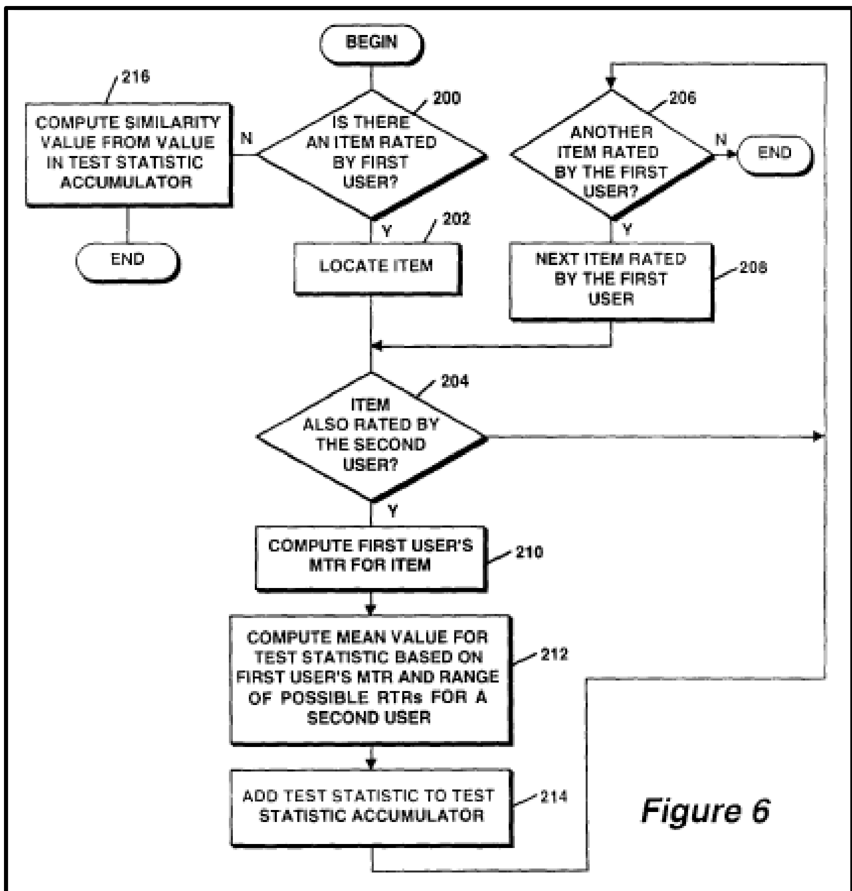

Fig. 5 (showing the generation of recommendation data).[37]

74. The rising volume of content and data made possible by the internet drives the need to identify relevant products and content using filtering technologies such as that disclosed in the '282 patent.

[37] '282 patent, fig. 6.

> With the development and popularity of WWW, billions of web pages are retrievable via search engines like Google. Despite it is not a perfect method to find what we want, most search engines still use keywords in documents and queries to calculate the relevance. As the only interface for users accessing tremendous web pages, queries are one of the most important factors that affects the performance of search engines. However, web pages returned from search engines are not always relevant to user search intentions. An independent survey of 40,000 web users found that after a failed search, 76% of them will try to rephrase their queries on the same search engine instead of resorting to a different one.[38]

75. Dan Darnell, a Senior Director of Product Marketing at Baynote, similarly described collaborative filtering as directed to solving problems specific to the internet.

> In its simplest form, collaborative filtering really works when data from multiple sources comes together and is sorted into categories. It is a must these days for any e-commerce site striving to deliver a basic level of website personalization.[39]

76. Academics have recognized that the development of collaborative filtering recommendation systems is directly tied to and an outgrowth of information overload problems created by and unique to the internet.

> The challenge of finding the needed information from the web has led to the development of a number of recommender systems, which typically watch the user navigation behavior as a sequence of pages and suggest another set of web pages, products and other information besides the actual information. With the exponential growth of the web, the study of modeling and predicting a user's access on the web has become crucial to the researchers and portal developers.[40]

> To overcome this so called "information overload" problem, in the mid-1990s researchers started to investigate recommender systems. A recommender system (RS) uses knowledge about your preferences (and those of others) to recommend items you are likely to enjoy. Users can offer feedback on items they are familiar with for example, and the recommender system uses the

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[38] Zhiyuan Liu & Maosong Sun, *Asymmetrical Query Recommendation Method Based on Bipartite Network Resource Allocation*, in PROC. OF WWW'08 1049 (2008).

[39] Dan Darnell, *Collaborative Filtering and Its Importance to Personalized Recommendations in eCommerce*, INTELLIGENCE COLLECTED: THE BAYNOTE BLOG, April 18, 2013, http://www.baynote.com/2013/04/how-collaborative-filtering-impacts-product-recommendations/ (Dan Darnell is a Senior Director of product marketing at Baynote).

[40] Gopinath Ganapathy & P.K. Arunesh, *Feature Analysis of Recommender Techniques Employed in the Recommendation Engines*, J. COMPUT. SCI. 6(7): 748—55 (2010).

> information to predict their preference for yet unseen items and subsequently recommends items with the highest predicted relevance.[41]

77. A 2009 paper supported by the Samsung Research Fund, ties collaborative filtering technologies to solving problems unique to the internet – the generation of information using a common communications infrastructure.

> The amount of information on the Web is increasing according to the growth of information and communication infrastructure. As a result, recommender systems (RSs) for personalization are required. An RS provides contents or items considering the tastes of individual users. Among the various RSs, collaborative filtering (CF) is the process of filtering for information or patterns using collaborative techniques involving multiple users.[42]

78. Years after the Ringo system was developed (the Ringo system is referenced on the face of the '282 patent), the use of collaborative filtering techniques was described as "innovative" by data scientists.

> Ringo also provides an innovative solution that inverts the basic CF approach; music albums are treated as 'participants' that can recommend users to other music album participants.[43]

79. One or more of the '282 patent's claims relate to a computer-implemented method to transform website user data in a particular manner – by inserting information into user data and using the code to recommend content and/or products. This insertion enables the computer system to recommend content and/or products and generate similarity values.

80. One or more of the claims in '282 patent go beyond manipulating, reorganizing, or collecting data by actually adding information associated with a user and using that information to generate a recommendation of a product or content over a computer network,
thereby fundamentally altering ratings data associated with a user.

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[41] Joost de de Wit, *Evaluating Recommender Systems -- An Evaluation Framework to Predict User Satisfaction for Recommender Systems in an Electronic Program Guide Context* 9 (May 2008), Master's thesis, University of Twente, http://essay.utwente.nl/59711/.
[42] Hyeong-Joon Kwon et al., *Improved Memory-based Collaborative Filtering Using Entropy-based Similarity Measures*, in SYMPOSIA AND WORKSHOPS ON UBIQUITOUS, AUTOMATIC AND TRUSTED COMPUTING (WISA'09) (May 2009) (this work was supported by Samsung).
[43] Sonny Han Seng Chee et al., *Rectree: An Efficient Collaborative Filtering Method*, in 3RD INT. CONF. ON DATA WAREHOUSING AND KNOWLEDGE DISCOVERY (DAWAK 2001) 141 (2001).

81. One or more of the claims in the ‘282 patent require ‘transforming’ data to generate “randomized ratings data” by “adding a uniformly distributed random number to the ratings data provided by the plurality of users.” Therefore, the claims in the ‘282 patent alter data associated with a user and go beyond the mere collection, organization, manipulation, or reorganization of data. The claimed invention goes beyond manipulating, reorganizing, or collecting data by actually adding a new subset of numbers or characters to the data, thereby fundamentally altering the original information.

82. One or more of the claims in the ‘282 patent requires ‘transforming’ one thing (‘ratings data’) ‘to create’ something else (‘randomized ratings data’) and further recites a particular manner of transforming (‘by adding a uniformly distributed random number to the ratings data provided by the plurality of users’). Therefore, claimed features in the ‘282 patent “fundamentally alter” data or “transform” the data.

83. Nor does collaborative filtering merely “support an existing activity.” Professor Loren G. Terveen of the University of Minnesota[44] and Will Hill of AT&T Labs described collaborative filtering as improving the functioning of computer-based recommendation systems by updating a computer database and transforming data.

> Collaborative filtering does not simply support an existing activity. Instead, it requires users to engage in a somewhat novel computationally mediated activity. This activity has a single combined role, the recommendation seeker / preference provider. We describe this as *role uniformity*. Everyone does the same work (rates items) and receives the same benefits (gets rated items as recommendations). We might describe rating items as an “ante” – to get recommendations, you have to give them. ***This leads naturally to growth in the system’s knowledge (and thus to better recommendations), since using the database leads to the database being updated***.[45]

84. IBM white papers describe computer-implemented recommendation systems as transforming the data of a previously static website – generating preference information that

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[44] Loren Terveen was a Principal Member of the Technical Staff at AT&T Labs.
[45] Loren Terveen & Will Hill, *Beyond Recommender Systems: Helping People Help Each Other*, in HCI IN THE NEW MILLENNIUM 13 (Jack Carroll, ed., Addison-Wesley, 2001) (emphasis added).

previously did not exist. Recommendation systems like the inventions disclosed in the ‘282 patent utilize a system for modifying data that has a concrete effect in the field of website and internet usage.

> Recommendation systems changed the way inanimate websites communicate with their users. Rather than providing a static experience in which users search for and potentially buy products, recommender systems increase interaction to provide a richer experience. Recommender systems identify recommendations autonomously for individual users based on past purchases and searches, and on other users' behavior.[46]

85. Further, the ‘282 patent claims improve upon the functioning of a computer system. “Performance improves as the number of entries in the database increases.” ‘282 patent, col. 23:29-30. The claims and specification of the ‘282 patent also describe the use of “cluster analysis,” which improves the functioning of a computer handling the making of recommendations. “As a means for more efficient processing, cluster analysis can be used.” *Id.* 20:36-37.

86. One or more of the claims of the ‘282 patent recite a means or step for performing a specified function. The corresponding structure(s) in the ‘282 patent specification and appendix include computer code that improves the functioning of a computer by being more “RAM-efficient.” ‘282 patent, cols. 33:1-39:60.

87. Academic research has confirmed that using ratings improves the functioning of a computer conducting collaborative filtering.

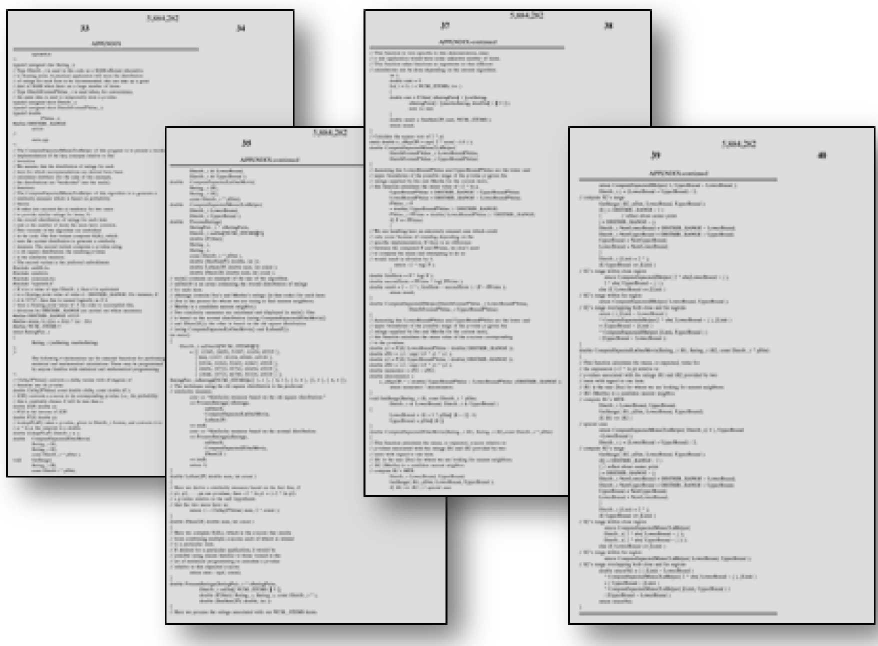
> One way to make recommendations of regular, but interesting items, more likely consists in assigning weights to items that devalue ratings given to popular items and appreciate ratings given to regular items. . . . The results of the first set of experiments are shown in Fig. 5. The precision@n values show that when using the weighting functions, the resulting precision@n is slightly higher for low values of n than for the unweighted approach for the Moviepilot dataset (n=5). For the Movielens dataset, the unweighted approach seems to have the upper hand. However, as n increases, the improvement decreases and at a relatively large n (n=50) the weighted

[46] M. Tim Jones, *IBM Developer Works: Recommender Systems, Part 1: Introduction to Approaches and Algorithms* 2 (December 12, 2013), *available at* http://www.ibm.com/developerworks/library/os-recommender1/.

> approaches perform worse than the non weighted one. In the Movielens case, the unweighted approach always outperforms the weighted ones, irrelevant of n's value. This seems to be in agreement with the findings by Herlocker et al. Results for the Euclidean and cosine measures showed very similar trends and have thus been omitted.[47]

88. One or more of the claims in the '282 patent recite means-plus-function claim limitations governed by 35 U.S.C. § 112, ¶ 6.

89. The '282 patent discloses computer algorithms in an appendix to the specification. In addition to the structures and algorithms disclosed throughout the specification, these algorithms correspond to means-plus-function claims in the '282 patent.



'282 patent, cols. 39-40 (computer algorithms disclosed in an appendix to the specification).

90. Means-plus-function claims such as those included in the '282 patent are inherently not abstract ideas. Stanford Law Professor Mark Lemley described his analysis:

> If the patent is interpreted as a means-plus-function claim, it will be limited to the particular software implementation the patentee actually built or

[47] Alan Said et al., *Analyzing Weighting Schemes in Collaborative Filtering: Cold Start, Post Cold Start and Power Users*, in PROCEEDINGS OF THE 27TH ANNUAL ACM SYMPOSIUM ON APPLIED COMPUTING (SAC'12) 2035, 2039 (2012).

> described. Such a narrow, specific claim should not be an unpatentable "abstract idea."[48]

> But if you wrote it [an algorithm] and you included it in the step I think you could survive the *Aristocrat* line of cases and then the question will become well what does equivalent thereof mean? Can I show you my algorithm and say, yeah, this is the approach I took but these other four approaches are equivalent and a computer programmer would look at those and say I don't care which one of those you use. ***And if you can do that then you might end up with a claim that's still pretty broad even though it's in means plus function format***.[49]

COUNT I
INFRINGEMENT OF U.S. PATENT NO. 5,885,282

91. Fellowship Filtering references and incorporates by reference paragraphs 1 through 90 of this Complaint.

92. Adobe makes, uses, sells, and/or offers for sale in the United States products and/or services for generating product and/or content recommendations. On information and belief, at least some of Adobe's recommendation products and/or services provide or support generating product and/or content recommendations based on enhanced collaborative filtering technologies to drive more successful and relevant recommendations.

93. Adobe operates the internet site http://www.adobe.com/marketing-cloud.html ("Adobe Marketing Cloud Site").

94. Adobe operates the internet site ww.adobe.com/Target ("Adobe Target"). Adobe has created and offers to its customers the applications and services: Adobe Marketing Cloud and Adobe Target, (collectively, "Adobe Products").

95. On information and belief, one or more of the Adobe Products include collaborative filtering technology.

96. On information and belief, one or more of the Adobe Products enable the

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[48] Mark A. Lemley, *Software Patents and the Return of Functional Claiming*, 2013 WISC. L. REV. 905 (2013).
[49] Eugene Quinn, *The Ramifications of Alice: A Conversation with Mark Lemley*, IPWATCHDOG BLOG, September 4, 2014, http://www.ipwatchdog.com/2014/09/04/the-ramifications-of-alice-a-conversation-with-mark-lemley/id=51023/ (emphasis added).

calculation of recommendations based on Affinity, so People who bought this bought that or People who viewed this bought that, or People who viewed this viewed that are recommended relevant content or products.

97. On information and belief, Adobe Products are available to businesses and individuals throughout the United States.

98. On information and belief, Adobe Products are provided to businesses and individuals located in the Eastern District of Texas.

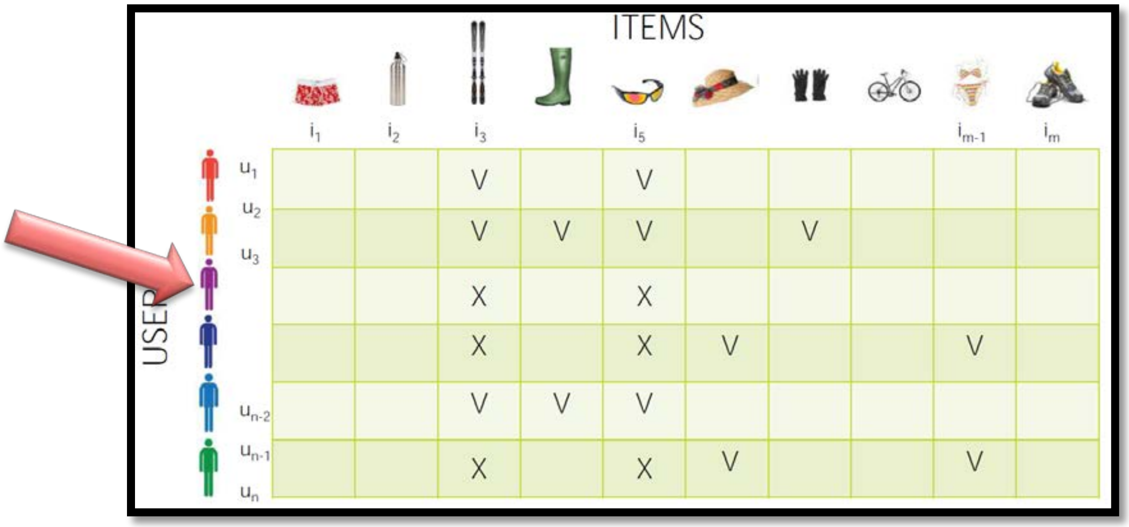
99. On information and belief, one or more of the Adobe Products conduct recommendations based on "previous product interests."

100. On information and belief, one or more of the Adobe Products contain functionality to calculate a general score that does not take into account the user profile.

101. On information and belief, it is advantageous for one or more of the Adobe Products to generate recommendations based on algorithms that account for the overall ratings and/or data distribution of a piece of content.

102. On information and belief, Chris Akhurst and Pradeep Javangula provided a presentation at the 2013 Adobe Summit that identified recommendations being generated from user to user matching.

103. On information belief, the following slide from Chris Akhurst and Pradeep Javangula's 2013 presentation at the 2013 Adobe Summit show's a system for recommending items based on ratings data between users.



A Chris Akhurst & Pradeep Javangula, *Revealing the Wizard: Behind the Curtain with Data Modeling Algorithms*, ADOBE SUMMIT 2013 58 (2013).

104. On information and belief, at least one of the Adobe Products generates a contextual score as part of creating a recommendation of a product and/or content.

105. On information and belief, Adobe Target contains functionality to recommend content and/or products based on "high affinity items."

106. On information and belief, Edward Ramirez and Lily Chiu-Watson presented AT&T with features relating to Adobe Target including "High Affinity Items."

107. On information and belief, one or more of the Adobe Products conduct "Propensity Scoring."

108. On information and belief, "Propensity Scoring" can be calculated using "statistical decision trees," "propensity scores," and/or "random trees."

109. On information and belief, "Propensity Scoring" in one or more of the Adobe Products uses "out-of-the-box" functionality that includes algorithms that use averaging to improve predictive accuracy.

110. On information and belief, in one or more of the Adobe Products use KMeans++ to generate recommendations of products and/or content.

111. On information and belief, "Propensity Scoring" in one or more of the Adobe Products enables the identification of similar customers using focused and objective means.

112. On information and belief, one or more of the Adobe Products enable the identification of recommended products and/or content based on linking products to users' browsing and purchase history.

113. On information and belief, Pradeep Javangula, Director of Engineering at Adobe, stated that "consider the classic association-rule example of beer and diapers: during certain times of the day, male shoppers tend to buy them together, even though on the surface, the items are completely unrelated. Valuable insights can be gained from uncovering these unexpected associations. Understanding the affinity of one item to another based on observed user behavior can be a significant analytics challenge."[50]

114. On information and belief, one or more of the Adobe Products incorporate one or more of the following technologies: (1) item-item similarity based on User Item Metric; (2) affinities based on view-view, view-bought, bought-bought similarity; or (3) similarity measure using a Log Likelihood measure.

115. On information and belief, Adobe's 2014 Digital Marketing Optimization Survey found, "[w]hether targeting a particular audience group or just an audience of one, optimized personalization enables marketers to enhance the relevance and efficiency of new and repeat visitor experiences. Respondents targeting more than 20% of visitors achieved two times the average conversion rate at 5%."[51]

116. On information and belief, one or more of the Adobe Products incorporates the Site Affinities Algorithms.

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[50] Pradeep Javangula, *Getting the Most from Recommendations*, ADOBE DIGITAL MARKETING BLOG, June 10, 2013, http://blogs.adobe.com/digitalmarketing/personalization/gettingthemostfromrecommendations/.

[51] *Adobe 2014 Digital Marketing Optimization Survey Results* 4, ADOBE TARGET WEBSITE, June 2, 2014, http://adobe-target.com/etc/designs/target-microsite/images/50825_target_Q214_optimization_survey_whitepaper_ue_v3.pdf.

117. On information and belief, one or more of the Adobe Products enable the generation of Statistical Confidence Reports.

118. On information and belief, one or more of the Adobe Products uses algorithmic approaches to generate recommendations and preference data.

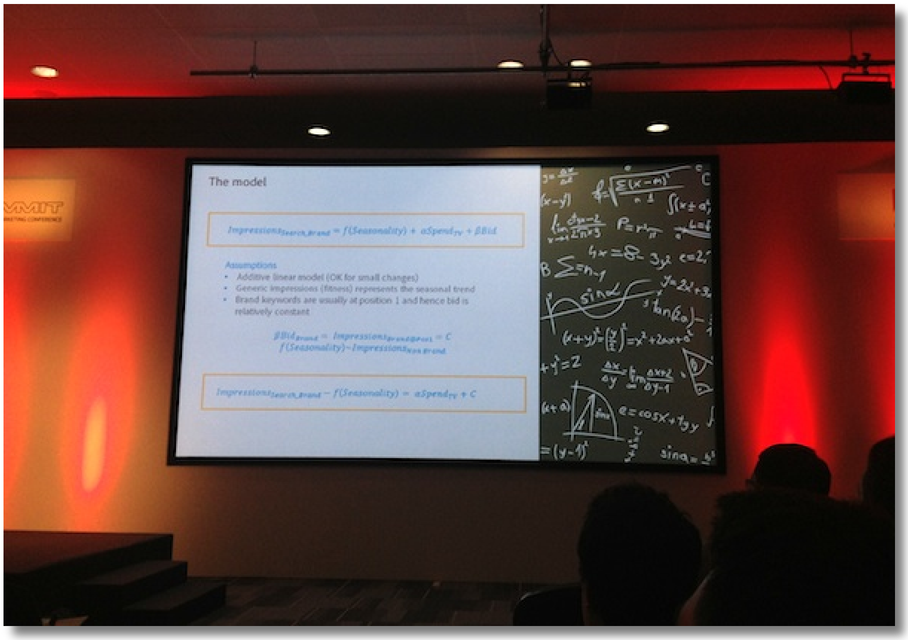

Image of Dr. Sid Shah's (Director of Business Analytics at Adobe) presentation at Adobe Summit EMEA 2013 (showing some of the econometric techniques used to generate forecasting and recommendation data).

119. On information and belief, one or more of the Adobe Products transforms data associated with a user to provide product and/or content recommendations.

120. On information and belief, Adobe has directly infringed and continues to directly infringe the '282 patent by, among other things, making, using, offering for sale, and/or selling collaborative filtering products and services, including but not limited to, the Adobe Products, which include infringing content and product recommendation technologies. Such products and/or services include, by way of example and without limitation, the Adobe Marketing Cloud and Adobe Target, which are covered by one or more claims of the '282 patent, including but not limited to, claims 19 and 25.

121. By making, using, testing, offering for sale, and/or selling the Adobe Products, Adobe has injured Fellowship Filtering and is liable to Fellowship Filtering for directly infringing one or more claims of the ‘282 patent, including at least claims 19 and 25, pursuant to 35 U.S.C. § 271(a).

122. On information and belief, Adobe also infringes indirectly the ‘282 patent by active inducement under 35 U.S.C. § 271(b).

123. On information and belief, Adobe has had knowledge of the ‘282 patent since at least service of this Complaint or shortly thereafter, and on information and belief, Adobe knew of the ‘282 patent and knew of its infringement, including by way of this lawsuit.

124. On information and belief, Adobe intended to induce patent infringement by third-party customers and users of the Adobe Products and had knowledge that the inducing acts would cause infringement or was willfully blind to the possibility that its inducing acts would cause infringement. Adobe specifically intended and was aware that the normal and customary use of the accused products would infringe the ‘282 patent. Adobe performed the acts that constitute induced infringement, and would induce actual infringement, with the knowledge of the ‘282 patent and with the knowledge, or willful blindness to the probability, that the induced acts would constitute infringement. For example, Adobe provides the Adobe Products that have the capability of operating in a manner that infringe one or more of the claims of the ‘282 patent, including at least claims 19 and 25, and Adobe further provides documentation and training materials that cause customers and end users of the Adobe Products to utilize the products in a manner that directly infringe one or more of the claims of the ‘282 patent. By providing instruction and training to customers and end users on how to use the Adobe Products in a manner that directly infringes one or more claims of the ‘282 patent, including at least claims 19 and 25, Adobe specifically intended to induce infringement of the ‘282 patent. On information and belief, Adobe engaged in such inducement to promote the sales of the Adobe Products, *e.g.*, through Adobe’s user manuals, product support, marketing materials, and training materials to actively induce the users of the accused products to infringe the ‘282 patent. Accordingly, Adobe has induced and

continues to induce users of the accused products to use the accused products in their ordinary and customary way to infringe the ‘282 patent, knowing that such use constitutes infringement of the ‘282 patent.

125. To the extent applicable, the requirements of 35 U.S.C. § 287(a) have been met with respect to the’282 patent.

126. As a result of Adobe’s infringement of the '282 patent, Fellowship Filtering has suffered monetary damages in an amount adequate to compensate for Adobe’s infringement, but in no event less than a reasonable royalty for the use made of the invention by Adobe, together with interest and costs as fixed by the Court.

PRAYER FOR RELIEF

WHEREFORE, Plaintiff Fellowship Filtering respectfully requests that this Court enter:

A. A judgment in favor of Plaintiff Fellowship Filtering that Adobe has infringed, either literally and/or under the doctrine of equivalents, the '282 patent;

B. An award of damages resulting from Adobe's acts of infringement in accordance with 35 U.S.C. § 284;

C. A judgment and order requiring Adobe to provide accountings and to pay supplemental damages to Fellowship Filtering, including, without limitation, prejudgment and post-judgment interest; and

D. Any and all other relief to which Fellowship Filtering may show itself to be entitled.

JURY TRIAL DEMANDED

Pursuant to Rule 38 of the Federal Rules of Civil Procedure, Fellowship Filtering requests a trial by jury of any issues so triable by right.

Dated: May 25, 2015

Respectfully submitted,

/s/ Elizabeth L. DeRieux
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