An architecture for non-linear discovery of aggregated multimedia document web search results

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The recent proliferation of multimedia information on the web enhances user information need from simple textual lookup to multi-modal exploration activities. The current search engines act as major gateways to access the immense amount of multimedia data. However, access to the multimedia content is provided by aggregating disjoint multimedia search verticals. The aggregation of the multimedia search results cannot consider relationships in them and partially blended. Additionally, the search results' presentation is via linear lists, which cannot support the users' non-linear navigation patterns to explore the multimedia search results. Contrarily, users' are demanding more services from search engines. It includes adequate access to navigate, explore, and discover multimedia information. Our discovery approach allows users to explore and discover multimedia information by semantically aggregating disjoint verticals using sentence embeddings and transforming snippets into conceptually similar multimedia document groups. The proposed aggregation approach retains the relationship in the retrieved multimedia search results. A non-linear graph is instantiated to augment the users' non-linear information navigation and exploration patterns, which leads to discovering new and interesting search results at various aggregated granularity levels. Our method's empirical evaluation results achieve 99% accuracy in the aggregation of disjoint search results at different aggregated search granularity levels. Our approach provides a standard baseline for the exploration of multimedia aggregation search results.

An Architecture for Non-Linear Discovery of Aggregated Multimedia Document Web Search Results

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ABSTRACT

The recent proliferation of multimedia information on the web enhances user information need from simple textual lookup to multi-modal exploration activities. The current search engines act as major gateways to access the immense amount of multimedia data. However, access to the multimedia content is provided by aggregating disjoint multimedia search verticals. The aggregation of the multimedia search results cannot consider relationships in them and partially blended. Additionally, the search results' presentation is via linear lists, which cannot support the users' non-linear navigation patterns to explore the multimedia search results. Contrarily, users' are demanding more services from search engines. It includes adequate access to navigate, explore, and discover multimedia information. Our discovery approach allows users to explore and discover multimedia information by semantically aggregating disjoint verticals using sentence embeddings and transforming snippets into conceptually similar multimedia document groups. The proposed aggregation approach retains the relationship in the retrieved multimedia search results. A non-linear graph is instantiated to augment the users' non-linear information navigation and exploration patterns, which leads to discovering new and interesting search results at various aggregated granularity levels. Our method's empirical evaluation results achieve 99% accuracy in the aggregation of disjoint search results at different aggregated search granularity levels. Our approach provides a standard baseline for the exploration of multimedia aggregation search results.

INTRODUCTION

Traditionally, the web contains only the textual content (Bianchi-Berthouze et al., 2003). The progressive easy access to the internet has transformed the web into an infinitely complex virtual organism consisting of immense multimedia content (Batrinca and Treleaven, 2015). The format of the information is now extremely varied. The individual bits of data coming from blogs, articles, web services, picture galleries, etc., are resulting in exponential growth of multimedia data on the web (Batrinca and Treleaven, 2015; Rashid and Bhatti, 2017). The web is becoming the most ubiquitous platform ever since its birth and has increased in both quantity and quality (Taheri et al., 2018). In 2009, less than 1 petabyte of digital data was created daily (Kumar and Ogunmola, 2020). It grew to approximately 2.5 exabytes in 2012 and reached 4.4 zettabytes in 2013. On the web, the digital data in different formats created, replicated, and consumed exponentially (Oussous et al., 2018). It is doubling every 2 years. By 2015, digital data grew to 8 zettabytes, and the volume of data will reach 40 zettabytes by the end of 2020 (Oussous et al., 2018).

Keywords-based general web search engines have made early efforts to provide access to multimedia information (Lewandowski, 2008). These search engines required a user to enter one or a few keywords, and the search engines produced the relevant results in a short time (Lewandowski, 2008). Kerne and Smith (2004) first discussed a new search paradigm called information discovery. They elaborated discovery as a long journey of search that begins with a vague description of a problem, may have an articulated set of criteria during which a searcher specify a query and evaluate the returned information surrogates, and may continue iteratively by re-evaluating the result sets and forming a sense of desired results. Marchionini (2006) gives the same idea in a broader perspective by categorizing the search

paradigm into an exploratory by incorporating not only lookup searches but learning and investigation activities. Adequate support in the users' search leads to the discovery of new information items.

In contrast, many current search systems assume an exploratory search process as a series of homogeneous steps of submitting a query and consulting search results. Research in information seeking has shown that users go through discrete phases in their search journey, from exploring and identifying preliminary information to refining and narrowing their information needs and search strategies to finalize the search. It is reported as a highly complex problem bridging the different areas of information seeking, interactive information retrieval, and user interface design (Gäde et al., 2015). Moreover, the increasing amount of heterogeneous content on the web has transformed user needs from simple lookup-based queries to broader exploratory queries, requiring the diverse heterogeneous contents to satisfy the desired information needs (Rashid and Bhatti, 2017).

Several studies indicate that more intricate tasks resulted in a diversity of the information sought and more varied approaches to information seeking (Campbell, 2013). Today, to find interesting multimedia content, an enormous number of users use search engines (Deldjoo et al., 2018). It has changed users' information need from textual to multi-modal (audio, image, and video) searching. Approximately 40%-50% of users engage in dynamic and unplanned nature of web multimedia searches (Tseng et al., 2009). When the information need is ambiguous and dynamic (e.g., in exploratory search), people often consult more multimedia search results (Bron et al., 2013). The need for multimedia documents, in this case, increases to 58% (Tseng et al., 2009).

As human information needs and search tasks become complex, the users have to collect and assemble information from diverse information sources. The goal is to compose the most appropriate responses to the tasks at hand in the form of multimedia documents (Kopliku et al., 2014). A multimedia document is a collection of co-existing heterogeneous multimedia objects sharing the same semantics (Rashid and Bhatti, 2017). Users prefer aggregation of useful multimedia information residing in diverse sources through unified interfaces (Kopliku et al., 2014; Rashid and Bhatti, 2017). Similarly, the user interface presenting aggregated contents encouraged participants to view more diversified sources from the search results, and 75% of the participants found this blended approach more comfortable to use (Sushmita et al., 2009). The user, click-through rate analysis, reported approximately 33% on augmented multimedia artifacts and nearly 55% multimedia artifacts were found relevant and useful during information exploration activities (Sushmita et al., 2010). Overall, users explore the multimedia contents 78% of the time to answer their dynamic information needs (Kopliku et al., 2011). Based on recent user behavior in complex information needs, we can easily forecast even more increasing multimedia artifacts consumption from the users in satisfaction of complex information needs and discovering information.

Aggregating disjoint verticals provide access to diverse multimedia documents. A vertical is defined as a specialized assembly of same-typed documents (Bakrola and Gandhi, 2016). This assembly can be media-specific or domain-specific. The former may include media types (e.g., video, blog, image, etc.). The latter may consist of verticals (e.g., travel, shopping, news, etc.). The aggregation process consists of either Cross-vertical Aggregated Search (cvAS) or Relational Aggregated Search (RAS). The (cvAS) ignores the relation during retrieval and aggregation of multimedia content. The (RAS) considers the relationships in the multimedia information. Despite the key-role of aggregation in bridging the modality gap, this area of research only received limited attention in the past (Achsas and Nfaoui, 2019). Without substantial creativity, this area of research will soon be abandoned. Our discovery approach aims to bring innovation and creativity in this area of search. We envision bridging the modality gap and shortcomings of current search engines, allowing users to discover multimedia information by aggregating disjoint verticals.

Contributions of our solution have three-folds. Firstly, we presented a creative search results aggregation technique using state-of-the-art semantic analysis. Secondly, we enhanced the current search engine shortcomings in information exploration and discovery activities by augmenting non-linear information seeking patterns. Thirdly, we bridged the information modality gap by encoding the search results in various representations. Our proposed solution is the first to address all of the stated challenges of information aggregation, exploration, and discovery.

The rest of the discussion is organized as follows. We discuss the related work in Section 2. We highlight the deficiencies in the existing approaches and motivation behind this research in section 3. We provide the theoretical foundation and formalization of our proposed approach in Section 4. We present the implementation of the architecture in Section 5. We discuss the experimental results in Section 6.

101 Finally, we compare our approach with state-of-the-art and conclude our discussion in Sections 7 and 8,
102 respectively.

RELATED WORK

104 **Theoretical Background and Frameworks**   According to Kerne et al., information discovery tasks
105 require finding and collecting relevant information elements; filtering the collected elements; developing
106 an understanding of the found elements and their relationships (Kerne et al., 2008). The overall goal
107 is assembling information and connecting answers to open-ended questions (Kerne et al., 2008). It is a
108 multidisciplinary approach and is built on anomalous states of knowledge (Belkin et al., 1982), berry-
109 picking (Bates, 1989), psychological relevance (Harter, 1992), exploratory search (White et al., 2006),
110 information foraging (Pirolli and Card, 1999), information seeking (Marchionini, 1997) and sensemaking
111 (Baldonado and Winograd, 1996; Russell et al., 1993).

112   During a task performed by a user, the lack of information triggers the requisite for the information
113 needs. The recognized information needs refer to as an anomalous state of knowledge (Belkin et al.,
114 1982). During the recognized anomalous state of knowledge, the users refer to the information retrieval
115 systems to initiate the information seeking journey (Marchionini, 1997). During this journey, the user
116 picks relevant information analogous to an organism picking berries in the forest scattered on the bushes;
117 they do not come in bunches. One must select them one at a time (Bates, 1989). Similar to this analogy,
118 the user has to forage for the information and pick items from information patches giving information
119 scent the most (Pirolli and Card, 1999). Information scents are the cues that help the user in making sense
120 of the provided information. It can be augmented by sensemaking activity. It involves making sense
121 of the data during data analysis, searching for representation, and encoding the data to answer specific
122 task-oriented questions (Russell et al., 1993). This whole journey can incorporate lookup search, learning,
123 and investigation activities, resulting in a non-linear search pattern.

124   To do this non-linear search of the information successfully, researchers must leverage their skills and
125 experience to develop search systems that actively engage searchers using semantics, inherent structure,
126 and meaningful categorization (White and Roth, 2009). In general, the user cannot precisely specify
127 what is needed to resolve recognized information anomaly (Belkin et al., 1982). It often results in the
128 shortcomings of the existing retrieval systems in a scenario where the user cannot correctly formulate
129 information need expression resulted in low precision of the retrieval systems (Belkin et al., 1982). In
130 such case, the users' information needs are not fully satisfied by a single final retrieved set, but by a series
131 of selections of individual bits of information at each stage of the ever-modifying search strategies (Bates,
132 1989). Hence, these tasks require more recall over precision (Tablan et al., 2015). We must consider the
133 user perspective of information relevance, taking into account how effective the topic of the information
134 retrieved matches the subject of interest and how to represent a piece of information that induces a change
135 in the users' cognitive state (Harter, 1992).

136   Our proposed solution encodes the multimedia search results semantically by aggregating them in
137 multimedia documents. These documents allow users to pick the most suitable collection of informa-
138 tion sufficing their information need the most. Furthermore, we provide multimedia document groups,
139 analogous to patches of information, allowing the user to forage for the information patches giving the
140 most information scent. We increased the information scent for multimedia documents and groups by
141 summarizing the data inside them. Semantically aggregating disjoint multimedia verticals provide the
142 conceptualization of multimedia documents and groups. Furthermore, we augment the non-linear infor-
143 mation searching and seeking pattern by instantiating a non-linear graph comprising various granularity
144 levels of search results and proximally similar multimedia content links.

145 **From Federation To Aggregation & Diversification**   Traditional research mostly centered on assisting
146 users in providing relevant multimedia information federated from various sources and information
147 providers. Koh et al. (2006) provided discovery of search results by dispatching the user query to multiple
148 search engines and extracting the relevant pieces of text snippets and images snapshot on the user interface.
149 Similarly, Sushmita et al. (2008) provided a digest-based information exploration approach by collecting
150 various pieces of multimedia information from a variety of sources and encapsulating them in the form of
151 a digest. Afterward, researchers identified the modality gap of information with enormously increasing
152 heterogeneous content on the web, which hindered the information exploration. Hence, the first idea of
153 search results aggregation was presented in a workshop at ACM SIGIR 08 conference (Kopliku, 2009).

154 Later on, Sushmita et al. (2009) advanced this idea towards the blending and evaluation of disjoint
155 multimedia verticals into the web search results (Sushmita et al., 2010).

156 Information aggregation is now widely recognized, considered a bridge that narrows the information
157 modality gap and fosters information exploration. Meanwhile, search engines are also starting to adopt a
158 similar approach in their presentation of the search results (Bakrola and Gandhi, 2016). The progress in
159 multimedia retrieval presented another challenge in deciding the optimal choice and position of vertical in
160 the search engine result page and was explicitly labeled as a vertical prediction problem. Bakrola and
161 Gandhi (2016) provided a solution to this challenge by using implicit feedback of the user in the form
162 of several clicks and then using a support vector machine classifier to predict the most suitable vertical
163 sufficing the given user information needs.

164 Nowadays, the most common and popular commercial web search engines such as Baidu (`https://www.baidu.com/`), Bing (`https://www.bing.com/`), Google (`https://www.google.com/`), Yahoo! (`https://www.yahoo.com/`), Yandex (`https://yandex.com/`) etc, are blending some vertical-specific results, assembled from the other data sources into the linear ranked list of
165 standard results. Moreover, a recent trend focuses on the information diversification aspects of the
166 information Taramigkou et al. (2017). It usually involves integrating more diverse verticals (e.g., other
167 than image, news, video, and web). This diversification may include the integration of verticals from
168 social media, shopping, movies & dramas, maps, songs, etc. However, this integration of the verticals is
169 mostly partial-blended Rashid and Bhatti (2017). The relationship between the multimedia artifacts inside
170 each disjoint vertical is often ignored.
171
172
173

174 The aggregation approaches can be implmented as a multimedia or multimodal system. The multime-
175 dia system uses single modality (usually textual metadata associated with multimedia content) to bridge
176 the multiple modalities (Benavent et al., 2013). The multimodal systems incorporates multiple modalities
177 to provide access to multimedia content (Benavent et al., 2013). The aggregation of the multimedia
178 artifacts demands a better solution to enhance user interaction with the search results. It is essentially a
179 very broad problem and answered by (RAS) techniques. The researchers leveraged some effort in (Rashid
180 and Bhatti, 2017), they performed (RAS) using textual, visual, and acoustic descriptors of the multimedia
181 contents. However, this multimodal aggregation was provided using a generic similarity measure for
182 each modality and ignored the semantics relationships in aggregated multimedia documents. In (Achsas
183 and Nfaoui, 2018), researchers presented a stacked auto-encoders model for multimedia aggregation of
184 the disjoint verticals. However, their research addresses a small aspect of the aggregation and ignores
185 information exploration perspectives.

186 **Renovation in Information Exploration Data-Models & Semantic Web** The current practices for
187 information exploration include presenting the aggregated verticals as a linear list (Tablan et al., 2015).
188 It is due to a lack of data-model flexibility. Initially, using the semantic web techniques and ontologies
189 was perceived as a promising start. For instance, Tablan et al. (2015) presented an open-source semantic
190 framework providing indexes and searches using document structure, metadata, annotations, and semantics
191 through linked open data. The architecture supported both; information seeking and exploration &
192 discovery tasks by two distinct user interfaces designed, respectively.

193 Similarly, Lisena et al. (2017) developed a modern web application for music exploration and discovery
194 using semantic RDF graphs to establish links between entities and relationships among them. Khalili et al.
195 (2017) used inference techniques on the semantic linked open data to produce notably unique information
196 fostering discovery. However, due to scalability challenges in exploiting the whole web of Linked Data
197 limits the practicality of this aspect (Elzein et al., 2018).

198 Similarly, in (Kanjanakuha et al., 2019), researchers provided semantic data representation in a
199 hyperbolic tree format. Their framework consists of a 3-layers hyperbolic tree-based modal approach
200 that takes the input in the form of keywords from the user. The information is then presented in the form
201 of a graph. The 3-layer approach divides the complexity of information in each layer. It reduces the
202 confusion caused by information overload and enhances significant interaction and navigation. Similar to
203 our proposed approach, their graph data-model provides highlighting, node describing, zooming, panning,
204 and linking functionalities.

205 More researchers are presently making an effort to provide a generalized approach to exploring and
206 discovering multimedia artifacts on the web. It includes mixing different aspects of data-model, diverse
207 information aggregation, and visualization. For instance, in (Rashid and Bhatti, 2017), researchers provide
208 a generalized framework for relational aggregation of the multimedia artifacts belonging to disjoint sets

using a graph-based visualization and exploration of a multimedia search result space. Similarly, in (Zhang et al., 2018), researchers developed a discovery engine for artificial intelligence research. Their architecture crawls the web, downloads the research papers from various journal websites, and performs full-text indexing using a cosine similarity measure. It builds a similarity-based network having similarity links in documents. Users' stars, clicks, and tweets are primarily used to reinforce the graph's essential connections.

However, the past approaches focus on using a domain-specific dataset and data-model using generic textual and visual similarity metrics. We establish a data-model using the semantics that exists inside the data. Specifically, we semantically found part-of or containment relationships in the multimedia artifacts. Moreover, we also instantiate similarity links among the multimedia artifacts that allow navigation to similar multimedia artifacts. We opt to keep the data-model as generic as possible without relying on domain knowledge and explicit feedback, making our solution implementable on a wide range of domains.

PROBLEM & MOTIVATION

The users' complex information-seeking behavior is modeled as a non-linear journey requiring adequate support during the navigation of the information space (Ruotsalo et al., 2018). Users' forage for the information (Bates, 1989). Their complex information needs are not sufficed through the current ideology of returning the most precise information in response to the given queries (Russell-Rose and Tate, 2012). Instead, users picking the most interesting items like barries from various patches of information, providing more information scent ratio to the effort required for examining the information. It results in a non-linear information searching pattern of users (Russell-Rose and Tate, 2012).
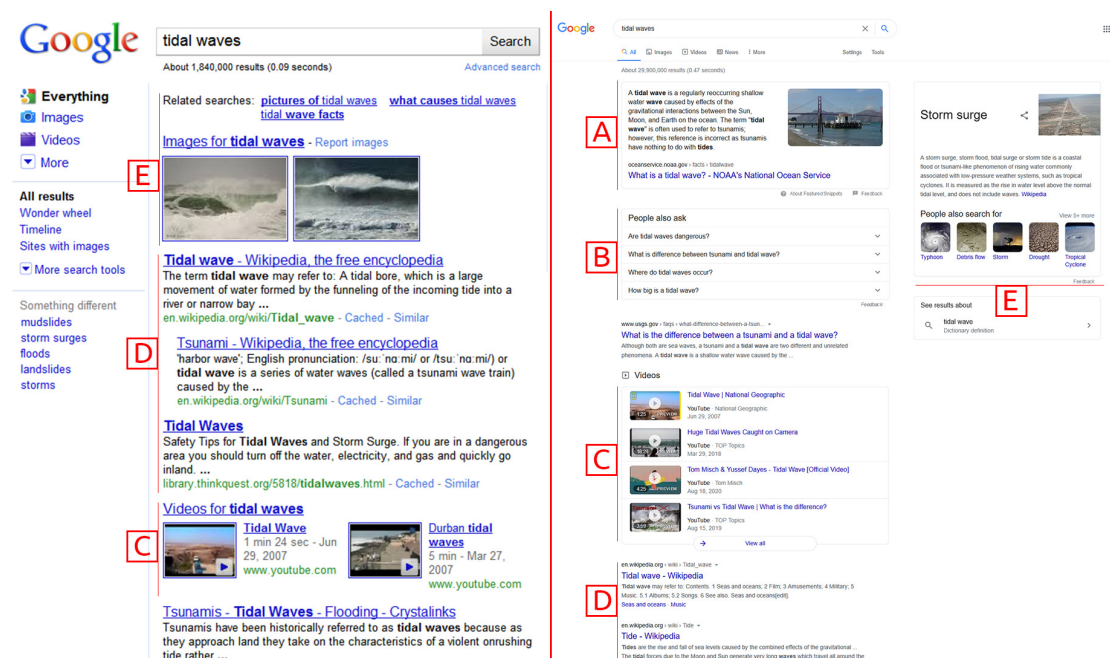
Figure 1. Comparison of Google SERP between 2010 (left) and 2020 (right). (A) Enhanced Snippet, (B) Question Answer Vertical, (C) Videos Vertical, (D) Web Vertical, (E) Images and Related Searchers. Screenshot credit: Google and the Google logo are trademarks of Google LLC.

The search engines are more tuned towards simple lookup searches favoring precision over recall (Tablan et al., 2015). However, even though they have recognized the users' multimedia information needs and started to blend some vertical-specific results assembled from the other data sources (Bakrola and Gandhi, 2016). The current practices of presenting information in a linear ranked list of standard results limit information exploration (Rashid and Bhatti, 2017). Furthermore, the integration of the verticals is mostly partial-blended (Rashid and Bhatti, 2017), which may suffice in simple lookup searches when a user knows what to look for; however, this strategy inadequately support complex information exploration and discovery tasks (Tablan et al., 2015). These tasks go beyond simple keyword-based queries. Users

237 often have difficulties in information need expression, and they usually are dynamic (Ruotsalo et al.,
238 2015a). Such tasks require more recall over precision and diversity of information sources (Tablan et al.,
239 2015). It challenges the current practices of displaying the search results belonging to different verticals
240 as disjoint sets (Rashid and Bhatti, 2017).
241   On the other hand, the search engines remain almost the same as they were about a decade ago. There
242 exist numerous problems (**P**) with current search engines. The figure 1 shows the difference between the
243 Google Search Engine Results Page (SERP) back in 2010 (Sullivan, 2020) and now in 2020 (Google,
244 2020). The verticals are integrated as disjoint components (P_1). The relationships between multimedia
245 objects are ignored (P_2). The information presented is still displayed as linear lists (P_3). This presentation
246 of the general search engines' information may suffice for simple lookup tasks but lacks adequacy for
247 complex exploratory and discovery tasks (Klouche et al., 2015). These tasks require increased recall
248 over precision (P_4), information scent (P_5), and sensemaking (P_6). The existing exploration approaches'
249 deficiencies demand a better mechanism to encode and present the multimedia information for discovery
250 (P_7).

ARCHITECTURE DESIGN: DEFINITION, FORMALIZATION & INSTANTIA-
TION

253 Existing techniques are usually specific to a problem and employed on a particular dataset. Many
254 researchers consider one side of the discovery, such as information diversification, visualization, data-
255 modal etc., and ignore the other factors highlighted in the previous section. To the best of our knowledge,
256 a generalized multimedia search results discovery mechanism, particularly in aggregated search, is the
257 first to address in this research. Notably, we provided a balanced architectural approach for information
258 discovery, emphasizing the dataset, data-model, information diversification equally. We used real-dataset
259 retrieved from the search engines in real-time. We instantiated a non-linear graph data modal consisting
260 of diverse information while preserving the semantics and similarity relationships. Finally, we provided a
261 theoretical background to foster exploration and discovery activities.
262   Our component-based architecture design includes sub-components. Each sub-component produces a
263 consumable output. There are five main components, referred to (A) Search Results Aggregation; (B)
264 Multimedia Document Creation; (C) Multimedia Documents Grouping; (D) Graph Instantiation; (E)
265 Semantic Lookup List, components as illustrated in figure 2. Each component is concerned with delegated
266 responsibility, and their internal working is separate from each other. A discussion on each component is
267 provided in the following sections.

(A) Search Results Retrieval & Aggregation

269 Search results retrieved from the search engines are presented in the form of disjoint verticals. Adversely,
270 users' information needs are becoming complex and multi-modal, requiring the employment of multimedia
271 artifacts for satisfaction. To aggregate scattered disjoint verticals (P_1), we introduced a search results
272 aggregation component. The aggregation process of this component is subdivided into three steps.

(i) Vertical Retrieval

Definition: We define vertical as a specialized assembly of same-typed search results and retrieval as a
275 process of obtaining them from some external source.

Formalization: Let S be the set of α, β, γ, λ respectively given as $S = \{\alpha, \beta, \gamma, \lambda,\}$, where α is defined
277 as a set of video snippets V given as $\alpha = \{\{V_1^\psi, V_2^\psi, V_3^\psi, ..., V_n^\psi\}, \{V_1^\Phi, V_2^\Phi, V_3^\Phi, ..., V_n^\Phi\}\}$, β is defined as
278 a set of news snippets N given as $\beta = \{\{N_1^\psi, N_2^\psi, N_3^\psi, ..., N_n^\psi\}, \{N_1^\Phi, N_2^\Phi, N_3^\Phi, ..., N_n^\Phi\}\}$, γ is defined as a
279 set of image snippets I given as $\gamma = \{\{I_1^\psi, I_2^\psi, I_3^\psi, ..., I_n^\psi\}, \{I_1^\Phi, I_2^\Phi, I_3^\Phi, ..., I_n^\Phi\}\}$, and λ is defined as a set
280 of web snippets W given as $\lambda = \{W_1^\psi, W_2^\psi, W_3^\psi, ..., W_n^\psi\}$, where ψ and Φ denotes the textual and visual
281 modality associated with a snippet respectively.

Instantiation: We retrieve top hundred search results from each **web**, **news**, **image**, and **video** verticals.
283 Since exploratory and discovery tasks require increased recall over precision (P_4), we chose to retrieve
284 maximum search results from the API provider. With each search result, we preserve the metadata
285 associate with it. The verticals are retrieved from the Google search engine in real-time because Google is
286 highly preferred by web users (Ali and Gul, 2016). The table 1 shows the vertical retrieval parameters.
287 Figure 3 outlines the possible features of a snippet.
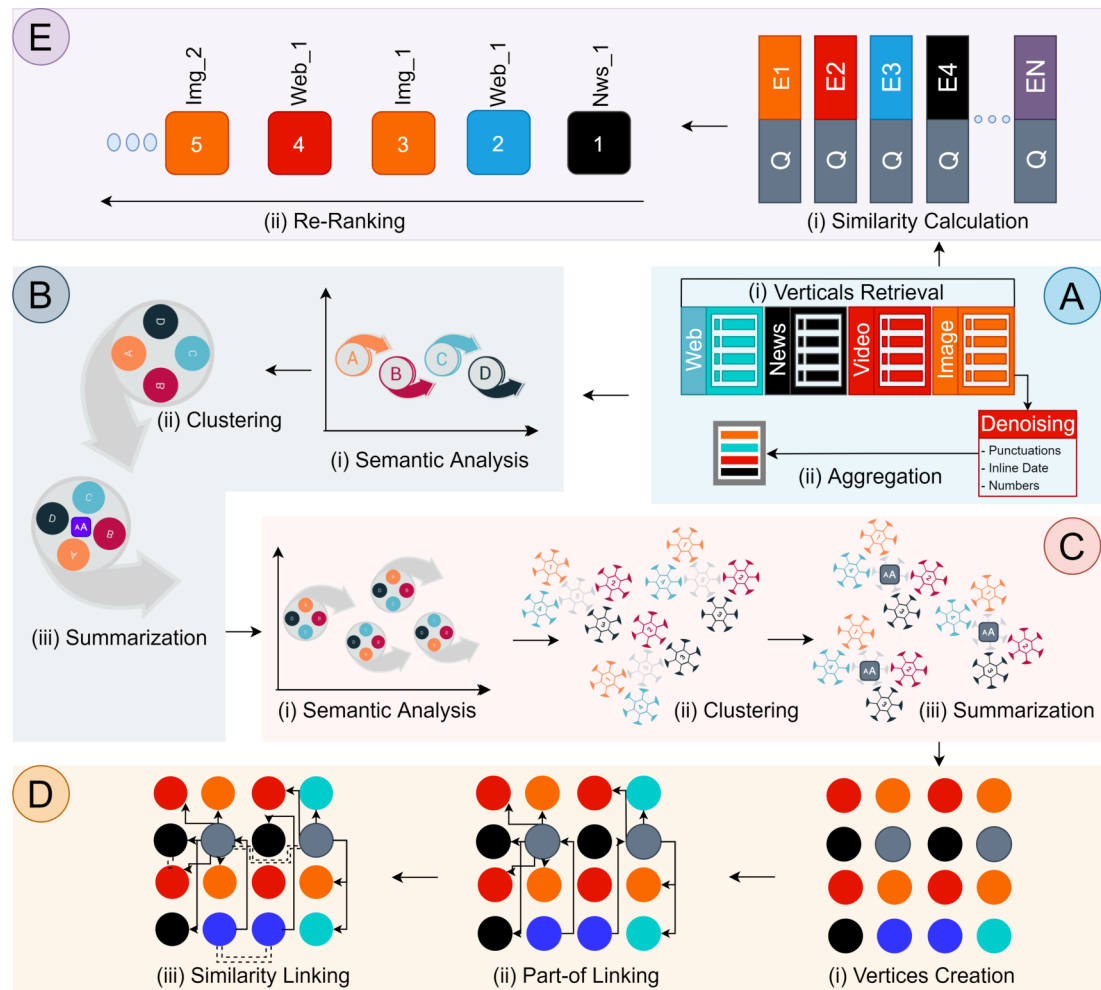
Figure 2. Discovery Architecture Design. Component (A) Search Results Aggregation, (B) Multimedia Documents Creation, (C) Multimedia Documents Grouping, (D) Graph Instantiation, (E) Semantic Lookup List
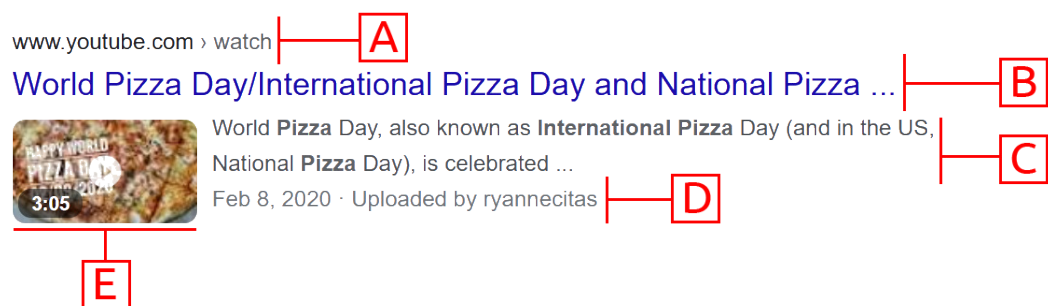
Figure 3. Anatomy of search result snippet. (A) URI, (B) Title, (C) Description, (D) Date, (E) Thumbnail. Screenshot credit: Google and the Google logo are trademarks of Google LLC.

Table 1. Parameters for verticals retrieval

Vertical	# of results (n)	Source	Modality	Feature(s)
Web	≤ 100	Google	Textual	Title, Description, URL
Video	≤ 100	Google	Textual + Visual	Title, Description, URL, Thumbnail, Date
News	≤ 100	Google	Textual + Visual	Title, Description, URL, Thumbnail, Date
Image	≤ 100	Google	Textual + Visual	Title, URL, Thumbnail

(ii) Verticals Aggregation

Definition: We define verticals aggregation as a single container of all the retrieved disjoint verticals.

Formalization: Let X be the subset of S consisting of the all the elements λ, α, β and γ from S. We consider only textual modality information given as $X = \sum_{i=1}^{n} S_i^{\psi}$.

Instantiation: Each retrieved snippet has unwanted data (e.g. HTML tags, numbers, special characters, etc.). These impurities do not add meaning to the semantics analysis. We are restraining to perform extra pre-processing steps such as stopwords removal and stemming. It results in the loss of contextual information necessary for semantic analysis. Afterward, we preserve the scattered disjoint verticals textual data inside a single container as a linear list.

(B) Multimedia Document Creation

Previous studies indicate user interest in exploring multimedia documents encapsulating relevant multimedia objects during information exploration (Rashid and Bhatti, 2017). We define a multimedia document as a semantic container of similar content belonging to multiple modalities. Instead of providing a linear list of snippets, which forces web users to locate scattered relevant multimedia objects from disjoint verticals, we give document-based multimedia exploration (P_6). The multimedia document semantically gathers the scattered multimedia objects belonging to various disjoint verticals. This process is again sub-divided into three steps.

(i) Semantic Analysis

Definition: We define semantic analysis as a process of obtaining semantic information (relatedness and containment) from transformed multidimensional vector representation of search results textual data (P_2).

Formalization: $\forall x \, \varepsilon \, X$ let E_x be the set of sentence embedding given as $E_x = \{e_1, e_2, e_3, ..., e_n\}$, where each element in E_x is represented by a multidimensional vector $\vec{e} = (\mathbf{r_1}, \mathbf{r_2}, \mathbf{r_3}, ..., \mathbf{r_{768}})$; $r \varepsilon (\mathbb{R})$.

Instantiation: Firstly, we transformed each multimedia snippet in the aggregated list into sentence embeddings. This transforms each snippet into a multidimensional vector space for semantic analysis. Since each snippet contains minimal textual description, sentence embedding is deemed a better choice over the Doc2Vec technique.

(ii) Clustering

Definition: We define clustering as a process of grouping the search results, having highly related intra-group coherence and otherwise for the inter-group search results.

Formalization: $E_x = c_1 \cup ... c_i \cup c_n ; c_i \cap c_j = \emptyset (i \neq j)$, where E_x denotes original data, c_i, c_j are clusters of E_x and n is the number of clusters. Let C_d be the set of clusters of E_x given as $C_d = \{c_1, c_2, c_3, ..., c_n\}$, where each cluster contains a set of coherent text t and $c = \{t_1, t_2, t_3, ..., t_n\}$.

Instantiation: We performed the agglomerative clustering on all the semantic search results vectors. Agglomerative clustering is chosen for due to flexibility in the clustering process as it allows the clusters to be obtained using cut-off criteria instead of predefined number of clusters. This process groups similar search results in various buckets, called multimedia document.

(iii) Summarization

Definition: We define summarization as a process of extracting the most representative words from the bucket of search results.

Formalization: Let W_d be a set of words sequence w from $c\ \varepsilon\ C_d$, generated by text summarizer representing the collection of text given in c as $W_d = \{w_1, w_2, w_3, ..., w_n\}$, let M_d be the multimedia document, we formed M_d by mapping function $M_d = \forall(C_d)\forall(W_d)(f(C_d) = f(W_d) \rightarrow C_d = W_d)$.

Instantiation: To enhance sensemaking (P_6), instead of merely labeling a multimedia document by assigning predefined categories, we are performing summarization based on the text of the snippets inside the multimedia document. Specifically, we perform extractive text summarization techniques to extract the combination of the most representing text inside the multimedia document for its representation.

(C) Multimedia Document Grouping

Prior research has shown that web user information exploration behavior is analogous to a foraging animal in the forest (Pirolli and Card, 1999). They look for the patches containing more information scent as compared to the effort performed. In traditional linear list presentation of the search results, a user has extreme difficulty locating the appropriate patches of information and comprehending search results space (Ruotsalo et al., 2015b). This component groups multimedia documents to provide patches of information and enhance search results in space comprehension (P_5). This process is sub-divided into three steps.

(i) Semantic Analysis

Definition: We define semantic analysis as a process of obtaining semantic information (relatedness and containment) from transformed multidimensional vector representation of multimedia documents.

Formalization: From W_d, we produce the set Y to perform semantic analysis, given as $Y = \sum_{i=1}^{n} W_{di}$. $\forall$ $y\ \varepsilon\ Y$ let M_x be the set of sentence embedding given as $M_x = \{e_1, e_2, e_3, ..., e_n\}$, where each element in M_x is represented by a multidimensional vector $\vec{\mathbf{e}} = (\mathbf{r_1}, \mathbf{r_2}, \mathbf{r_3}, ..., \mathbf{r_{768}})$; $r\varepsilon(\mathbb{R})$.

Instantiation: Firstly, we extract summaries of multimedia documents and aggregated them inside a linear list. Then we performed semantic analysis on each multimedia document summary using sentence embeddings. This transformed each multimedia document to a multidimensional vector space for semantic analysis. Similarly, since each multimedia document contains minimal textual description, sentence embedding is deemed a better choice over the Doc2Vec technique.

(ii) Clustering

Definition: We define clustering as a process of grouping the multimedia documents having high intra-group relatedness and otherwise for the inter-group multimedia documents.

Formalization: Let $M_x = c_1 \cup ...c_i \cup c_n; c_i \cap c_j = \emptyset(i \neq j)$, where M_x denotes original data, c_i, c_j are clusters of M_x and n is the number of clusters. Let C_g be the set of clusters of M_x given as $C_g = \{c_1, c_2, c_3, ..., c_n\}$, where each cluster contains a set of coherent text t and $c = \{t_1, t_2, t_3, ..., t_n\}$.

Instantiation: We performed the agglomerative clustering on all the semantic vectors of multimedia document summaries. Similarly, agglomerative clustering is chosen for flexibility in clusters creation process using a cut-off criteria. This process groups similar multimedia documents in various buckets.

(iii) Summarization

Definition: We define summarization as a process of extracting the most representative words from the bucket of multimedia documents.

Formalization: Let C_g be the set of clusters of M_x given as $C_g = \{c_1, c_2, c_3, ..., c_n\}$, where each cluster contains a set of similar text t $c = \{t_1, t_2, t_3, ..., t_n\}$; $t\varepsilon C_g$. Text summarizer W_g produces a set of words sequence w from $c\ \varepsilon\ C_g$ representing the collection of text given in c as $W_g = \{w_1, w_2, w_3, ..., w_n\}$. Similarly, Let M_c be the multimedia document cluster, we formed M_c by mapping function $M_c = \forall(C_g)\forall(W_g)(f(C_g) = f(W_g) \rightarrow C_g = W_g)$.

Instantiation: We call each generated bucket of multimedia documents from the clustering process a multimedia document group. To enhance sensemaking, instead of merely labeling a multimedia document group by arranging them in taxonomic order, we perform summarization based on the multimedia document summary. The summarization process is performed using extractive text summarization technique. This extracts the most representing text inside the multimedia document group.

(D) Graph Instantiation

Present search engines display the search results in a linear list and often ignores the relationship between multimedia content. As a result, users have to navigate the results space and berry-pick the relevant items of interest (Bates, 1989). This results in a non-linear searching pattern of a user in the exploration of information (Bates, 1989). To overcome these challenges, we instantiated a non-linear graph augmenting the users' non-linear exploratory information-seeking behavior while preserving the relationships (P_2). This process is sub-divided into three steps, as well.

(i) Vertices Creation

Definition: We define vertex as an atomic data structure encapsulating the complete details of the representing entity.

Formalization: Let a graph G be a set of vertices V and edges E, given as $G = (V, E)$ and vertices V represent all the vertical snippets, multimedia documents and clusters given as $V = \{S, M_d, M_c\}$.

Instantiation: Firstly, we represented each multimedia document group, multimedia document, and multimedia snippet as a vertex. We associate with each vertex the metadata. It includes a text summary for the multimedia documents and multimedia documents. Similarly, metadata belonging to the multimedia snippet include their title, description, URI, date, and thumbnail (where available).

(ii) Part-of Linking

Definition: We define part-of linking as a process of establishing containment relationship between vertices.

Formalization: The edge (δ) between the S and M_d denotes the part-of relationship given as δ : $\forall x \varepsilon S, \exists d \varepsilon M_d, f(M_d) = S$. Similarly, edge ($\delta$) between the M_d and M_c denotes the part-of relationship given as $\delta : \forall m \varepsilon M_d, \exists c \varepsilon M_c, f(M_c) = M_d$.

Instantiation: Since a multimedia document is a part of some multimedia documents group, similarly, a multimedia snippet is a part of some multimedia document, the edges established between them represents the part-of (or containment) relationship.

(iii) Similarity Linking

Definition: We define similarity linking a process of establishing proximally similarity-based relationship between vertices.

Formalization: Edges (δ) among M_c denotes the similarity relationship based on Cartesian product of M_c given as:

$$\delta : \begin{cases} M_c \times M_c = \sum_{i=1}^{n} \sum_{j=i+1}^{n} J(M_i^c, M_j^c), & if J > \theta \\ \emptyset, & \text{otherwise} \end{cases}$$

Similarly, edges (δ) among M_d in each M_c denotes the similarity relationship based on Cartesian product of M_d within M_c given as:

$$\delta : \begin{cases} \sum_{k=1}^{n} M_k^c \forall M_d \varepsilon M_k^c : M_d \times M_d = \sum_{i=1}^{n} \sum_{j=i+1}^{n} J(M_i^d, M_j^d), & if J > \theta \\ \emptyset, & \text{otherwise} \end{cases}$$

Where J is the Jaccard similarity defined as $J(A, B) = \frac{|A \cap B|}{|A \cup B|}$ and θ is the average similarity score of all the selected vertices pairs in the graph.

Instantiation: Exploratory search also involves navigation of proximally similar multimedia documents in the collection (Savolainen, 2018). It helps a user explore the environment to understand better how to exploit it, selectively seek and implicitly obtain cues about coming steps (Savolainen, 2018). Hence, we provide navigational links to proximally similar multimedia document groups and multimedia documents. These links are established if there is a high proximal similarity between the source and destination vertices. We chose the Jaccard similarity measure because it is computationally less expensive than other similarity techniques (Rashid and Bhatti, 2017).

(E) Semantic Lookup List

At present, the aggregation of the verticals on the major search engines is provided as partially-blended. The relationship between the multimedia snippets in those retrieved disjoint verticals is ignored (Rashid and Bhatti, 2017). On the other hand, information lookup is an eminent component of information exploration and discovery, and linear lookup lists have proven to be effective in information lookup (Tablan et al., 2015). To overcome this challenge of disjoint and relation-less aggregation of the verticals and provide ease in lookup searches, we introduce a semantic lookup list component that fully-blends the disjoint verticals using semantics of the multimedia snippets (P_1). This component consists of two steps.

(i) Similarity Calculation

Definition: We define similarity calculation a process of extracting numeric similarity score between pairs of text using a textual similarity measure.

Formalization: Let the E_x be the same set of sentence described previously, we also transformed user query Q as a sentence embedding Q_x represented by $\vec{Q}_x = \{r_1, r_2, r_3, ..., r_{768}\}$; $r\varepsilon(\mathbb{R})$. We calculated similarity as $L_s = \{\forall \vec{e}\varepsilon E_x \,|\, 0 \leq SIM(\vec{Q}_x, \vec{e}) \leq 1\}$, using a cosine similarity measure defined as $SIM(\vec{Q}_x, \vec{e}) = \frac{\vec{Q}_x . \vec{e}}{\|\vec{Q}_x\| \times \|\vec{e}\|}$.

Instantiation: In this part, we transform the user query itself into the sentence embeddings. This transformation eliminates the data representation gap. we perform a similarity calculation operation on the pair-wise (query and each snippet embedding) obtained semantics using a cosine similarity measure. We use cosine similarity because our query and search results are in vector representation.

(ii) Re-Ranking

Definition: We define re-ranking as a process of arranging search results in descending order of query and search results embedding pairwise intra-similarity scores.

Formalization: Using similarity scores L_s, we define L_r the ranked linear search results list, sorted in descending order of similarity, given as $L_r = \{l_1, ..., l_{|X|} \,|\, f(l_i) \geq f(l_j),\ i < j \leq |X|, l_i, l_j \in X\}$, where $f : X \to L_s$.

Instantiation: In lookup searches, the ordering of information is mandatory. The most relevant information must be present on the most top. The search engines return disjoint ranked verticals. To calculate the ranking order for snippets belonging to aggregated disjoint verticals, we re-rank each multimedia snippet in their descending order of similarity, allowing the most relevant snippet to appear first on the linear list.

ARCHITECTURAL IMPLEMENTATION

We implemented our architecture in *Python*3 programming language using publicly available libraries. Search results are retrieved using freely available APIs to fetch the verticals from a search engine in real-time. We used Google search engine to retrieve the search results belonging to the web, news, image, and video verticals. We preserved the metadata associated with each snippet, such as the URL, title, date, length, description, and thumbnail, where available. For text summarization, we used *LexRank* (https://gist.github.com/rodricios/fee45381356c8fb36004/) extractive text summarization algorithm. Semantic analysis is done using *SBERT's* (https://pypi.org/project/sentence-transformers/) sentence embedding on pre-optimized *bert − base − nli − mean − tokens* (https://github.com/UKPLab/sentence-transformers/) pre-trained modal and agglomerative clustering using the ward's linkage method from *sklearn* (https://scikit-learn.org/) python library to obtain the clusters. We used *Networkx* (https://networkx.github.io/) python library to instantiate an undirected network to build the graph. Each node represented either a web snippet, multimedia document, or a multimedia document cluster. The snippet nodes attribute includes their metadata. The multimedia document and multimedia document cluster nodes attribute include their summarized text. Figure 4 shows the visualization of the instantiated graph generated from *Cytoscape* (https://cytoscape.org/).
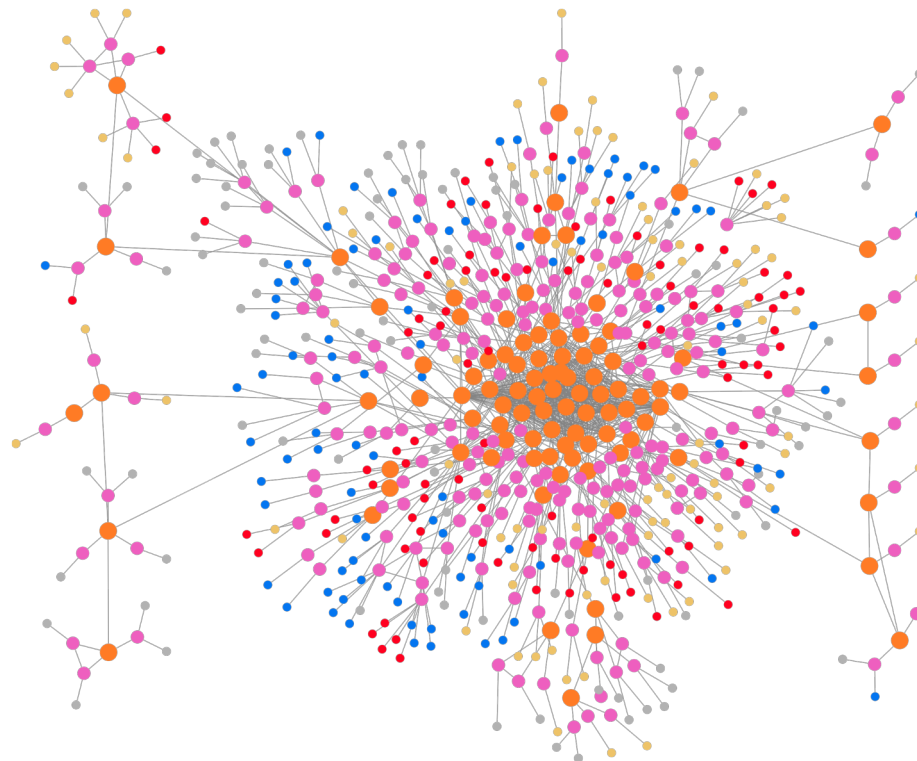
Figure 4. Visualization of the instantiated graph. The orange and pink color represents cluster and multimedia document respectively. The rest denotes snippets belonging to disjoint verticals.

RESULTS

There is still no standard empirical evaluation measures for evaluating the aggregated search approach effectiveness (Li et al., 2017). These approaches are mostly considered in terms of the achieved precision & recall (Rashid and Bhatti, 2017) and judgment reports from the human experts (Ruotsalo et al., 2018). Calculating precision and recall in our case is a non-trivial task. It is mainly due to the nature of the data. Therefore, we used a real dataset with no prior labeling by human experts. Our empirical evaluation measures mostly depend on metrics requiring no initial labeling of data. We used internal clustering stability measures to evaluate the internal cluster model stability (Wani and Riyaz, 2016), and clustering accuracy based on the judgment of the human experts (Ruotsalo et al., 2018). We obtained accuracy and stability scores by dispatching pre-defined queries on Google's real dataset.

We collected queries from the recently published ORCAS (Craswell et al., 2020) dataset consisting of 10 million distinct records. Selecting all queries in the dataset for evaluation purposes was not practical. Hence, we performed bi-gram and tri-gram query analysis on the ORCAS dataset. Afterward, we selected 25 queries from the top 100 most repeating bi-gram and tri-gram combinations. The average query length for this evaluation was set to 2.5 words. The chosen length was due to a recent study in (Degbelo and Teka, 2019) indicating average user query length between 2.44 and 2.67 words, which confirms that users' information needs are becoming exploratory. Since in exploratory search, user needs are ambiguous, and the primary objective is to gain an overview of the information. Users type short queries instead of well-articulated longer queries as in the lookup search scenarios (Athukorala et al., 2016). We selected queries covering broad aspects. Therefore, an average query length of 2.5 words was considered based on the average of 2.44 and 2.67 words.

Internal Clustering Parameterizing

We used agglomerative clustering for the creation of multimedia documents and multimedia documents groups. We specified cut-off threshold criteria for the cluster creation process θ to form the desired number of clusters. We chose θ empirically by determining the best possible average mean value of

Table 2. Empirical clustering results for (1) Multimedia Documents (2) Multimedia document groups

Experiment	Iteration	Optimal θ_1	# of Clusters$_1$	SC$_1$	CHI$_1$	DBI$_1$	Optimal θ_2	# of Clusters$_2$	SC$_2$	CHI$_2$	DBI$_2$
	1	15	174	0.11	3.40	1.15	17	79	0.08	4.97	1.79
	2	9	200	0.15	5.88	0.88	19	5	0.05	3.15	2.00
1	3	12	240	0.12	3.82	0.83	14	90	0.05	2.28	1.06
	4	14	148	0.11	3.59	0.98	17	54	0.05	2.66	1.47
	5	10	248	0.15	5.60	0.75	13	54	0.07	3.32	1.08
	Mean	12	202	0.13	4.46	0.92	16	56.4	0.06	3.28	1.48
	1	14	209	0.10	3.39	0.97	17	76	0.04	2.83	1.81
	2	15	157	0.09	3.56	1.27	16	81	0.04	2.61	1.42
2	3	15	160	0.11	3.36	1.28	15	113	0.05	2.51	1.21
	4	16	123	0.08	3.62	1.50	15	93	0.05	2.54	1.24
	5	13	255	0.15	4.08	0.74	16	97	0.06	2.73	1.28
	Mean	14.6	180.8	0.11	3.60	1.15	15.8	92	0.04	2.65	1.39
	1	13	187	0.08	3.49	1.08	15	61	0.05	2.93	1.58
	2	15	180	0.10	3.36	1.11	16	106	0.04	2.57	1.33
3	3	13	191	0.10	4.01	1.01	15	69	0.05	2.84	1.27
	4	16	102	0.09	4.51	1.59	15	77	0.04	2.69	1.24
	5	15	178	0.12	3.48	1.12	16	103	0.05	2.54	1.29
	Mean	14.4	167.6	0.10	3.77	1.18	15.4	83.2	0.05	2.71	1.34
	1	14	190	0.12	3.94	1.01	16	82	0.06	2.63	1.39
	2	14	160	0.10	3.80	1.20	16	55	0.06	2.84	1.56
4	3	14	205	0.09	3.06	1.06	16	85	0.04	2.64	1.43
	4	13	249	0.12	3.22	0.81	15	114	0.04	2.30	1.16
	5	13	186	0.17	4.47	0.88	15	78	0.05	2.58	1.18
	Mean	13.6	198	0.12	3.70	0.99	15.6	82.8	0.05	2.60	1.34
	1	14	166	0.10	4.04	1.16	15	78	0.04	2.76	1.27
	2	13	192	0.09	3.85	1.00	16	80	0.05	3.01	1.62
5	3	13	182	0.10	3.58	1.09	15	58	0.05	2.78	1.40
	4	12	204	0.10	4.06	0.96	14	60	0.06	3.01	1.13
	5	12	192	0.14	5.46	0.92	14	64	0.05	2.74	1.14
	Mean	12.8	187.2	0.11	4.20	1.03	14.8	62	0.05	2.86	1.31
Mean Average		**13.48**	**187.12**	**0.11**	**3.95**	**1.06**	**15.52**	**75.28**	**0.05**	**2.82**	**1.37**

Table 3. Clustering precision. Clusters precision for (1) Multimedia documents, (2) Multimedia documents groups, Relevancy scores by (a) Novice judge (b) Expert judge

Experiment	Iteration	Precision %age (1a)	Precision %age (1b)	Precision %age (2a)	Precision %age (2b)
	1	100.00	100.00	100.00	92.00
	2	100.00	100.00	100.00	100.00
1	3	100.00	96.70	100.00	100.00
	4	96.60	88.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
	Mean	99.32	96.94	100.00	98.40
	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
2	3	100.00	100.00	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
	Mean	100.00	100.00	100.00	100.00
	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
3	3	100.00	100.00	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	96.60	100.00	100.00	98.20
	Mean	99.32	100.00	100.00	99.64
	1	98.10	100.00	98.20	100.00
	2	100.00	100.00	96.90	100.00
4	3	96.90	96.90	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
	Mean	99.00	99.38	99.02	100.00
	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
5	3	100.00	96.60	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
	Mean	100.00	99.32	100.00	100.00
Mean Average		**99.53**	**99.13**	**99.80**	**99.61**
Average		**99.33**		**99.71**	
Cohen's Kappa		**0.474**		**0.398**	

internal cluster stability measures. We used a well-known Rousseeuw (1987) Silhouette Coefficient (SC), Caliński and Harabasz (1974) Index (CHI) and Davies and Bouldin (1979) Index (DBI) to calculate internal cluster stability. We calculated the mean average value of θ_1 by performing five experiments and taking their mean value to create multimedia documents. Based on the obtained θ_1 threshold, we again repeated the same procedure for multimedia documents clustering to obtain θ_2. This process of obtaining θ_1 and θ_2 is displayed in table 2. Finally, we parameterized the clustering model for multimedia documents and documents clusters based on empirically obtained values, as displayed in table 4.

Table 4. Clustering model parameters for (1) Multimedia documents (2) Multimedia document groups

Parameters	Description	Value$_1$	Value$_2$
n_clusters	# of clusters to find	None	None
affinity	Metric to compute linkage	Euclidean	Euclidean
distance_threshold	The linkage distance threshold for merging clusters	13.48	15.52
linkage	Distance method between set of observations	Ward	Ward

Clustering Precision

Precision is referred to as a fraction of relevant retrieved out of total relevant results (Rashid and Bhatti, 2017). In clustering, precision is a fraction of relevant results out of total results inside a cluster. Precision is mostly calculated by cross-matching obtained cluster results with correct labeled data. In a real dataset, the labeling of data is unavailable. We logged the search results retrieved from the pre-defined queries during the empirical internal clustering model parameterization process to overcome this challenge. These logged search results were then presented to two human experts to label relevant and irrelevant search results inside each cluster. The existing literature mostly use two human experts for verification of the judgments between the experts (Achsas and Nfaoui, 2018; Koh et al., 2006; Taramigkou et al., 2017). To perform the rigorous expert-based evaluation, we hired two human experts from opposite backgrounds, we then statistically measured their amount of agreement. To the best of our knowledge, this human-expert background diversity and their inter-relevance agreeability has not been considered previously. The first human expert is a graduate in education and had no prior knowledge about computing-related technical aspects. The second human expert is a graduate in computer science and had substantial knowledge about computing technical aspects, including the concept of clustering. This diversity in the background helps in obtaining unbiased validation of our clustering approach.

Table 3 show the results obtained from the human experts. We run a total of 25 experiments, divided into 5 iterations. From each iteration, we obtained the mean results. Afterward, we took the mean average of 5 iterations. This process was repeated for both; the multimedia documents and multimedia documents groups. The results show no significant change in the relevancy judgment scores from both the novice judge (99.53%) and the expert judge (99.13%) for multimedia documents. Similar results were achieved for multimedia documents groups from the novice judge (99.80%) and expert judge (99.61%). There is a moderate amount of agreement ($\kappa = 0.474$) between the novice and expert judges for multimedia documents. Similarly, there is a fair amount of agreement ($\kappa = 0.398$) between the novice and expert judges for multimedia documents. Since there was a very low average standard deviation (SD=0.15) in the obtained relevancy scores and there also existed a fair to moderate amount of agreement, the relevancy report from the two human experts is deemed comprehensive and complete.

COMPARISON & DISCUSSION

Our approach outperforms in terms of accuracy (99%) in comparison to the approach provided by Achsas and Nfaoui (2018) (89%). It mainly can be due to variations in the data used for model training, choice of deep learning model, and parameterization process. We have performed rigorous and statistically significant empirical evaluation using average scores from human experts having diverse backgrounds and internal clustering stability measures. It presents as a baseline, and a promising start for future search results aggregation approaches. This signifies that the previous researches in this domain are excessively concerned with innovations in the existing techniques, which we believe, is unnecessary while the present search engines are still suffering from the major issues discussed in this paper. We also made an effort to emphasize the fact that the existing techniques are sufficiently optimized to solve real issues and there exists a need for attention from the researchers towards more emerging trends.

Table 5. Comparison of the proposed approach with state-of-the-art

Category	Parameter	Values	(Koh et al., 2006)	(Ruotsalo et al., 2015a)	(Tablan et al., 2015)	(di Sciascio et al., 2016)	(Krishnamurthy et al., 2016)	(Khalili et al., 2017)	(Lisena et al., 2017)	(Rashid and Bhatti, 2017)	(Taramigkou et al., 2017)	(Zhang et al., 2018)	(Kanjanakuha et al., 2019)	**Proposed Approach**
Searching	Search Type	Full text	+	+	+	+	+	+		+	+	+		+
		Fielded			+			+	+					
		Semantic			+			+	+				+	+
		Federated	+		+		+			+	+			+
	Search Results Granularity	Snippets	+				+	+	+		+		+	+
		Document		+	+	+						+		+
		Document Clusters												+
		Lookup							+			+		+
	Search Activity	Exploratory	+	+	+	+	+	+		+	+	+	+	+
		Discovery	+	+	+		+	+	+		+		+	+
		Web	+				+				+	+		+
Data	Information Source	Repository	+	+	+	+	+	+	+	+	+		+	+
		Real	+				+				+			+
	Data Model	Linear		+	+	+	+				+			+
		Non-linear	+		+			+	+	+		+	+	+
	Data Relation	Part-of			+			+	+	+			+	+
		Similarity	+	+	+	+	+	+	+	+	+	+		+
		Semantic			+			+	+	+				+
Information Retrieval	Media Source	Textual	+	+	+	+	+	+	+		+	+	+	+
		Multimedia	+							+	+	+		+
	Retrieval Modal	Monomodal		+	+	+	+	+				+	+	
		Cross-Modal	+						+	+	+			+

Each research utilizes different techniques and mechanisms to provide information exploration and discovery. We have extracted the major parameters and their possible values for an in-depth comparison of our approach with existing state-of-the-art. To ease comprehension of these parameters, we have further categorized parameters according to their purpose, as displayed in the table 5. The provided functionalities are marked with the "+" symbol, whereas the missing functionalities are left blank.

Table 5 emphasizes the three significant aspects of discovery techniques. The first aspect is searching for search results, including search type, search results granularity, and searching activity. The second aspect concerns data management, including information sources, instantiation of data-modal, and assembling mechanism. Finally, the third aspect is concerned with technical information retrieval aspects of the discovery and exploratory approaches, including media sources and information retrieval modal.

The most crucial factor in information discovery is flexibility in representing the information to avoid information overload. Most of the existing research solely relies on filtering capabilities but lacks in providing appropriate granularity control of the search results (di Sciascio et al., 2016). Our approach provides three-level granularity; snippets, multimedia documents, and multimedia documents clusters. The data-modals employed by the existing researches are mostly centered around a specific domain and specific data. They mainly include the scientific domain having millions of literature as a dataset. Approaches providing real datasets were also primarily concerned with integrating a few verticals such as web and image (Koh et al., 2006). To enable our approach to be generic and applicable to all the domains and datasets, we presently use only real datasets to observe our approach's integrity even in the most variate and uncertain data coming from the search engines in real-time.

Information exploration and discovery is a long, non-trivial, and non-linear journey. To foster non-linear navigation of the search results, existing literature mostly instantiated a graph data-modal using either existing domain knowledge, such as ontologies (Khalili et al., 2017; Lisena et al., 2017; Kanjanakuha et al., 2019), or using some generic similarity measures (Rashid and Bhatti, 2017). Our approach uses domain-independent semantics and similarity measures to construct a non-linear graph to provide non-linear means of search results exploration and discovery.

Information management is also an essential factor in enabling information discovery and a compelling

exploration of the search results. Numerous information management approaches organize and present the users' search results, increasing their cognitive abilities. These approaches include linear and non-linear browsing of information and summarization. However, previously, these were implemented as disjoint components, combined on a single interface (Fung and Thanadechteemapat, 2010). Our approach unifies all of the specific techniques and encapsulates it in a single component. With our generic information discovery architecture based on a strong theoretical background and promising empirical evaluation results, we hope to provide a new baseline for future researches on relational aggregated search and search engines alike.

CONCLUSION & FUTURE WORK

In this research, we proposed a generic discovery architecture using multimedia search engine results. A brief discussion on information exploration and theoretical discovery background was provided, and an architectural solution was formalized and instantiated. Before this work, the exploration and discovery of information on the web search engine were leveraged using traditional heuristics. We identified potential gaps and issues in the current general web search engine approach. To overcome these issues, we presented a new baseline using search results aggregation. Our approach was employed using state-of-the-art sentence embeddings. We bridged the gap between the abundant multimedia contents by encapsulating semantically multimedia artifacts in multimedia documents and summarizing them. Moreover, we eased the navigation problem in the search results space by grouping multimedia documents in semantically similar patches.

The proposed discovery architecture emphasizes all the aspects of the discovery, including information exploration and lookup. We supported information exploration by providing the nonlinear proximal navigation and exploration support through the instantiation of a complex graph and lookup searches through a semantically fully-blended ordered linear search results list. Finally, a comprehensive empirical evaluation was presented. The empirical evaluation out-performed previous aggregation approaches at all granularity levels of aggregation provided in this research. To the best of our knowledge, our approach is the first to be assessed comprehensively from the system and the user perspective on the dataset and the queries obtained from the user and the search engine, respectively, in real-time.

We believe that the user experience and the user interface both play an important role to influence information discovery. This aspect requires a detailed and comprehensive discussion, which was out of the scope of this research. In the future, we look forward to providing a more ablative evaluation from the usability perspective of architecture involving an even broader audience with extremely varied backgrounds and experiences with more focus on human aspects, including user interfaces. We have intentions to provide the adaptable clustering of multimedia documents by considering the users' diverse information need and information-seeking behavior. We are interested in investigating multimodal verticals aggregation and exploiting various nonlinear data models consisting of multiple modalities in the enhanced discovery of aggregated multimedia based document search results in real-time scenarios.

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