

Eye Gaze Relevance Feedback Indicators for Information Retrieval

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Abstract: There is a growing interest in the research on interactive information retrieval, particularly in the study of eye gaze-enhanced interaction. Feedback generated from user gaze features is important for developing an interactive information retrieval system. Generating these gaze features have become less difficult with the advancement of the eye tracker system over the years. In this work, eye movement as a source of relevant feedback was examined. A controlled user experiment was carried out and a set of documents were given to users to read before an eye tracker and rate the documents according to how relevant they are to a given task. Gaze features such as fixation duration, fixation count and heat maps were captured. The result showed a medium linear relationship between fixation count and user explicit ratings. Further analysis was carried out and three classifiers were compared in terms of predicting document relevance based on gaze features. It was found that the J48 decision tree classifier produced the highest accuracy.

Index Terms: Eye gaze, information retrieval, user experiment, implicit feedback, eye tracking, intelligent system.

1. Introduction

Information gathering and retrieval have been as old as mankind. Humans have developed approaches for collecting, sorting, keeping and retrieving their items over the years. These items can be in the form of objects, text, audio, video and so on. Since the advancement of Information Technology, storage and retrieval mechanism has evolved over the years, leading to a more efficient way of keeping and retrieving items. One of the valuable phenomena that have been stored using technology is data and information; This has been made possible due to the paradigm shift from manual storage to computerization. Information is growing every day on the web and algorithms for effective retrieval has been developed by researchers to address the problem of information overload [1-3].

Much research work has been carried out on developing retrieval algorithms using the Probabilistic model, Markov model, Vector space model and other retrieval algorithms [4]. Efforts are currently made to enhance information retrieval through inferring users' intentions. These users' intentions can be captured from their query input and their explicit and implicit interactions with the system [1, 2, 5]. Studies on improving document recommendation through augmenting query inputs with user implicit and explicit behaviour have been carried out over the years [6, 7]. These enhanced interactive retrieval approaches have given insight and useful results towards optimizing information retrieval and helping users find their needed web resources within a minimal time [1, 8, 9].

Past studies have shown that the eye gaze carries vital information about the attention of users and their thought processes [10]. However, data obtained from such natural interaction processes like looking at the screen is still not completely explored today. Considering the progress made in the development of eye gaze tracking technology, there has been improved accuracy in the measurement of eye gaze features [10, 11]. This improvement in eye gaze tracking technology has also led to increased studies in eye features such as Fixation Count (FC), Fixation Duration (FD), Saccade, Pupil Dilation and Heat maps. It is important to comprehend how the eyes relate to focus points and how the movements of the eyes signify relevance. This research estimates the predicting strength of gaze features such as FC, FD and Heat maps in relation to the explicit judgement of document relevance. For this reason, this research seeks to answer the following questions:

1. Is there a relationship between gaze generated indicators and explicit judgment of relevance on a given set of documents?
2. Does a Heat map tell if a document is relevant or not?

The remaining section of this paper is presented as follows: The review of related literature is in Section 2, Section 3 describes the research methodology, the results and discussion are presented in Section 4. The later part of this paper is the conclusion, followed by the future work.

2. Related Work

There is a growing interest in the information retrieval community in the use of implicit relevance feedback as an unobtrusive way of replacing explicit feedback parameters which are intrusive. Previous work shows that implicit feedback parameters are relevant in improving the quality of Information Retrieval [3, 12, 13]. Claypool et al. [14] examined implicit parameters like mouse movement, amount of scroll, active time and other low-key indicators and found that the amount of scroll and active time are good indicators for measuring relevance. Other studies also found active time as an important indicator of relevance [15-17]. Click-through data is another indicator of interest used to infer relevance on the Search Engine Result Page (SERP) [18].

Users often focus on the things that are of interest to them. The design of a head-mounted eye tracker was one of the early innovations in the field of eye tracking. Early work on gaze tracking by Yarbus [19] focused on exploring the saccade feature of eye gaze. His research recorded and evaluated observations as users gazed at natural scenes and objects. He suggested that gaze paths are dependent on the task performed by the observer. Other early works focused on improving the precision and accuracy of eye trackers [20], leading to the development of eye trackers that are less intrusive, more precise with minimal error rate.

Eye Gaze data are employed in the field of information retrieval to improve document recommendation [21, 22]. Gwizdka and Zhang [23] research suggest that queries can be improved from gaze features of a read document which can be used for the prediction of unseen documents. Hardoon et al. [24] also inferred queries from user eye movements. Buscher et al. [10] used two studies to examine how gaze features can be used to enhance retrieval. They found gaze features very useful for enhancing the retrieval of relevant documents. Ajanki et al. [21] found fixation duration on a word as a factor for selecting additional query terms. Similar research was carried out by Davari et al. [25]. They evaluated fixation as a gaze feature in predicting query terms and found that query terms can be predicted with a degree of accuracy from word-eye-fixation, even with little training data.

Hansen et al. [11] examined the authenticity of news headlines from user gaze data. A total number of 55 participants read 108 news headlines. The results showed that false headlines were viewed less than true headlines. Research by Loboda et al. [26] also found that users fixated on relevant sentence-terminal words than non-relevant words. Gwizdka and Zhang [23] research suggest that relevant documents are continuously read by users while non-relevant documents are scanned. Pfeiffer et al. [27] demonstrated that user's choices during shopping can be inferred from eye-tracking. Their model was able to classify users' intention by 85% accuracy in physical reality and 80% accuracy in virtual reality. Balatsoukas and Ruthven [28] produced a contrary result from previous studies, they found that users spent a longer time fixating on non-relevant document surrogates. Buscher et al. [10] did not see any correlation between fixation and user ratings for relevance. In the context of modelling in a particular domain, Prasov and Chai [29] contends that eye-gaze can be used to make up for the limitations inherent with domain modelling for resolving references. In this research, an investigation was conducted to examine if there is a relationship between user explicit relevance ratings and fixation/heat map. The gaze measures studied are heat map and fixation (fixation duration and fixation count). Also, classification techniques were compared to examine if the gaze generated indicators can be used to group documents based on relevance.

2.1. Gaze generated features examined

The features investigated in this work in relation to user explicit relevance judgement are Fixation Duration, Fixation Count and Heat Map. Fixation occurs for an information task when the eye is focused on something of interest within the period of 225ms to 300ms [30]. Systems that employ eye gaze uses fixation duration to determine user interest [31]. Fixation Duration (FD) sums individual fixation time that occurs when a user focuses on a given area of interest. Fixation Count (FC) on the other hand is the frequency of the fixation duration on an area of interest. Heat Map is used for visualisation, to distinguish areas that have more fixation from areas with less fixation. It shows areas that are more fixated tend to be denser than less fixated areas. Table 1 further reviews previous works done in the area of implicit feedback indicators and eye gaze studies.

Table 1. Review of implicit feedback indicators and eye gaze studies

<i>S/n</i>	<i>Reference</i>	<i>Dwell Time</i>	<i>Mouse Movement</i>	<i>Mouse Click</i>	<i>Scroll Movement</i>	<i>Keystroke</i>	<i>Other Implicit Indicators (bookmark, save, print)</i>	<i>Eye Gaze</i>
1	[14]	Good implicit indicator.	There exists a relationship between the dwell time and relevance judgement	The mouse click is not a good implicit indicator	Scroll movement is a good implicit indicator.	The keypress is not a good indicator of relevance	Not captured	Not captured

2	[15]	The dwell time is a good implicit indicator to measure interest.	The distance of the mouse movement corresponds with the dwell time	A mouse click is a good implicit indicator next to mouse movement.	Scrolling is also a good indicator for measuring interest.	The more the number of up and down key movements, the more the interest.	When a document is printed, bookmarked or saved, there is a 95% assurance that a user has an interest in it.	Not captured
3	[32]	Not captured	Not captured	There is a bias in clicking a link on the SERP.	Not captured	Not captured	Not captured	Fixation is a good indicator of interest
4	[33]	Not captured	Not captured	Not captured	Not captured	Not captured	Not captured	Markov model is best for predicting document relevance based on eye gaze
5	[18]	Not captured	The time taken to hover the cursor around the SERP decreases with rank while the arrival time increases with rank.	When hover activities are added to clicks, it strengthens the relationship between clicks and user explicit ratings.	Not captured	Not captured	Not captured	Gaze duration drops off as the ranking decreases than cursor hover time.
6	[30]	Not captured	Not captured	Not captured	Not captured	Not captured	Not captured	Fixation is a good indicator for interest
7	[34]	The time taken to arrive at the bottom-ranked result on a SERP is longer.	Not captured	Users click on a lower link only if they have clicked the higher-ranked link.	Not captured	Not captured	Not captured	Users spend a long time looking at top-ranked results.
8	[35]	In a sophisticated feedback mechanism, Dwell time can replace an eye tracker.	Not captured	Not captured	Not captured	Not captured	Not captured	Eye tracker data predict relevant documents than the display time.
9	[36]	Not captured	Eye gaze and mouse positions coordinates, and they coordinate more in a vertical direction	Not captured	Not captured	Not captured	Not captured	Eye gaze and mouse positions coordinates, and they coordinate more in a vertical direction
10	[37]	Post click behaviour is more effective in predicting relevance than dwell time alone. Also, dwell time is an important indicator for measuring relevance.	Cursor movement complements dwell time information.	Not captured	Scrolling slowly signifies relevance and more relevance if it is done horizontally. Vertical scrolling with speed signifies scanning, therefore low relevance.	Not captured	Not captured	Not captured

11	[38]	Not captured	Not captured	Not captured	Not captured	Not captured	Used text selection. to re-rank the search result.	Not captured
12	[21]	Not captured	Not captured	Not captured	Not captured	Not captured	Not captured	Feedback obtained by eye movement is not relevant like that obtained from a user query.
13	[18]	Not captured	A user examines a search result if he hovers over it.	Prediction improves when cursor data is added to clickthrough data.	A user is likely to examine search results when the user scrolls through a set of search results.	Same with scroll	Not captured	Not captured
14	[10]	Not captured	Not captured	Not captured	Not captured	Not captured	Not captured	No relationship between fixation duration and relevance.
15	[39]	Not captured	Not captured	Not captured	Not captured	Not captured	Not captured	In a current task, eye gaze is a good predicting indicator.

3. Methodology

Baeza-Yate, Riberro-Neto [40] suggested two types of information retrieval query design viz the batch design and the interactive query design. The batch system involves the evaluation of search engine performance while the interactive query design is based on user experience evaluation. This research employs the interactive query design since it enables a comprehensive evaluation of the user and the interface. The research was carried out in the Gaze Tracking Laboratory at Coventry University Technology Park, UK. The laboratory setting was necessary for this experiment to capture user eye gaze behaviour without unnecessary distractions that are associated with a naturalistic setting. A total number of 9 undergraduate students at Coventry University participated in the experiment. The students were between the age of 19 to 23. They were given six documents to sequentially read and rate them based on relevance to a given task, using a 6-point rating scale. The overall time for the experiment was 30 mins. To begin the experiment, the participants completed a consent form after listening to a brief tutorial of the experiment from the researcher. A five-point calibration scale was used to calibrate the eyes of the subjects for optimal gaze generated results (FD, FC and Heat map). The researcher sat behind the subjects during the experiment, observing and ensuring that the process was followed. Each of the participants received a £10 worth of gift card.

3.1. Gaze generated features examined

Tobii TX300 desk-mounted eye tracker with a 300Hz tracking frequency was paired with a 23-inch LCD monitor for capturing the gaze generated data. The monitor's resolution was 1920 X 1080 pixels while the visual angle of the eye tracker was 0.4. Tobii SDK Software was used to capture the Heat map, Fixation Count and Fixation Duration.

4. Results and Discussion

Gaze generated data (FC and FD, heat map) were analysed. To analyse the eye tracker data, the researcher began by cleaning up the data. It was discovered that gaze data was not generated from one of the documents read by a particular participant (record 6) due to poor calibration. This particular row was removed from the dataset. The remaining dataset is presented in Tables 2 and 3.

Table 2. Generated data for Fixation Count and Fixation Duration

Subjects	Web Doc 1		Web Doc 2		Web Doc 3		Web Doc 4		Web Doc 5		Web Doc 6	
	FC	FD	FC	FD	FC	FD	FC	FD	FC	FD	FC	FD
Rec 01	117.0	33.9	583.0	150.8	166.0	35.0	127.0	27.6	37.0	10.2	297.0	70.1
Rec 02	361.0	99.9	359.0	92.2	137.0	44.3	68.0	19.2	21.0	5.4	298.0	135.4
Rec 03	542.0	74.0	531.0	73.8	226.0	35.3	239.0	42.3	72.0	11.6	348.0	77.4
Rec 04	12.0	0.9	163.0	19.8	172.0	21.4	26.0	2.4	8.0	0.4	31.0	4.1
Rec 05	5.0	0.7	614.0	65.6	121.0	17.1	9.0	0.3	13.0	0.9	180.0	29.4
Rec 06	68.0	11.3	12.0	1.4	0.0	0.0	1.0	0.1	0.0	0.0	0.0	0.0
Rec 07	2325.0	211.0	360.0	106.4	171.0	64.0	554.0	75.1	163.0	16.4	641.0	181.5
Rec 08	1523.0	451.8	2115.0	856.4	836.0	217.4	485.0	180.2	809.0	127.7	1407.0	579.2
Rec 09	622.0	77.0	1484.0	221.0	236.0	64.7	61.0	14.9	189.0	33.3	403.0	76.0
All Records	619.4	106.7	691.2	176.4	229.4	55.5	174.4	40.3	145.8	22.9	400.6	128.1

Table 3. Generated data for Explicit relevance ratings

Web documents	Rec 01	Rec 02	Rec 03	Rec 04	Rec 05	Rec 06	Rec 07	Rec 08	Rec 09	All Records
Web Doc 1	4	4	4	4	2	4	5	4	3	3.75
Web Doc 2	5	4	4	5	4	4	4	4	4	4.25
Web Doc 3	4	5	3	5	2	3	4	3	3	3.625
Web Doc 4	4	2	4	2	2	3	4	5	2	3.125
Web Doc 5	3	3	3	5	2	2	5	4	4	3.625
Web Doc 6	4	2	2	2	1	3	3	4	3	2.625

The Fixation Duration is represented as FD and the Fixation Count is represented as FC while the perceived relevance rating is represented as Ratings. Table 4 is the descriptive statistics of the data, it shows a dataset of 48, with the minimum value of the FC as 5.0, the maximum value is 2325.0, the mean as 422.229 and the standard deviation is 528.1523. The minimum value of the FD is 0.3, the maximum value is 856.4, the mean is 99.071 and the standard deviation is 157.0524.

Table 4. Descriptive statistics of the gaze generated data

	N	Minimum	Maximum	Mean	Std. Deviation
Fixation Count (FC)	48	5.0	2325.0	422.229	528.1523
Fixation Duration (FD)	48	0.3	856.4	99.071	157.0524

SPSS was used to calculate the correlation (r) for the user ratings vs FC and user ratings vs FD. There was a medium correlation of 0.32 between user explicit ratings and Fixation Count, with a statistically significant coefficient (p -value = 0.025). There was no statistically significant correlation between Fixation Duration and the user explicit ratings as shown in Table 5.

Table 5. User explicit ratings vs gaze generated data

	Pearson Correlation	
	Fixation Count (FC)	Fixation Duration (FD)
User explicit rating	$r = 0.32, p = 0.025$	$r = 0.22, p = 0.14$

A boxplots graph showing how the user explicit ratings are related to FC and FD is given in Fig 1. Although there are 5 outliers, the graph of user rating vs FC shows a steady increasing upper quartile from ratings 1 to ratings 4, and an increasing median for ratings 3 to 4. There were seven outliers in the graph of FD vs user rating. The upper whiskers and the upper quartile of the user explicit ratings increases with the FD.

Further analysis was carried out to classify the fixation according to low relevance and high relevance. The explicit ratings were merged into low relevance (0-3) and high relevance (4-5) in order to have a proper classification problem, with 0 representing low relevance and 1 representing high relevance. The FC and the FD were used as the input parameters while the re-grouped relevance ratings were used for the output. The dataset was passed through several classification algorithms using WEKA and the result produced an accuracy of 56.25% for KNN, 58.33% for J48. Multilayer Perceptron Neural Network classifier also produced 56.25%, the same as the KNN as shown in Table 6 and Fig. 2 respectively.

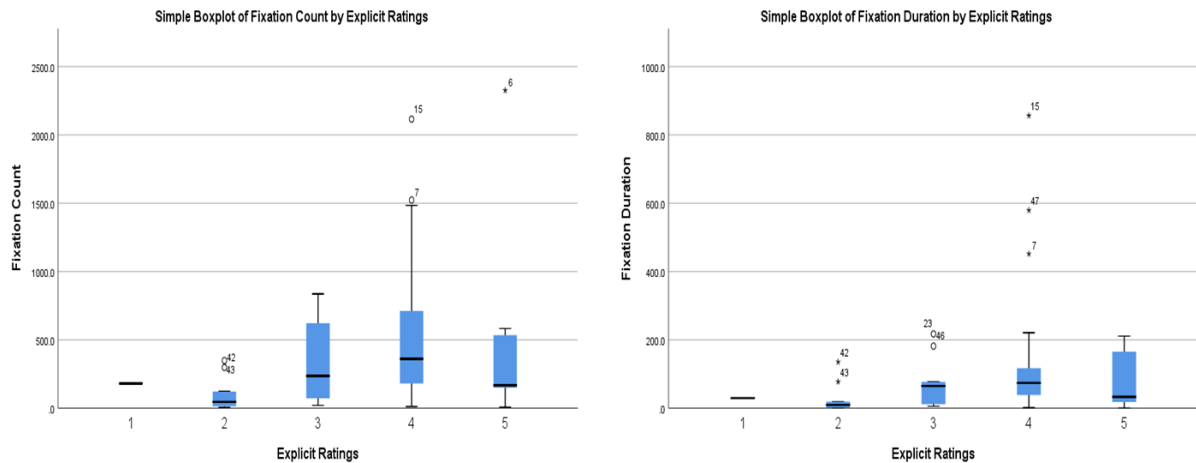


Fig.1. Graph of Fixation Count vs Explicit ratings and Fixation Duration vs Explicit ratings

Table 6. Comparison results of classification methods

Classifier	Accuracy
KNN	56.25%
MLP	56.25%
J48 Decision Tree	58.33%

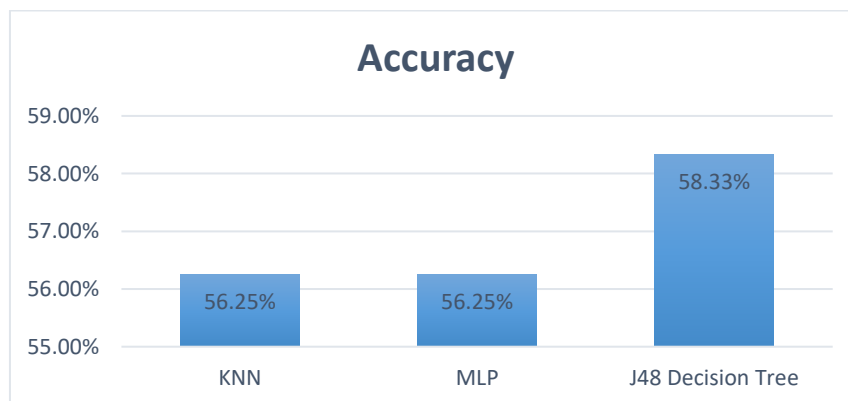


Fig.2. Comparison results of classification methods

The results obtained from the Heat map gives a visual description of the relationship between the gaze data and the user explicit ratings. As can be seen in Fig. 3, the denser documents have higher relevance ratings. Though this inference does not apply to all documents as can be seen in documents 3 and 6. Further investigation shows that shorter documents had high density irrespective of ratings, suggesting that document height is an extraneous variable in measuring the relationship between user relevance ratings and gaze generated data such as Heat maps. The URLs for the web documents used are presented in the appendix.

Previous research by Granka, et al. [30] says that fixation is an indicator of relevance. This was further supported by research by Joachims et al. [32] and Cole et al. [39]. In this work, a relationship between gaze generated data and user relevance judgements of documents was investigated. It was hypothesized that fixation duration and fixation count have a linear relationship with user relevance ratings. Pearson Correlation was used to examine if there is a relationship between fixation duration vs user relevance ratings, and fixation count vs user relevance ratings. The result of the correlation was statistically significant for fixation count as reported in Akuma et al. [41]. The relationship can also be seen in the boxplots diagram in Fig. 1. The result for fixation duration differs from that of Granka et al. [30], Joachims et al. [32] and Cole et al. [39], but supports the research by Buscher et al. [10]. The result from the heat map shows that documents rated high in terms of relevance by users are denser. Although this was not true for two documents that were less dense but had high ratings for relevance. Further investigation on the two documents suggests that they were shorter than the other documents, inferring that the length of a document is an extraneous factor in finding the relationship between the heat map density and user relevance judgment of documents.

Further analysis was carried out to determine if documents can be classified based on relevance using Fixation Duration and Fixation Count as input data. To do this, the six-scale relevance ratings were reduced to a two-scale relevance rating with the high relevance group having 5- and 4-point ratings, while that of low relevance had 3, 2, 1 and

0 ratings. KNN, J-45 and Multilayer Perceptron were used for the classification. The J48 decision tree produced the highest accuracy of 58.33%. Similar classification techniques were used by Liao et al. [42], Chuang et al. [43] and Oh and Kwak [44] for gaze classification in the automotive industry; Hardoon et al. [24] and Salojärvi et al. [33] used a similar classification method for addressing information retrieval problem, while Akuma and Ndera [45] used the approach in the context of predicting students' learning style.

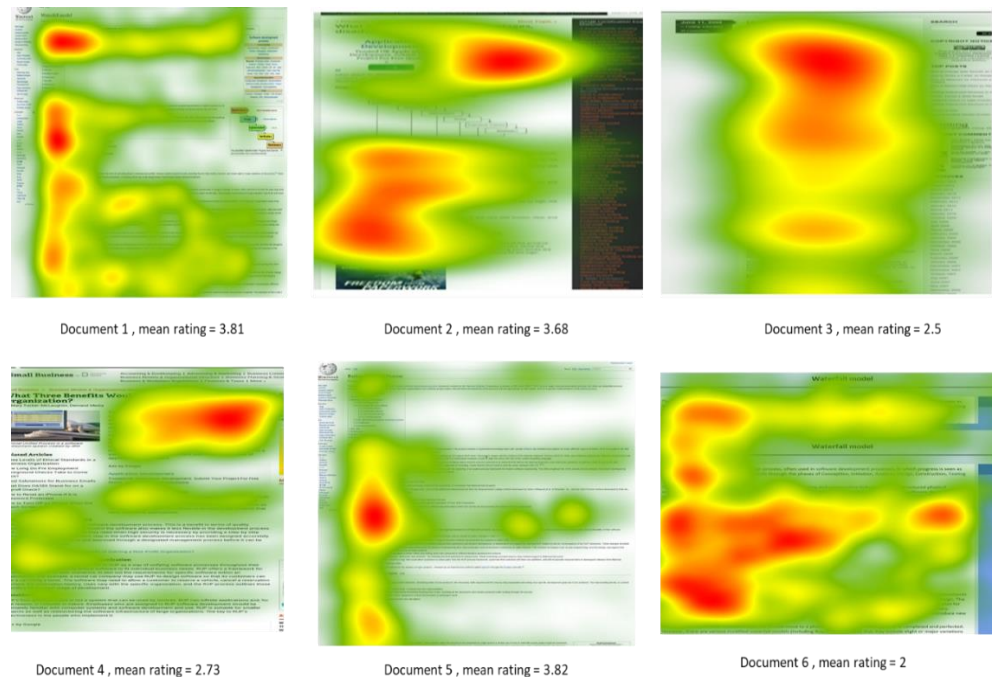


Fig.3. Gaze generated heat maps from the six documents read by users and their mean explicit relevance ratings

5. Conclusion

In this work, gaze features like Fixation and Heat maps were used to investigate if document relevance can be inferred from user eye movements. Correlation and classification techniques were used for the analysis. It was discovered that fixation count has a medium correlation with user judgment for relevance. The classification of documents based on relevance using Fixation Count and Fixation Duration gaze generated data as inputs produced the highest accuracy of 58.33% for the J48 decision tree classifier as compared to other classifiers. It was discovered that Heat maps can be used for relevance judgment of documents provided the height of each document is put into consideration. Future work will look at other traditional eye gaze generated features like Saccade, Pupil Dilation, and Blinking as a novel gaze feature in the context of information retrieval. Analyses of these features will focus on integrating them with query inputs for improved information retrieval.

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Appendix

Web Doc 1: http://en.wikipedia.org/wiki/Waterfall_model (mean = 3.81)

Web Doc 2: <http://istqbexamcertification.com/what-is-waterfall-model-advantages-disadvantages-and-when-to-use-it> (mean = 3.86)

Web Doc 3: <https://ccollins.wordpress.com/2008/06/11/unified-process-vs-agile-processes/> (mean 2.5)

Web Doc 4: <http://smallbusiness.chron.com/three-benefits-would-rup-bring-organization-32161.html> (mean 2.73)

Web Doc 5: http://en.wikipedia.org/wiki/Rational_Unified_Process (mean = 3.82)

Web Doc 6: http://www.princeton.edu/~achaney/tmve/wiki100k/docs/Waterfall_model.html (mean = 2)

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