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Semantic Search and Summarization of Judgments Using Topic Modeling

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Abstract. Online legal document libraries, such as WorldLII, are indispensable tools for legal professionals to conduct legal research. We study how topic modeling techniques can be applied to such platforms to facilitate searching of court judgments. Specifically, we improve search effectiveness by matching judgments to queries at semantics level rather than at keyword level. Also, we design a system that summarizes a retrieved judgment by highlighting a small number of paragraphs that are semantically most relevant to the user query. This summary serves two purposes: (1) It explains to the user why the machine finds the retrieved judgment relevant to the user's query, and (2) it helps the user quickly grasp the most salient points of the judgment, which significantly reduces the amount of time needed by the user to go through the returned search results. We further enhance our system by integrating domain knowledge provided by legal experts. The knowledge includes the features and aspects that are most important for a given category of judgments. Users can then view a judgement's summary focusing on particular aspects only. We illustrate the effectiveness of our techniques with a user evaluation experiment on the HKLII platform. The results show that our methods are highly effective.

Keywords. Topic modeling, Semantic search, Judgment summarization

1. Introduction

In common law jurisdictions, prior judgments (a.k.a. *precedents*) are important parts of the law. Retrieving relevant judgments is an important task in legal research. To find existing judgments, one may resort to legal databases such as the World Legal Information Institute (WorldLII) [1]. Although existing legal database systems provide search functions that facilitate judgment retrieval, they are mostly limited to simple keyword search. It is well known that keyword-based search suffers from poor query expressiveness.

In this paper we address the judgment retrieval problem by applying topic modeling techniques to perform semantic search and judgment summarization. Specifically, our approach consists of the following three components.

[Semantic Search] Existing search engines deployed in legal database systems such as HKLII mostly retrieve judgments based on keyword matching. This is ineffective especially when the search intent involves abstract concepts that can be expressed in various wordings or in technical terms that the query issuer is not familiar with. We achieve semantic search by applying *topic modeling*. In a nutshell, topic modeling is a

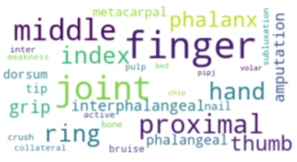


Figure 1. Word cluster that expresses a topic on "*finger injury*"

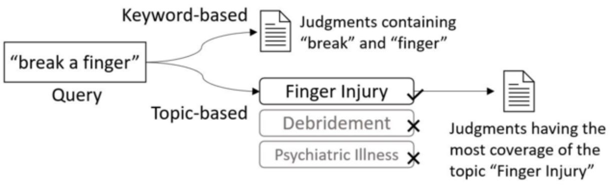

Keyword-based
Judgments containing "break" and "finger"
"break a finger"
Query
Topic-based
Finger Injury
Debridement
Psychiatric Illness
Judgments having the most coverage of the topic "Finger Injury"

Figure 2. Topic-based semantic search

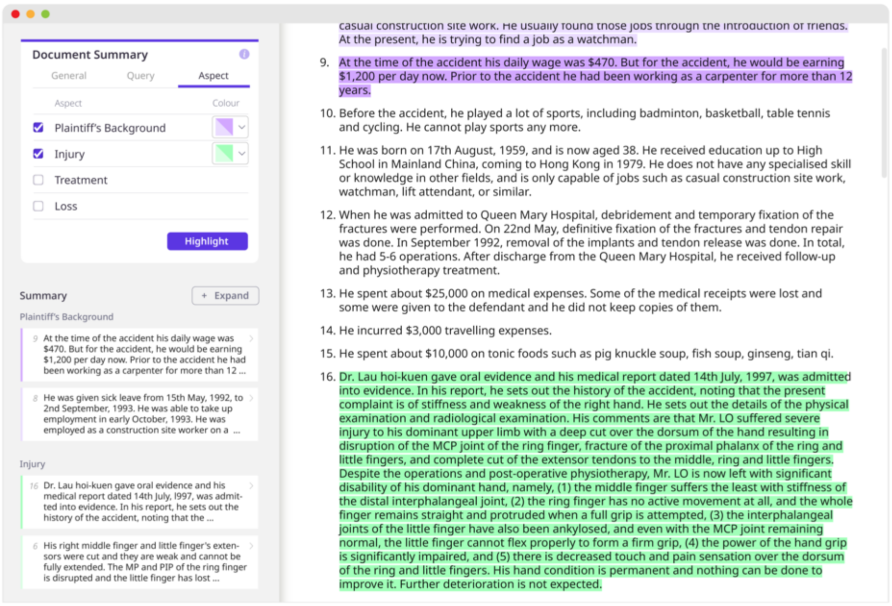
statistical framework that analyzes a document corpus to identify distinguishing words that have strong associations (e.g., based on co-occurrences of words in documents). A "*topic*" can be considered as a cluster of words based on their associations, which, collectively, express certain abstract concept. Figure 1 shows an example word cluster that expresses the concept (or topic) of "finger injury". Our method of semantic search is to first analyze court judgments to discover topics (in topic-modeling sense) and identify the topics that are covered by each specific judgment. When given a query, the topic that is most relevant to the query is found and the judgments that have the best coverage of the topic are retrieved. Figure 2 illustrates our idea.

[Query-driven Summarization] A search engine often returns search results as a list of hypertext links, each with the corresponding document title displayed. It is difficult for the user to determine if a document is really relevant to his/her query by inspecting the title only. As we observed in analyzing the HKLII search log, very often a user would click and read many returned documents that turned out to be irrelevant to the search intent. This is a major source of inefficiency in judgment search as users toil through long and complex judgments. Our approach to ameliorating unproductive search results filtering is to perform *automatic judgment summarization*. Specifically, a small fraction (such as 5%) of a judgment's paragraphs are selected by the machine based on their relevancy to the given user query. These paragraphs are highlighted in the judgment and they serve as a query-specific summary of the judgment. By reading this small (5%) summary, the query issuer gets to know why the machine thinks that the judgment is relevant to the query, obtains a basic understanding of the judgment's content, and thus is able to quickly determine if the judgment should be filtered or collected.

[Aspect-driven Summarization] After a user accepts a judgment as relevant with the help of a query-specific summary, the user typically needs to know more about the judgment with respect to different aspects of the case concerned. To address this, our system provides aspect-specific summaries of judgments. Our approach is to first consult legal experts on the most important features and aspects of each judgment category. For example, for personal injury cases, aspects of interests include a plaintiff's *background*, *treatments*, *losses*, and *compensations*. The machine would then summarize a judgment based on each aspect by finding a small number of paragraphs in the judgment that are most relevant to the chosen aspect. Figure 3 shows an example.

2. Algorithms

In this section we discuss how topics are generated (Section 2.1) and how we use the generated topics in semantic search and judgment summarization (Section 2.2).



Aspect	Colour
✓ Plaintiff's Background	🟪
✓ Injury	🟩
☐ Treatment	
☐ Loss	

Summary

Plaintiff's Background

9 At the time of the accident his daily wage was $470. But for the accident, he would be earning $1,200 per day now. Prior to the accident he had been working as a carpenter for more than 12 ...

8 He was given sick leave from 15th May, 1992, to 2nd September, 1993. He was able to take up employment in early October, 1993. He was employed as a construction site worker on a ...

Injury

16 Dr. Lau hoi-kuen gave oral evidence and his medical report dated 14th July, l997, was admitted into evidence. In his report, he sets out the history of the accident, noting that the ...

6 His right middle finger and little finger's extensors were cut and they are weak and cannot be fully extended. The MP and PIP of the ring finger is disrupted and the little finger has lost ...

casual construction site work. He usually found those jobs through the introduction of friends. At the present, he is trying to find a job as a watchman.

9. At the time of the accident his daily wage was $470. But for the accident, he would be earning $1,200 per day now. Prior to the accident he had been working as a carpenter for more than 12 years.

10. Before the accident, he played a lot of sports, including badminton, basketball, table tennis and cycling. He cannot play sports any more.

11. He was born on 17th August, 1959, and is now aged 38. He received education up to High School in Mainland China, coming to Hong Kong in 1979. He does not have any specialised skill or knowledge in other fields, and is only capable of jobs such as casual construction site work, watchman, lift attendant, or similar.

12. When he was admitted to Queen Mary Hospital, debridement and temporary fixation of the fractures were performed. On 22nd May, definitive fixation of the fractures and tendon repair was done. In September 1992, removal of the implants and tendon release was done. In total, he had 5-6 operations. After discharge from the Queen Mary Hospital, he received follow-up and physiotherapy treatment.

13. He spent about $25,000 on medical expenses. Some of the medical receipts were lost and some were given to the defendant and he did not keep copies of them.

14. He incurred $3,000 travelling expenses.

15. He spent about $10,000 on tonic foods such as pig knuckle soup, fish soup, ginseng, tian qi.

16. Dr. Lau hoi-kuen gave oral evidence and his medical report dated 14th July, 1997, was admitted into evidence. In his report, he sets out the history of the accident, noting that the present complaint is of stiffness and weakness of the right hand. He sets out the details of the physical examination and radiological examination. His comments are that Mr. LO suffered severe injury to his dominant upper limb with a deep cut over the dorsum of the hand resulting in disruption of the MCP joint of the ring finger, fracture of the proximal phalanx of the ring and little fingers, and complete cut of the extensor tendons to the middle, ring and little fingers. Despite the operations and post-operative physiotherapy, Mr. LO is now left with significant disability of his dominant hand, namely, (1) the middle finger suffers the least with stiffness of the distal interphalangeal joint, (2) the ring finger has no active movement at all, and the whole finger remains straight and protruded when a full grip is attempted, (3) the interphalangeal joints of the little finger have also been ankylosed, and even with the MCP joint remaining normal, the little finger cannot flex properly to form a firm grip, (4) the power of the hand grip is significantly impaired, and (5) there is decreased touch and pain sensation over the dorsum of the ring and little fingers. His hand condition is permanent and nothing can be done to improve it. Further deterioration is not expected.

Figure 3. Interface for aspect-driven summarization

2.1. *Topic Generation*

We adopt *Latent Dirichlet Allocation* (LDA) [2] as the topic modeling method. Given a collection of documents, LDA generates *topics* by computing two sets of distributions: (1) A *word distribution* for each topic. The word distribution captures the words that express the topic. An example is shown in Figure 1. (2) A *topic distribution* for each document. The topic distribution reflects the probability of each topic occurring in the document. In the following discussion, we use *personal injury compensation cases in Hong Kong* to illustrate our methods. We consider three ways of applying LDA to judgment data. They differ in how judgment documents are processed and whether expert knowledge on specific judgment category is taken into account. Figure 4 illustrates the three approaches. Next, we give details of the approaches.

[No Domain Knowledge (NoDK)] Judgments are first preprocessed by removing numbers and stop words. Then, we run LDA on the judgments using MALLET's implementation [3] to generate topics. This is illustrated in Figure 4(a).

[Feature Domain Knowledge (DK-F)] We consult legal experts to obtain a list of features that are important for the specific category of judgments in the corpus. For example, for PI judgments, these features include "*age at the time of incident*" and "*whether the injury is permanent*". Judgments are then manually annotated to identify spans of text that contain information related to the features. We call these spans of text "*labeled text*". We strip each judgment of its unlabeled text; Only labeled text is retained to which we apply LDA. The idea is to remove unimportant details so that the topics generated are related to the more important contents of judgments. Figure 4(b) illustrates this approach.

[Aspect Domain Knowledge (DK-A)] We further consult legal experts to group features into *aspects*. For example, for PI cases, four aspects are given, namely, (plaintiff's) *background*, *injury*, *treatment*, and *loss*. We perform topic modeling on the labeled text under each aspect separately. For example, with respect to the background aspect, we

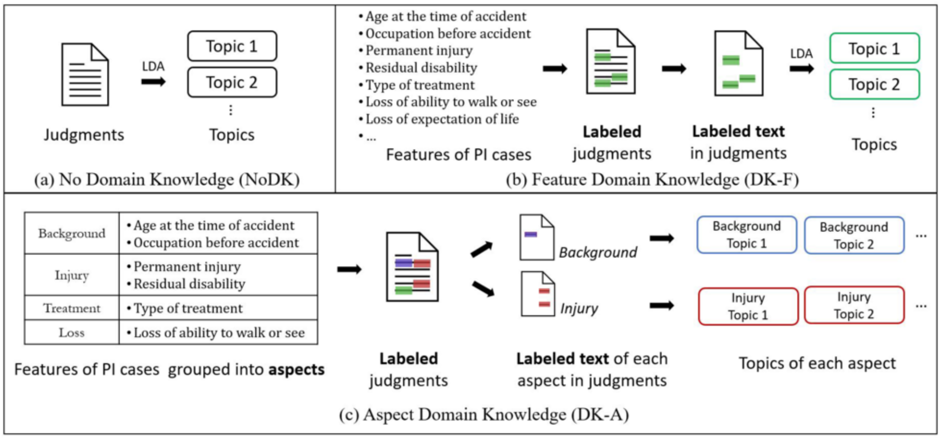

Judgments
LDA
Topic 1
Topic 2
Topics
(a) No Domain Knowledge (NoDK)
• Age at the time of accident
• Occupation before accident
• Permanent injury
• Residual disability
• Type of treatment
• Loss of ability to walk or see
• Loss of expectation of life
• ...
Features of PI cases
Labeled judgments
Labeled text in judgments
LDA
Topic 1
Topic 2
Topics
(b) Feature Domain Knowledge (DK-F)
Background
• Age at the time of accident
• Occupation before accident
Injury
• Permanent injury
• Residual disability
Treatment
• Type of treatment
Loss
• Loss of ability to walk or see
Features of PI cases grouped into aspects
Labeled judgments
Background
Injury
Labeled text of each aspect in judgments
Background Topic 1
Background Topic 2
Injury Topic 1
Injury Topic 2
Topics of each aspect
(c) Aspect Domain Knowledge (DK-A)

Figure 4. Topic Modeling Approaches

retain only the labeled text for background-related features in judgments before applying LDA. The idea is to generate aspect-specific topics so that judgments can be summarized based on a desired aspect. Figure 4(c) illustrates this approach.

2.2. Applications

In this section we discuss how we make use of the generated topics to perform semantic search and judgment summarization.

2.2.1. Semantic Search

Let $\mathcal{T} = \{T_1, \ldots, T_N\}$ be the set of N topics obtained from LDA. Given a query q and a judgment J, we evaluate the relevancy of q and J w.r.t. the N topics. The similarity of q and J is then measured by their overlapping topics. Specifically, a topic T_i is represented by a word vector $[w_{i,1}, \ldots, w_{i,k}, \ldots]$, where each $w_{i,k}$ is a word with probability $p_{i,k}$ of being relevant to topic T_i. For each word $w_{i,k}$, we apply word2vec [4] to obtain its word embedding vector $\mathbf{w}_{i,k}$. We then compute the average of all word embedding vectors $\mathbf{w}_{i,k}$'s weighted by their probabilities $p_{i,k}$'s. We call the resulting embedding vector the *topic semantic vector* $\mathbf{v}_{T_i}$ of topic T_i. Next, we process the query q in a similar fashion: we first obtain the word embedding vector of each word in q and then compute the vectors' average. We call the resulting embedding vector the *query semantic vector* $\mathbf{v}_q$ of query q. The *query-topic similarity score*, $s_{q,i}$, between query q and topic T_i is measured by the cosine similarity of the semantic vectors, i.e., $\mathbf{v}_{T_i} \cdot \mathbf{v}_q / \|\mathbf{v}_{T_i}\| \, \|\mathbf{v}_q\|$. We collect the similarity scores over all topics into a *query-topic probability vector* $\mathbf{p}_q = [s_{q,1}, \ldots, s_{q,i}, \ldots]$ of query q. This vector summaries the relevancy of each topic to the query q. For a judgment J, LDA produces a *judgment-topic probability vector* $\mathbf{p}_J = [t_{J,1}, \ldots, t_{J,i}, \ldots]$ where $t_{J,i}$ is the probability that judgment J is relevant to topic T_i. Finally, we compute the similarity between query q and judgment J by taking the dot product $\mathbf{p}_q \cdot \mathbf{p}_J$. Given a query q, we return the judgments with the highest similarities as the search results.

2.2.2. Query-Driven Summarization

Given a query q and a judgment J, our objective is to find a small fraction (e.g., 5%) of the paragraphs in J that are the most relevant to q. These selected paragraphs serve as a query-specific summary of J to q, which helps the user understand whether J is indeed desired. To achieve that, we first find the most relevant topic T_q, which is the topic that gives the highest query-topic similarity score, i.e., $T_q = \arg\max_{T_i}(s_{q,i})$. Next, for each paragraph G in J, we compute a *paragraph semantic vector* $\mathbf{v}_G$ by averaging the word2vec embedding vectors of the words in G. The similarity between paragraph G and topic T_q is then measured by the cosine similarity of their semantic vectors, i.e., $\mathbf{v}_{T_q} \cdot \mathbf{v}_G / \|\mathbf{v}_{T_q}\| \|\mathbf{v}_G\|$. Paragraphs with the highest similarities are selected as the summary.

2.2.3. Aspect-Driven Summarization

In Section 2.1 we discussed three ways of generating topics. In particular, with DK-A, topics are grouped into aspects (see Figure 4(c)). Given a judgment J and an aspect A, our objective is to find a small number of paragraphs in J that best describe the case w.r.t. aspect A. For simplicity, we explain our approach assuming that *plaintiff's background* is the aspect of interest. Our method can be generalized to cover any other given aspect. Let $\mathcal{T_B} = \{T_1, \ldots, T_M\}$ be a set of M topics generated by the DK-A model under the "plaintiff's background" aspect. For a judgment J, we consider its *judgment-topic probability vector* $\mathbf{p}_J$ (see Section 2.2.1) and find the topic in $\mathcal{T_B}$ that gives the highest probability among those in $\mathbf{p}_J$. We denote this top-ranked topic T_J. Formally, $T_J = \arg\max_{T_i \in \mathcal{T_B}} t_{J,i}$. Next, we measure the similarity between each paragraph G in judgment J and the topic T_J in the same way as we did in query-driven summarization, i.e., by the cosine similarity of $\mathbf{v}_G$ and $\mathbf{v}_{T_J}$. Paragraphs with the highest similarities are selected as the summary.

3. Evaluation

In this section, we present the evaluation of our topic modeling appraoches. In particular, we give experimental results comparing different topic generation methods using query-driven summarization as the target application.

We collected 832 judgments on personal injury (PI) compensation cases handed down in Hong Kong from 1999 to 2021. The judgments contain 606 to 11,257 words each, with an average length of 4,552 words. Our legal experts suggested 79 features for PI cases, among which 48 are of interests to this study. These 48 features are grouped into four aspects, namely, "*background*" (11 features), "*injury*" (9 features), "*treatment*" (8 features), and "*loss*" (20 features). We hired 10 law students to manually label these features in the judgments. The data is used to derive topic models under the NoDK, DK-F, and DK-A approaches (see Figure 4).

To evaluate the quality of the query-specific summaries provided by each method, we prepared a set of 20 *test queries* that search for PI judgments. These queries are real user queries extracted from the HKLII search log. We submitted each query q to HKLII search engine and retrieved the top-ranked PI judgment J after filtering out those in the search results that were irrelevant to q. This gave us a query-judgment (q-J) pair. We then applied query-driven summarization (Section 2.2.2) to determine a similarity score of each paragraph in J w.r.t. the query q. The paragraphs were then ranked based on their similarity scores and the top 5% of the paragraphs were selected as the summary of J. We considered 3 approaches to generate topics, namely, NoDK, DK-F, and DK-A. Each of them resulted in a summary, which might differ from those of others. Hence, we got three summaries for each *q-J* pair corresponding to the three methods.

We recruited 8 legal experts (who either have the *Postgraduate Certificate in Laws* qualification or are currently practising law) to evaluate the summaries. Given a *q-J* pair, we merged the three summaries obtained from the methods into a single collection and presented the paragraphs to an expert for "grading". The expert was asked to read the query and the judgment, and then assign a score of '0' (not relevant), '1' (somewhat relevant), or '2' (relevant) to each paragraph in the collection. During the process, the expert was totally blind to which method was used to select the paragraphs. Each *q-J* pair was graded by 1 to 3 experts.

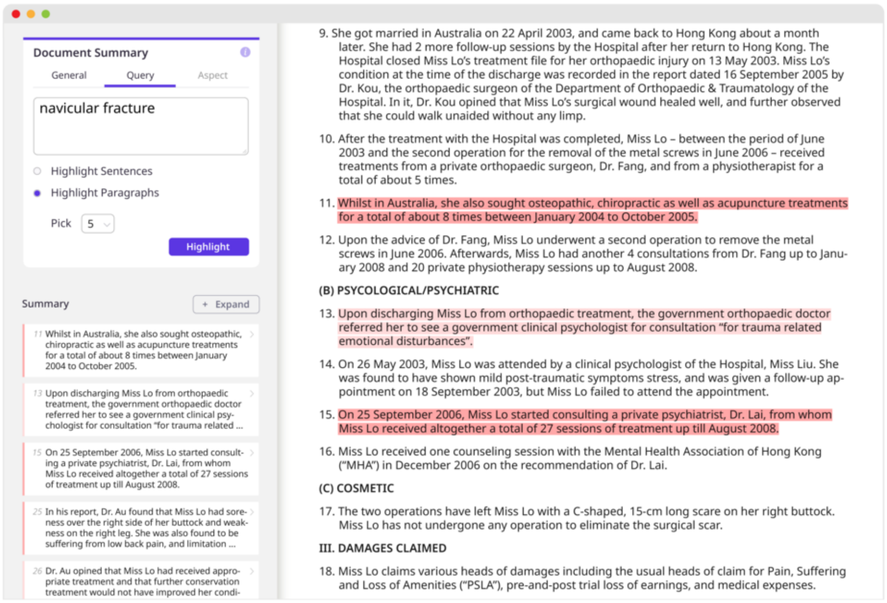
We evaluate a summary's quality by comparing it with the *optimal summary* using the *normalized discounted cumulative gain (nDCG)* metric [5]. Specifically, let $S_X = \{G_1, G_2, ..., G_k\}$ be a summary of k paragraphs taken from a judgment J by method X (X = NoDK, DK-F, or DK-A), such that the paragraphs G_i's are sorted in decreasing order of their similarities with the identified topic (i.e., $\mathbf{v}_{T_q} \cdot \mathbf{v}_G / \|\mathbf{v}_{T_q}\| \|\mathbf{v}_G\|$, see Section 2.2.2). Let $s(G_i)$ be the average relevancy score of G_i given by the human assessors. The DCG score of summary S_X is given by $DCG(S_X) = \sum_1^k s(G_i)/\log_2(i+1)$. The (theoretical) optimal summary, denoted by $\tilde{S}$, is constructed by collecting paragraphs in J that are given the highest average relevancy scores by the assessors until k paragraphs are collected. The nDCG score of summary S_X is then given by $DCG(S_X)/DCG(\tilde{S})$. Note that nDCG scores of summaries range from 0 to 1, with 1 indicating that the summary matches the optimal one perfectly in selecting paragraphs and assessing their relevancy to the query.

Table 1 shows the average nDCG scores of the summaries obtained by the three different methods. Moreover, we consider summaries with nDCG ≥ 0.75 (< 0.5) to be of good (poor) quality. Table 1 shows the number of good/poor summaries for each method. From the table, we see that DK-A, which considers domain knowledge of different PI aspects, significantly outperforms NoDK and DK-F. First, DK-A has a very high average nDCG score (0.86) compared with NoDK (0.66) and DK-F (0.64). Secondly, DK-A produces 18 good summaries for the 20 query-judgment pairs and no poor summaries. The reason for DK-A's excellent performance is that it generates topics with respect to different aspects. That allows DK-A to generate more topics than other methods and the topics are more precise and focused. Table 1 further shows that NoDK and DK-F have comparable performance in terms of average nDCG scores. On closer inspection, we find that there is not a clear advantage of one over the other; For some *q-J* pairs, NoDK gets better scores, while DK-F is better for other *q-J* pairs. As we mentioned in Section 2.1, DK-F ignores unlabeled text in generating topics. That helps remove unimportant content in judgments and improve topic modeling. Occasionally, however, DK-F is too aggressive and some content that is useful in generating topics is inadvertently removed, resulting in poor summary quality.

Table 1. Quality of query-driven summaries

	NoDK	DK-F	DK-A
Average nDCG	0.66	0.64	0.86
# of good summaries (nDCG $\geq$ 0.75)	9	9	18
# of poor summaries (nDCG < 0.50)	7	9	0

Figure 5 shows a screenshot of our query-specific summary design. A user types a query in a search box (top of left panel). The retrieved judgment is shown in the right panel with paragraphs in the summary highlighted. Excerpts of the summary paragraphs



navicular fracture

Pick 5

Summary

11 Whilst in Australia, she also sought osteopathic, chiropractic as well as acupuncture treatments for a total of about 8 times between January 2004 to October 2005.

13 Upon discharging Miss Lo from orthopaedic treatment, the government orthopaedic doctor referred her to see a government clinical psychologist for consultation "for trauma related ...

15 On 25 September 2006, Miss Lo started consulting a private psychiatrist, Dr. Lai, from whom Miss Lo received altogether a total of 27 sessions of treatment up till August 2008.

25 In his report, Dr. Au found that Miss Lo had soreness over the right side of her buttock and weakness on the right leg. She was also found to be suffering from low back pain, and limitation ...

26 Dr. Au opined that Miss Lo had received appropriate treatment and that further conservation treatment would not have improved her condi-

9. She got married in Australia on 22 April 2003, and came back to Hong Kong about a month later. She had 2 more follow-up sessions by the Hospital after her return to Hong Kong. The Hospital closed Miss Lo's treatment file for her orthopaedic injury on 13 May 2003. Miss Lo's condition at the time of the discharge was recorded in the report dated 16 September 2005 by Dr. Kou, the orthopaedic surgeon of the Department of Orthopaedic & Traumatology of the Hospital. In it, Dr. Kou opined that Miss Lo's surgical wound healed well, and further observed that she could walk unaided without any limp.

10. After the treatment with the Hospital was completed, Miss Lo – between the period of June 2003 and the second operation for the removal of the metal screws in June 2006 – received treatments from a private orthopaedic surgeon, Dr. Fang, and from a physiotherapist for a total of about 5 times.

11. Whilst in Australia, she also sought osteopathic, chiropractic as well as acupuncture treatments for a total of about 8 times between January 2004 to October 2005.

12. Upon the advice of Dr. Fang, Miss Lo underwent a second operation to remove the metal screws in June 2006. Afterwards, Miss Lo had another 4 consultations from Dr. Fang up to January 2008 and 20 private physiotherapy sessions up to August 2008.

(B) PSYCOLOGICAL/PSYCHIATRIC

13. Upon discharging Miss Lo from orthopaedic treatment, the government orthopaedic doctor referred her to see a government clinical psychologist for consultation "for trauma related emotional disturbances".

14. On 26 May 2003, Miss Lo was attended by a clinical psychologist of the Hospital, Miss Liu. She was found to have shown mild post-traumatic symptoms stress, and was given a follow-up appointment on 18 September 2003, but Miss Lo failed to attend the appointment.

15. On 25 September 2006, Miss Lo started consulting a private psychiatrist, Dr. Lai, from whom Miss Lo received altogether a total of 27 sessions of treatment up till August 2008.

16. Miss Lo received one counseling session with the Mental Health Association of Hong Kong ("MHA") in December 2006 on the recommendation of Dr. Lai.

(C) COSMETIC

17. The two operations have left Miss Lo with a C-shaped, 15-cm long scare on her right buttock. Miss Lo has not undergone any operation to eliminate the surgical scar.

III. DAMAGES CLAIMED

18. Miss Lo claims various heads of damages including the usual heads of claim for Pain, Suffering and Loss of Amenities ("PSLA"), pre-and-post trial loss of earnings, and medical expenses.

Figure 5. Screenshot for query-driven summarization

are collected and displayed in the lower part of the left panel. The user can read the paragraphs excerpts in the summary to determine if the retrieved judgment is relevant to his/her search intent. By clicking on a paragraph excerpt, the system will display the corresponding paragraph in the judgment in the right panel. This allows the user to read the context of the summary paragraphs for further details.

4. Conclusion

In this paper we studied the problem of effective semantic search and judgment summarization in digital legal library systems. We proposed a general framework to achieve the tasks through topic modeling. We considered three approaches (NoDK, DK-F, and DK-A) of generating topics. We also proposed algorithms for generating query-specific and aspect-specific judgment summaries, and algorithms for performing semantic search.

Acknowledgement

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