Automatic Text Summarization of Chinese Legal Information

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Abstract. Article is devoted to a method of automatic text summarization of the legal information provided in Chinese. The structure of the abstract and the model of its formation is considered. Two approaches are suggested. First one is determination of weight of separate hieroglyphs instead of words in the texts of documents and abstracts for sentences importance level determination process. Second approach is to consider a model of document as a network of sentences for detection of the most important sentences by parameters of this network. Various methods of automatic text summarization are performed and tested. A cosine measure and Jensen-Shannon divergence are applied as two estimates of quality of the paper abstracts without participation of experts. Compared to other summarizing methods, given one on the basis of the suggested network model of the document was the best by criteria of a cosine measure and Jensen-Shannon's distances for abstracts which volume exceeds 2 sentences. The suggested approach, with minimal modifications, can be applied to texts on any subject of scientific, technical or news information.

Keywords: Automatic Text Summarization, Legal Information, Chinese Language, Cosine Measure, Jensen-Shannon Divergence.

1 Introduction

Processing of natural languages practically began with statement of problems of the artificial translation and automatic text summarization. The first fundamental works on automatic text summarization appeared in the middle of the last century [1].

The task is connected with the solution of the most important problem – reduction of the volumes of information consumed by the person, fight against information noise. This task is very relevant today due to the constant growth of the information space. Automatic referencing is known to all users of network search engines -¬ in response to the request they receive not only the title of documents, but also their short automatically created descriptions (snippets). Mobile users want to see a brief description of the articles before they go on to read more. Persons who make important management decisions have to familiarize themselves with thousands of documents a day, deliberately dismissing information noise.

Now there are hundreds of industrial systems of automatic text summarization, for example, such packages as Office Word AutoSummarize, Mac OS X Summarize, IBM Tivoli Monitoring Summarization and Pruning Agent, Oracle Text, plug-ins for browsers Chrome, Mozilla.

Numerous approaches to automatic text summarization are known, recently, neural network technologies, deep training are applied more and more widely. There are also numerous linguistic approaches associated with automatic parsing of sentences submitted in different languages. Traditional type of systems of automatic text summarization – extractive (quasi summarizing) at which the paper consists from of the separate, sometimes poorly connected among themselves sentences of the initial document. He is succeeded by abstractive type of text summarizing at which the systems close to the systems of artificial intelligence in a short form retell contents of the initial document "by the own words".

However, it should be noted that today still practically all industrial systems of automatic text summarization belong to extractive systems.

It would seem, the subject of automatic text summarization of texts is already rather studied, the main results are received. However, and in this article it is about creation of system of automatic text summarization.

There are several reasons for development of new system of automatic text summarization. First the problem of automatic text summarization of legal information is solved. And it is texts which can't fully be considered free, unstructured. There is a structure of separate types of documents and use of the best universal systems of summarizing doesn't yield satisfactory results. Secondly, the authors deal with the texts of documents presented in Chinese, which significantly narrows the range of possible ready-to-use systems. For processing Chinese texts, as a rule, segmentation of words is required – in the Chinese language words are often not separated by separators.

Thirdly, the program capable in corporate system to process big data flows with an acceptable productivity and quality, built in the existing system of document flow has to be developed.

Besides, retelling of documents in this case is unacceptable. Any "imaginations", liberties of retelling by the computer of legal acts it isn't admissible. Exit one – to develop some hybrid algorithm and, respectively, the program of extractive type capable to consider features of legal acts of the People's Republic of China. At the same time the program has to be capable to process separate documents which unite to big documentary arrays. This program has to be capable to allocate obviously set objects in the parts of documents marked with semantic markers, to reveal the most important parts of documents (including by statistical criteria), to form networks of sentences and to remove the necessary volume of target information in the abstract.

2 The Suggested Approach

In addressing the problem, two approaches were proposed that could be considered new in this area. To solve the problem of determining the level of importance of individual parts of documents (in our case, sentences) it was suggested to move to the definition of weight values of separate hieroglyphs, not words in the text of documents and abstracts. It was also suggested that the document model should be considered as a network of sentences to identify the most important sentences for the parameters of the network. The weight of the links of the two sentences in this network is determined by the weight of the common hieroglyphs included in them.

Within the traditional statistical approach to the processing of natural languages, the weight of sentences is usually calculated on the basis of the estimated weights of lexical units (words, phrases) included in these sentences [2] - [5]. In this study it is proposed as such elements for the Chinese language to use separate hieroglyphs.

The transition from the words considered in the classical model to hieroglyphs allows avoiding the relatively complex procedure of words segmentation the text, which is inevitable with all other meaningful methods of Chinese texts automatic analysis. Of course, this approach is not applicable to European languages, where the number of different letters does not exceed several dozens. However, for the purpose of automatic text summarization of Chinese texts, the proposed approach provides acceptable results, which will be shown below.

It is known, that in the Chinese language there are more than 40 thousand hieroglyphs, therefore each of them (though not always, fully reflecting a semantic unit) it is possible to attribute a weight value calculated on the known formulas, for example, $TF \cdot IDF$ [6].

$TF \cdot IDF$ (TF — term frequency, IDF — inverse document frequency) is a statistical measure used to evaluate the importance of a word (in this case, not a word, but a hieroglyph) in the context of a document that is part of an array of documents. The weight of some hieroglyph is proportional to the number of its use in the document, and is inversely proportional to the frequency of occurrence of this character in all documents of array.

Thus, the measure $TF \cdot IDF$ depends on the word t (hieroglyph), the document d, the whole array of documents *D*, and is a product of two factors:

$$TF \cdot IDF(t,d,D) = tf(t,d) \times idf(t,D).$$

Here the expression $tf(t,d)$ is the ratio of the number of occurrences of some hieroglyph to the total number of characters in the document (to the length of the document, actually). Thus, the frequency of the hieroglyph within a single document is estimated.

The second factor, $idf(t,D)$ (inverse document frequency — the reverse frequency of the document) is the inversion of the frequency with which some hieroglyph occurs in the documents of array D.

IDF accounting allows you to reduce the weight of hieroglyphs that occur very often. There is only one IDF value for each t within the entire array of the documents *D*:

$$idf(t,D) = \log \frac{|D|}{|\{d \in D \mid t \in D\}|}.$$

In addition, unlike classical approaches to the definition of weight values of sentences, a new, network model is proposed. Under this model, a non-directional network is considered, with nodes appearing as separate sentences in the document, between which the links are established if they have common hieroglyphs. The weight of the relationship between the two sentences is defined as the sum of the weights common to these sentences. For this network, the weight of each sentence of the textis calculated as the sum of the weights of the links of all links that emanate from the node. Naturally, the weight of the proposals is then normalized, since long sentences without this procedure will on average have a deliberately greater weight. Practice has shown that a good normalization is the division by the logarithm of the length of the corresponding sentence.

3 Automatic Text Summarization of Legal Information

Procedures of automatic text summarization of an extractive class are based on determination of weight values (importance degree) of separate sentences which, in turn, depend on scales of words. In the study, as weight word meanings, the classical criterion $TF \cdot IDF$ was used though it is not only are possible for the solution of a problem of summarizing approach [7]. Traditionally for definition of weight word meanings two known algorithms were used – in the first case the weight of the sentence was considered as the sum of weights, rated on length of this sentence, of the words entering it, and in the second case was used, so-called, a symmetric summarizing algorithm [8]. In this case the weight of the sentence was defined as the sum of weights of its links with the previous and subsequent sentence.

In addition, this paper proposes a network algorithm, which, unlike the second case, calculates the relationship not only between adjacent sentences, but also between all the sentences in the text. This approach, of course, is computationally more complex than the first two, but, as practice has shown, leads to better results. At the same time, the complexity of the algorithm, in the case of the considered approach of texts summarization in Chinese, is compensated by the fact that instead of words (segmentation of which in this case is not required) are considered only separate characters.

So let's present the basic steps of three considered algorithms of definition of weight values of sentences:

Step 1. For each hieroglyph t_i the value $DF = df(t_i,D)$ is calculated as the number of documents d_j from the documentary array D that contain this hieroglyph, that is

$$DF := |\{d_j \in D : t_i \in d_j\}|.$$

Step 2.For each hieroglyph t_i and document d the value as frequencies $TF = tf(t_i,d)$ of emergence of this term in the document is calculated:

$$TF := \frac{\#\{t_i \in d\}}{|d|}.$$

Then hieroglyph weight is calculated

$$w_i = TF \cdot IDF = TF \cdot \log\frac{|D|}{DF}.$$

Step 3.Segmentation of sentences, i.e. the text of the document is divided into separate sentences p_i and then the definition of their weight values wp_i.Let's introduce notation: let the sentence p_i of the set of sentences P ($p_i \in P$) consists of hieroglyphs $t_{i,k}$ with weight $w_{i,k}$.Let's write in a brief form the essence of three different algorithms.

Step 4a) Algorithm of the sum of hieroglyphs weights ($\sum tf \cdot idf$):

$$wp_i = \frac{1}{|p_i|}\sum_{k=1}^{|p_i|} w_{i,k}.$$

Step4b) Symmetrical algorithm for calculating the power of connection of the sentence p_i with the nearest sentences (Nearest):

$$wp_i = \frac{1}{\log|p_i|}\sum_{k=1}^{|T|}\left(w_{i,k}w_{i-1,k} + w_{i,k}w_{i+1,k}\right),$$

where T is the general composition of the hieroglyphs of the array. If the character is not present in the document, its weight in it is equal to zero.

Step 4c) Network algorithm of calculation of force of link of the sentence(Network):

$$wp_i = \frac{1}{\log|p_i|}\sum_{\substack{j=1,\\ j\neq i}}^{|P|}\sum_{k=1}^{|T|} w_{ik}w_{jk} \ .$$

Step 5. The weight of the sentence is corrected depending on its location in the document. Weight values of initial and last sentences of the document artificially increase.

It should be noted that the specifics of legal information, requirements to the structure and volume of the abstract, allowed to use the above-mentioned universal approaches to the solution of a private special task.

The structure and volume of the abstract of the legal document (examples of such documents can be found on the website http://www.gov.cn/in the section /zhengce) are put forward requirements that have found their programmatic implementation:

1. Abstract start with the title of the document, given almost without changes.
2. The abstract notes the type of document (announcement"通告", report “报告",results of work "工作成果", provisions"政策"etc.).
3. If the document indicates its purpose ("目的", "奖补目的", "调整目的", "普查的目的和意义", etc.), it is also reflected in the abstract.
4. If the first or second sentence of the document identifies the subjects of appointment of documents (which is also visible by special markers), such a proposal is also included in the abstract.
5. If in the title of the document or in the designation of its purpose explicitlythere are objects from the number of the previously known (included in the base objects table), these objects should be highlighted in the abstract.

6. EIf the document belongs to the type not subject to further processing (awards "表彰", announcements of bids"招标", letters "函"etc.), the abstract is considered prepared.
7. All sentences containing the objects selected from the title and purpose are selected from the text of the document. If such proposals are less than the required number (given in advance or calculated on the basis of the volume of the document), they are presented in the abstract in the same sequence as in the primary document. The abstract is considered prepared.
8. If the sentences are more than the required number, they are weighed according to the above algorithm (based on the results of testing the network algorithm is selected). After that the sentences ranked by weight and are presented in the abstract in the same sequence as in the primary document. The abstract is considered prepared.

According to the submitted requirements the program of automatic text summarization of the legal information provided in Chinese was developed. The web interface of the user of this program is given in the Figure 1.

4 Adjacent Tasks

Automatic text summarization of texts is one of important problems of technologies of the deep analysis of texts which includes some more directions, such as extraction of entities (Information extraction), creation of networks of words (Language Networks) reflecting features of subject domains, a clustering (Cluster Analysis).

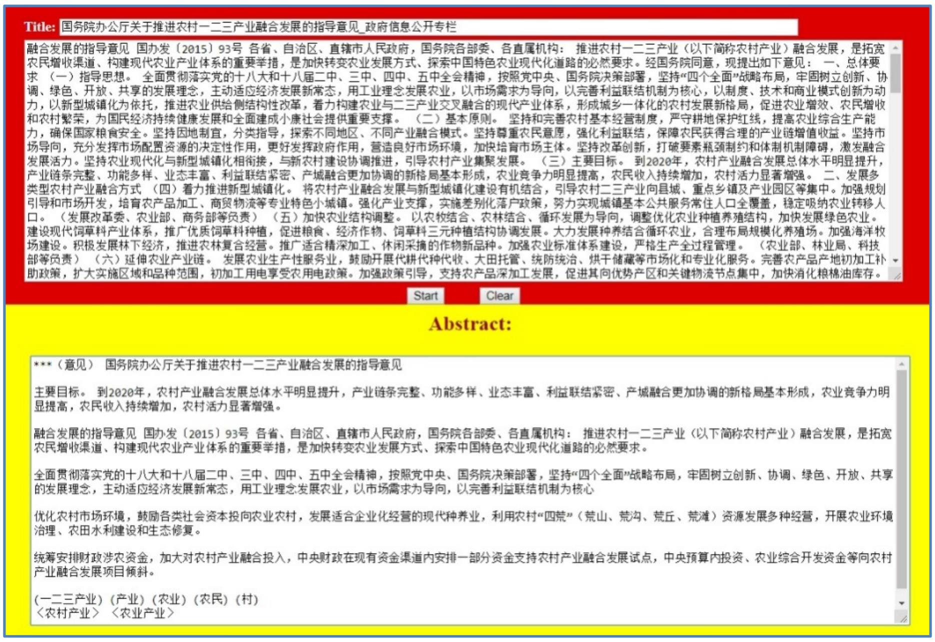
The algorithm offered for summarizing leans on some set of in advance prepared words reflecting the main objects presented in legal documents (for example, "人口" – the population, "产业" – the industry, "儿童" – children, etc.).

At the same time, if you apply the algorithm of words segmentation, and then rank them, it is easy to identify the most common "extensions" of starting objects, for example, the concept of "organization" (组织) to expand to the concept of "international organization" (国际组织), "public organization" (社会组织), and the concept of "defense" (事业) to the concept of "people's air defense" (人民防空事业). As a result, the documents of the array of legal information have been put in line with the basic concepts that can act as "keywords", descriptors, basis for the construction of domain models (Subject domain).

As one of the types of domain models can be considered a words network, the nodes of which correspond to separate concepts. There were proposed and implemented such simple rules of building this network, i.e. rules of communication between nodes:

1. All objects from the base, pre-prepared list, included in one document are linked by links.
2. If two objects are in N different documents, the force of link between them equals N.

3. Concepts that are extensions of concepts from the starter kit are linked with the corresponding basic concepts.



Title: 国务院办公厅关于推进农村一二三产业融合发展的指导意见_政府信息公开专栏

融合发展的指导意见 国办发〔2015〕93号 各省、自治区、直辖市人民政府，国务院各部委、各直属机构： 推进农村一二三产业（以下简称农村产业）融合发展，是拓宽农民增收渠道、构建现代农业产业体系的重要举措，是加快转变农业发展方式、探索中国特色农业现代化道路的必然要求。经国务院同意，现提出如下意见： 一、总体要求 （一）指导思想。 全面贯彻落实党的十八大和十八届二中、三中、四中、五中全会精神，按照党中央、国务院决策部署，坚持“四个全面”战略布局，牢固树立创新、协调、绿色、开放、共享的发展理念，主动适应经济发展新常态，用工业理念发展农业，以市场需求为导向，以完善利益联结机制为核心，以制度、技术和商业模式创新为动力，以新型城镇化为依托，推进农业供给侧结构性改革，着力构建农业与二三产业交叉融合的现代产业体系，形成城乡一体化的农村发展新格局，促进农业增效、农民增收和农村繁荣，为国民经济持续健康发展和全面建成小康社会提供重要支撑。 （二）基本原则。 坚持和完善农村基本经营制度，严守耕地保护红线，提高农业综合生产能力，确保国家粮食安全。坚持因地制宜，分类指导，探索不同地区、不同产业融合模式。坚持尊重农民意愿，强化利益联结，保障农民获得合理的产业链增值收益。坚持市场导向，充分发挥市场配置资源的决定性作用，更好发挥政府作用，营造良好市场环境，加快培育市场主体。坚持改革创新，打破要素瓶颈制约和体制机制障碍，激发融合发展活力。坚持农业现代化与新型城镇化相衔接，与新农村建设协调推进，引导农村产业集聚发展。 （三）主要目标。 到2020年，农村产业融合发展总体水平明显提升，产业链条完整、功能多样、业态丰富、利益联结紧密、产城融合更加协调的新格局基本形成，农业竞争力明显提高，农民收入持续增加，农村活力显著增强。 二、发展多类型农村产业融合方式 （四）着力推进新型城镇化。 将农村产业融合发展与新型城镇化建设有机结合，引导农村二三产业向县城、重点乡镇及产业园区等集中。加强规划引导和市场开发，培育农产品加工、商贸物流等专业特色小城镇。强化产业支撑，实施差别化落户政策，努力实现城镇基本公共服务常住人口全覆盖，稳定吸纳农业转移人口。 （发展改革委、农业部、商务部等负责） （五）加快农业结构调整。 以农牧结合、农林结合、循环发展为导向，调整优化农业种植养殖结构，加快发展绿色农业。建设现代饲草料产业体系，推广优质饲草料种植，促进粮食、经济作物、饲草料三元种植结构协调发展。大力发展种养结合循环农业，合理布局规模化养殖场。加强海洋牧场建设。积极发展林下经济，推进农林复合经营。推广适合精深加工、休闲采摘的作物新品种。加强农业标准体系建设，严格生产全过程管理。 （农业部、林业局、科技部等负责） （六）延伸农业产业链。 发展农业生产性服务业，鼓励开展代耕代种代收、大田托管、统防统治、烘干储藏等市场化和专业化服务。完善农产品产地初加工补助政策，扩大实施区域和品种范围，初加工用电享受农用电政策。加强政策引导，支持农产品深加工发展，促进其向优势产区和关键物流节点集中，加快消化粮棉油库存。

Abstract:

***（意见） 国务院办公厅关于推进农村一二三产业融合发展的指导意见

主要目标。 到2020年，农村产业融合发展总体水平明显提升，产业链条完整、功能多样、业态丰富、利益联结紧密、产城融合更加协调的新格局基本形成，农业竞争力明显提高，农民收入持续增加，农村活力显著增强。

融合发展的指导意见 国办发〔2015〕93号 各省、自治区、直辖市人民政府，国务院各部委、各直属机构： 推进农村一二三产业（以下简称农村产业）融合发展，是拓宽农民增收渠道、构建现代农业产业体系的重要举措，是加快转变农业发展方式、探索中国特色农业现代化道路的必然要求。

全面贯彻落实党的十八大和十八届二中、三中、四中、五中全会精神，按照党中央、国务院决策部署，坚持“四个全面”战略布局，牢固树立创新、协调、绿色、开放、共享的发展理念，主动适应经济发展新常态，用工业理念发展农业，以市场需求为导向，以完善利益联结机制为核心

优化农村市场环境，鼓励各类社会资本投向农业农村，发展适合企业化经营的现代种养业，利用农村“四荒”（荒山、荒沟、荒丘、荒滩）资源发展多种经营，开展农业环境治理、农田水利建设和生态修复。

统筹安排财政涉农资金，加大对农村产业融合投入，中央财政在现有资金渠道内安排一部分资金支持农村产业融合发展试点，中央预算内投资、农业综合开发资金等向农村产业融合发展项目倾斜。

(一二三产业) (产业) (农业) (农民) (村)
〈农村产业〉 〈农业产业〉

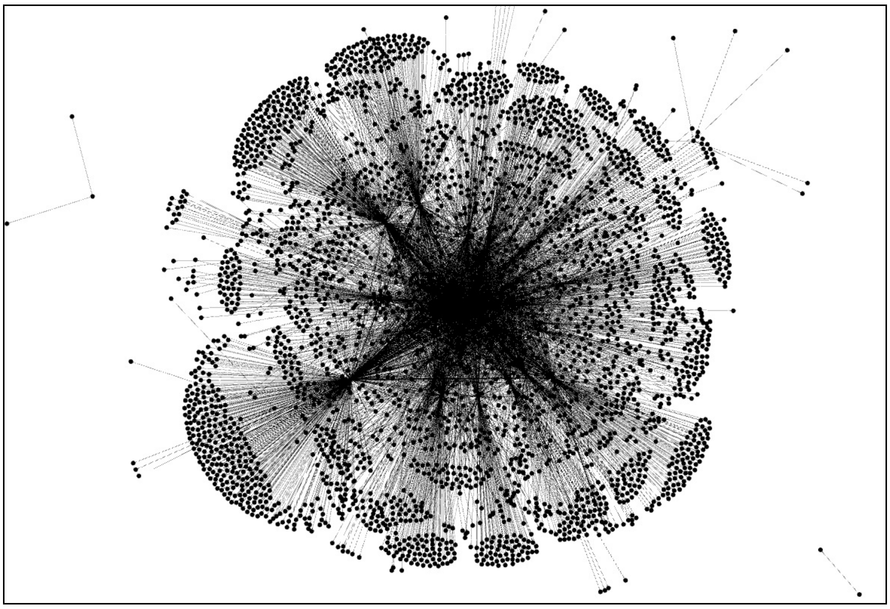
Fig. 1. The web interface of the system of automatic summarization.

With the help of the program Gephi (http://gephi.org) [9] the built network has been visualized (Figure 2) and received such parameters of the built network: number of nodes: 3364 (number of objects from the starting set – 220); - number of links: 10167; network density: 0.001; number of connected components: 6; average path length: 3,013; average clustering factor: 0859.

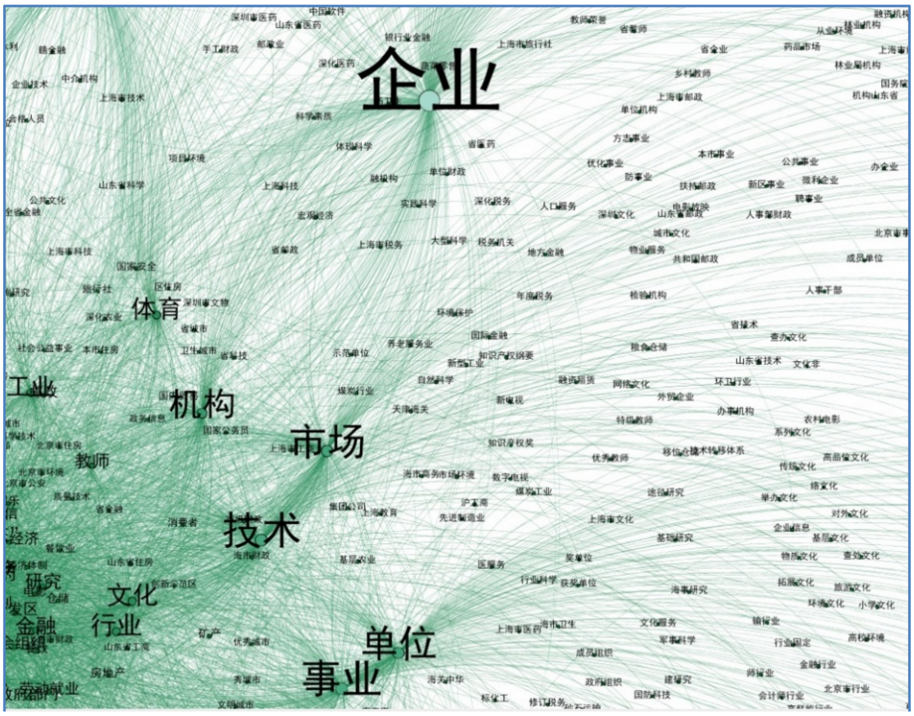
The topology features of the built network include a very large average clustering factor. This is due to the ode of a large number of concepts related only to the natal of their concept (the absence of other neighbors), and on the other hand the strong cohesion of objects from the start list. The small average length of the path indicates that the network is a Small World [10].

With the help of the program Gephi also received lists of the most important nodes in accordance with the criterion of PageRank and the greatest hubs by the criterion of HITS [11] (Figure 3).

The general view of network of words given on the Figure 2 clearly demonstrates a further possibility of a clustering of network, the choice of subsets – clusters from words (concepts). This procedure allows to allocate thematic subsets within the considered subject domain.



General view of words network

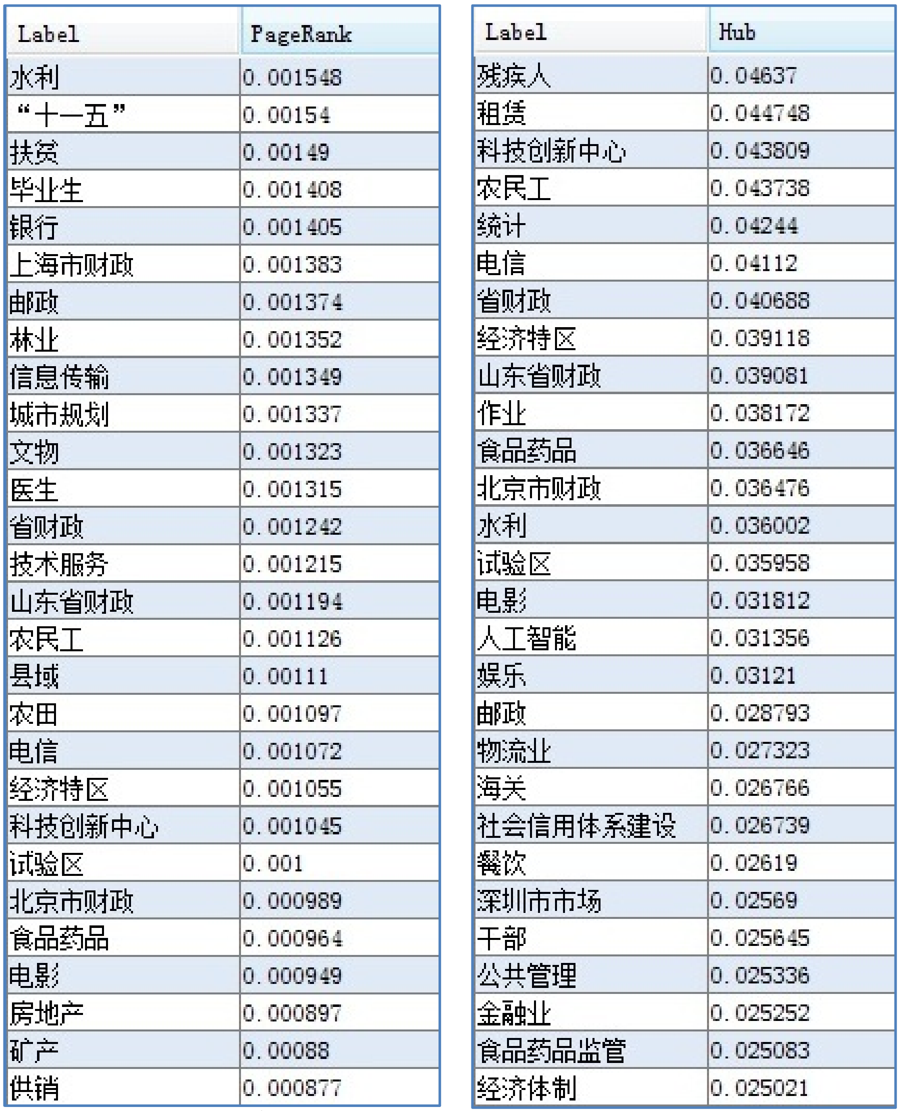


A fragment of the words network

Fig. 2. The web interface of the system of automatic summarization.

5 Methods of Results Evaluation

To evaluate the results, two assessments of the quality of the abstract are applied without experts – the cosine measure and the divergence of Jensen-Shannon (Jensen – Shannon), the justification of which is substantiated in the work [12].



Label	PageRank
水利	0.001548
“十一五”	0.00154
扶贫	0.00149
毕业生	0.001408
银行	0.001405
上海市财政	0.001383
邮政	0.001374
林业	0.001352
信息传输	0.001349
城市规划	0.001337
文物	0.001323
医生	0.001315
省财政	0.001242
技术服务	0.001215
山东省财政	0.001194
农民工	0.001126
县域	0.00111
农田	0.001097
电信	0.001072
经济特区	0.001055
科技创新中心	0.001045
试验区	0.001
北京市财政	0.000989
食品药品	0.000964
电影	0.000949
房地产	0.000897
矿产	0.00088
供销	0.000877

PageRank

Label	Hub
残疾人	0.04637
租赁	0.044748
科技创新中心	0.043809
农民工	0.043738
统计	0.04244
电信	0.04112
省财政	0.040688
经济特区	0.039118
山东省财政	0.039081
作业	0.038172
食品药品	0.036646
北京市财政	0.036476
水利	0.036002
试验区	0.035958
电影	0.031812
人工智能	0.031356
娱乐	0.03121
邮政	0.028793
物流业	0.027323
海关	0.026766
社会信用体系建设	0.026739
餐饮	0.02619
深圳市市场	0.02569
干部	0.025645
公共管理	0.025336
金融业	0.025252
食品药品监管	0.025083
经济体制	0.025021

HITS

Fig. 3. The web interface of the system of automatic summarization.

Let us explain the possibilities of using these approaches. The document's d hieroglyphic dictionary is supposed to consist of N elements $\{t_1,t_2,...,t_N\}$. Each hieroglyph corresponds to its weight, calculated according to the rule $TF \cdot IDF$. An array of these weights can be represented as a vector: $\overline{d}=(w_1,w_2,...,w_N)$. Accordingly, the hieroglyphic dictionary of the abstract r consists of a subset of the dictionary of the document and the abstract can also be put in line with the vector of weight values: $\overline{r}=(\hat{w}_1,\hat{w}_2,...,\hat{w}_N)$. In this case, we give a natural definition:

$$\hat{w}_i=\begin{cases} w_i, & if \quad t_i \in r; \\ 0, & if \quad t_i \notin r. \end{cases}$$

It is known that the scalar product of two nonzero vectors in Euclidean space A and B is defined by a formula:

$$\overline{A}\cdot\overline{B}=\left\|\overline{A}\right\|\left\|\overline{B}\right\|\cos\theta$$

Here θ – a corner between the considered vectors. It is natural if the direction of vectors coincides, the value θ becomes equal to zero (respectively, $\cos\theta=1$). I.e. than closer $\cos\theta$ to unit, the direction of vectors is closer to those that is easily substantially interpreted for a case of the document and its abstract (the short summary). It is accepted function of proximity between vectors A and B to designate as $Sim(\overline{A},\overline{B})$ (from word Similarity). In case of studying of a cosine measure of proximity we have:

$$Sim(\overline{A},\overline{B})=\cos\theta=\frac{\overline{A}\cdot\overline{B}}{\left\|\overline{A}\right\|\left\|\overline{B}\right\|}=\frac{\sum_{i=1}^{n}A_iB_i}{\sqrt{\sum_{i=1}^{n}A_i^2}\sqrt{\sum_{i=1}^{n}B_i^2}},$$

where A_i and B_i – components of vectors $\overline{A}$ and $\overline{B}$, respectively.

According to definition of a cosine measure for calculation of proximity of the document and the paper it is possible to use a formula:

$$Sim(d,r)=\frac{\sum_{i=1}^{N}w_i\hat{w}_i}{\sqrt{\sum_{i=1}^{n}w_i^2}\sqrt{\sum_{i=1}^{n}\hat{w}_i^2}},$$

Proceeding from the fact that $\sum_{i=1}^{N}w_i\hat{w}_i=\sum_{i=1}^{N}\hat{w}_i\hat{w}_i,$ we receive a formula which in is used at practical calculations:

$$Sim(d,r)=\frac{\sum_{i=1}^{N}\hat{w}_i\hat{w}_i}{\sqrt{\sum_{i=1}^{n}w_i^2}\sqrt{\sum_{i=1}^{n}\hat{w}_i^2}}=\sqrt{\frac{\sum_{i=1}^{N}\hat{w}_i^{\,2}}{\sum_{i=1}^{N}w_i^{\,2}}}.$$

Another used criterion for formal identification of the degree of closeness –Jensen-Shannon divergence, which is based on the formalism of information theory and mathematical statistics, in particular, on the relative entropy of Kullback-Leibler [13], [14].

The Kulbak-Leibler entropy is generally defined as a non-negative functional, which is an asymmetric measure of the distance between two probability distributions defined on a common space of elementary events.

The divergence distribution Q relatively P is designated $D(P\|Q)$. Distribution Q often serves as distribution P approach. This measure of distance in the theory of information is also interpreted as the size of losses of information when replacing true distribution P to distribution Q. The functional value can be understood as the number of unaccounted information of distribution Q if it was used for approach the distribution P.

For discrete probability distributions P $\{p_1, p_2, ..., p_n\}$ and Q $\{q_1, q_2, ..., q_n\}$ the Kulbak-Leibler entropy is defined as follows:

$$D(P\|Q) = \sum_{i=1}^{n} \log \frac{p_i}{q_i} p_i.$$

The entropy of Kulbak-Leibler, substantially close to the concept of distance, could be called a metric in the space of probability distributions, but this would be incorrect, since it is not symmetrical $D(P\|Q) \neq D(Q\|P)$ and does not satisfy the inequality of the triangle. In the future, we will use Jensen-Shannon divergence (JSD), which is based on Kulbak-Leibler entropy, but is a metric [15], [16], so it is also called "Jensen-Shannon distance" [17], [18], [19].

Jensen-Shannon's divergence is defined as follows:

$$JSD(P\|Q) = \frac{1}{2}\left(D(P\|M) + D(Q\|M)\right),$$

where $M = \frac{1}{2}(P + Q)$.

In case of application of distance of Jensen-Shannon to a problem of assessment of quality of abstracts s the number of the lost information in the abstract in comparison with the initial document is estimated. As well as in a cosine measure, it is supposed that to the document d there corresponds the vector of the hieroglyphsweights $\bar{d} = (w_1, w_2, ..., w_N)$, and to the abstract r – a vector of weight values: $\bar{r} = (\hat{w}_1, \hat{w}_2, ..., \hat{w}_N)$. The "average" vector used in Jensen-Shannon's method is presented in the following form:

$$\bar{M} = \frac{1}{2}\left(\bar{d} + \bar{r}\right).$$

Respectively,

$$JSD = \frac{1}{2}\left(D(\bar{d}\|\bar{M}) + D(\bar{r}\|\bar{M})\right) = \frac{1}{2}\left(\sum_{i=1}^{N} \log\left(\frac{w_i}{\frac{1}{2}\left(w_i + \hat{w}_i\right)}\right) w_i + \sum_{i=1}^{N} \log\left(\frac{\hat{w}_i}{\frac{1}{2}\left(w_i + \hat{w}_i\right)}\right) \hat{w}_i\right).$$

Let's consider the given sums on two areas of index values: the 1st area where hieroglyphs of the document and the abstract coincide and 2nd, where do not coincide, i.e. where $\hat{w}_i = 0$:

$$JSD = JSD_1 + JSD_2 \ .$$

In the first area, obviously,

$$JSD_1 = \frac{1}{2}\sum_{i=1}^{N} \log\left(\frac{w_i}{\frac{1}{2}\left(w_i + w_i\right)}\right) w_i + \frac{1}{2}\sum_{i=1}^{N} \log\left(\frac{w_i}{\frac{1}{2}\left(w_i + w_i\right)}\right) w_i = 0.$$

In the second area, respectively,

$$JSD_1 = \frac{1}{2}\sum_{i=1}^{N} \log\left(\frac{w_i}{\frac{1}{2} w_i}\right) w_i + \frac{1}{2}\sum_{i=1}^{N} \log\left(\frac{\hat{w}_i}{\frac{1}{2}\left(w_i\right)}\right) \cdot \hat{w}_i \to \frac{1}{2}\sum_{i=1}^{N} w_i.$$

Strictly speaking, the second term in the latter formula is not correct (you can consider the limit of expressions under the sign of the sum of when $\hat{w}_i \to 0$), but at the same time, we can make a fairly obvious conclusion that the Jensen-Shannon measure corresponds to the loss of information when summarizing and proportional to the total weight of the words (in our case – characters) included in the document, but missing in the abstract.

6 Comparison of Methods

When summarizing the new idea of determination of weight values of sentences on the basis of weights of separate hieroglyphs, but not words as it is standard was realized. Therefore, the quality of summarizing is checked not only proceeding from accounting of scales of separate hieroglyphs, but also taking into account scales of the whole words included in the documents and abstracts to be convinced that the offered approach is satisfactory also by criteria of traditional systems of summarizing. Naturally, this had to perform resource-intensive procedure of segmentation of words [20]. It should be noted that this procedure was performed only for quality check of algorithms of summarizing and is not a part of these algorithms.

The tests were conducted on a real array of legal information of the People's Republic of China in the amount of 10 thousand documents.

In Fig. 4-7 the results of the conducted tests are shown. In Fig. 4 and 6 are the results, when the models of documents and abstracts corresponded to vectors, elements of which - weights of individual hieroglyphs from the text of the document by $TF \cdot IDF$. In Fig. 5 and 7 – results, when elements of vectors correspond to weight values of words, segmented from texts of documents and abstracts. In Fig. 4 and 6 the results are given in accordance with the cosine measure of the proximity of the document and the abstract, and in Fig. 5 and 7, according to the Jensen-Shannon distance.

On the horizontal axis on all figures the number of sentences included in the abstract is marked. The vertical axis shows the values of the corresponding criteria, which are averaged throughout the document array. It should be noted that in all examples, as the first sentence of the abstract includes the title of the document, so the values with argument 1 for all four types of algorithms ($\sum tf \cdot idf$, Nearest, Network, Random) are the same.

As you can see, for comparison to the three above-mentioned algorithms, the Random method is added – compiling the abstract from the random sentences of the text (except for the first sentence – title).

The test results allow to summarize:

The proposed approaches lead to results, the quality of which is not lower, presented at the well-known conference on the analysis of texts TAC [12].

If the criterion of cosine measure of the proximity of the document and the abstract when taking into account the weight values of the individual hieroglyphs, the best results showed the method $\sum tf \cdot idf$ (which, of course, on the sum $TF \cdot IDF$ determined the weight of proposals, with the most significant included in the abstract), then by the same criteria, the proposed network method was the best way to take into account separate words of natural language.

	1	2	3	4	5	6	7	8	9	10
Σtf-idf	0.851	0.936	0.951	0.958	0.967	0.97	0.974	0.976	0.978	0.98
Network	0.851	0.9	0.936	0.951	0.962	0.967	0.97	0.973	0.975	0.976
Nearest	0.851	0.89	0.93	0.944	0.954	0.961	0.965	0.97	0.972	0.974
Random	0.851	0.888	0.907	0.92	0.942	0.952	0.955	0.957	0.964	0.966

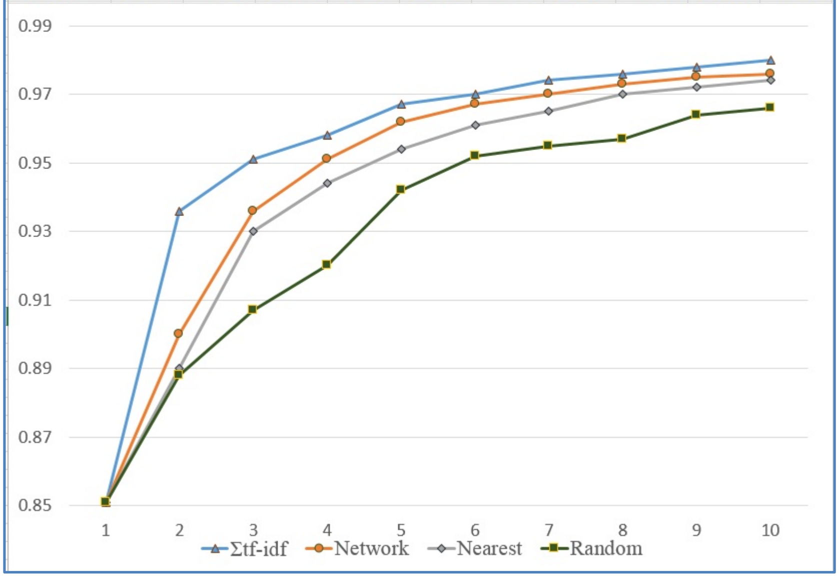
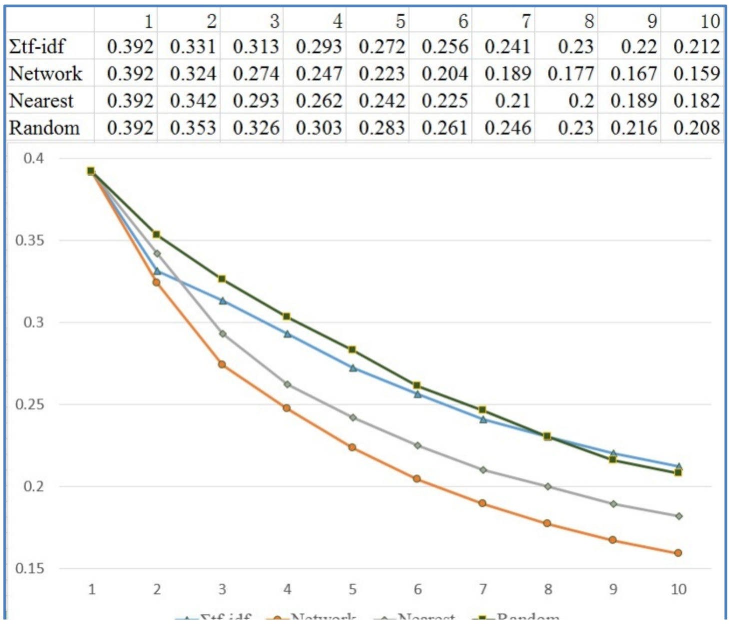
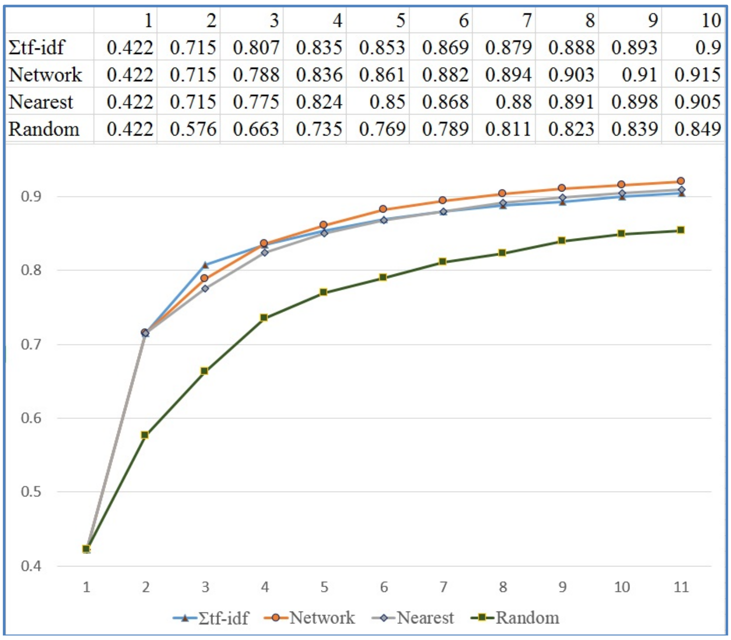


Fig. 4. A cosine measure of proximity of the text and abstract – accounting of the weight values of separate hieroglyphs.



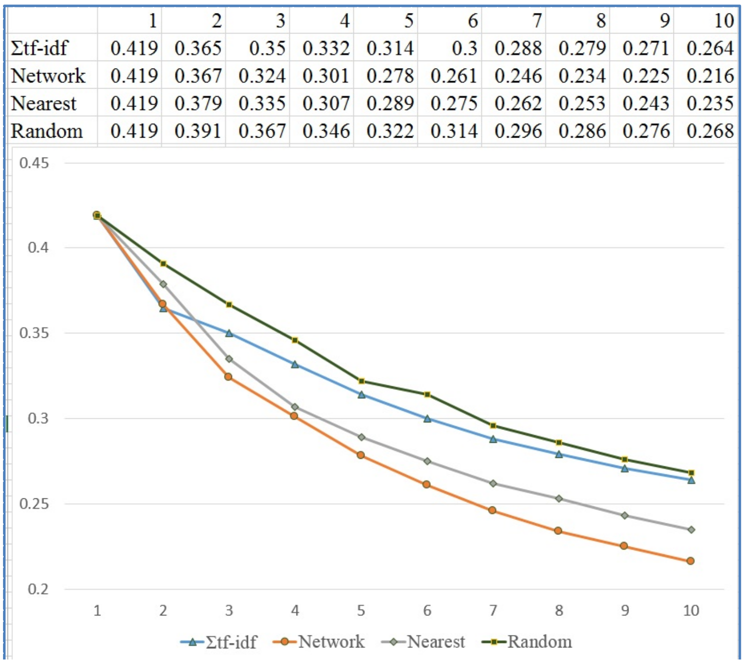
	1	2	3	4	5	6	7	8	9	10
Σtf-idf	0.392	0.331	0.313	0.293	0.272	0.256	0.241	0.23	0.22	0.212
Network	0.392	0.324	0.274	0.247	0.223	0.204	0.189	0.177	0.167	0.159
Nearest	0.392	0.342	0.293	0.262	0.242	0.225	0.21	0.2	0.189	0.182
Random	0.392	0.353	0.326	0.303	0.283	0.261	0.246	0.23	0.216	0.208

Fig. 5. Jensen-Shannon's divergence of loss of information when summarizing – accounting of weight of separate hieroglyphs.



	1	2	3	4	5	6	7	8	9	10
Σtf-idf	0.422	0.715	0.807	0.835	0.853	0.869	0.879	0.888	0.893	0.9
Network	0.422	0.715	0.788	0.836	0.861	0.882	0.894	0.903	0.91	0.915
Nearest	0.422	0.715	0.775	0.824	0.85	0.868	0.88	0.891	0.898	0.905
Random	0.422	0.576	0.663	0.735	0.769	0.789	0.811	0.823	0.839	0.849

Fig. 6. A cosine measure of proximity of the text and abstract – accounting of the weight values of separate words.



	1	2	3	4	5	6	7	8	9	10
Σtf-idf	0.419	0.365	0.35	0.332	0.314	0.3	0.288	0.279	0.271	0.264
Network	0.419	0.367	0.324	0.301	0.278	0.261	0.246	0.234	0.225	0.216
Nearest	0.419	0.379	0.335	0.307	0.289	0.275	0.262	0.253	0.243	0.235
Random	0.419	0.391	0.367	0.346	0.322	0.314	0.296	0.286	0.276	0.268

Fig. 7. Jensen-Shannon's divergence of loss of information when summarizing – accounting of weight of separate words.

7 Conclusions

We introduce a new hybrid method of automatic text summarization, covering statistical and marker methods, as well as taking into account the location of sentences in the text of the document. The offered model of the paper abstract reflects information need of customers during the work with legal information.

We brought the approach to determination of weights of separate hieroglyphs instead of segmented words in the text of documents. This technique avoids the expensive procedure of words segmentation required for other semantic methods of Chinese language processing.

Various methods of automatic text summarization are implemented and tested. Summarizing on the basis of the offered network model of the document was the best by criteria of a cosine measure and Jensen-Shannon's distances for papers which volume exceeds 2 sentences.

The offered approach, with minimal modifications, can be applied to texts on any subject of scientific, technical or news information.

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