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МОДЕЛИРОВАНИЕ ГОРЕНИЯ В РЕАКТОРЕ С ПОМОЩЬЮ КЛЕТОЧНЫХ АВТОМАТОВ

Проанализировано эволюцию сгорания топлива в ограниченном реакторе для системы с сильным перемешиванием вещества. Продемонстрировано тенденцию системы уменьшать общую длину фронта горения и подавлять меньшие диссипативные структуры большими. Показано, что малые тепловые шумы в системе воздействуют на эти структуры подобно повышенной диффузии. Так же выведена связь между коэффициентами, использованными в теоретической модели и стационарными кластерными образованиями.

Ключевые слова: процесс горения, обратная связь, равновесное состояние, диссипативные структуры,

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CLUSTERING OF CONCEPTS BY MEANS OF THE INTERNET

The approach to text information analysis using data from the Internet by example of clustering of concepts is considered in this paper. The problem of clustering of concepts is reduced to the problem of partition a graph into subgraphs in the case of not known in advance quantity of subgraphs. The algorithm of graph partitioning by the target function optimization is proposed, as well as the form of the target function for concepts clustering. The results are verified by experimental data.

Keywords: clustering, text analysis, graph partitioning, optimization.

Introduction. Possibility of automated text analysis is demanded by variety of problems. But a text is, as a rule, weakly formalized and its content can be defined only through the context, because the meaning of a specific word may differ depending on its interrelation with surrounding words. This fact causes impossibility of usage for creation such a text analysis system of the approach that is typical for compilers and interpreters of programming languages and requires existence of database which would integrate the concepts, words designating these concepts, and their interrelations. Such a database can be developed by transfer knowledge from a person or persons to some system that would save this knowledge in a suitable form. Difficulty and laboriousness of direct performing such a task is obvious.

Nevertheless human race has accumulated tremendous volume of mentioned above knowledge in the form of text. This form of data saving is comfortable and habitual for people but it cannot be used as automated knowledge base. That is why is seems natural to try to analyze existing texts and to build a database on their basis – this idea enables to take advantage of the work already made instead of doing it from the very beginning.

So the goal of the research is verification of proposed approach for building database on the example of semantic clustering of the concepts.

Generally, a text written by a person and appointed for understanding by other people contains concepts related in meaning. Respectively, a measure of cohesion for the pair of concepts can be obtained by means of analysis of frequency of appearance of the word pair in a text. In its simplest case, this approach cannot enable the construction of the knowledge base in a form offered in semantic web [1], when pair of concepts is connected by the third concept, but it gives the possibility to group the words to the clusters by themes.

At the moment the Internet contains huge amount of information. This fact, as well as simple access to this information, allows its using as the source of existing texts. A web page identified by URI is assumed as a text unit. With these assumptions, the task of separation the words into semantic clusters is reduced to the analysis of frequencies of appearance of the word pairs at the same URI and then to the association of the words into groups according to their meanings.

Thus, the problem is formulated in terms of concepts (represented by appropriate words) and measure of cohesion between these concepts. It makes possible to consider the set of input data as a weighted graph and reformulate the problem to the problem of optimal partition of the graph into subgraphs by criterion of "semantic cohesion". This problem is of NP-complete problems type, so precise methods, e.g. brute-force search, have no use because of their computational complexity.

Practically applicable algorithms of partitioning the graph, as a rule, allow finding not a global optimum for the task but some optimal result satisfactory for practice or, in more difficult cases, some optimum that can be obtained in limited time. In this way, precision and accuracy of algorithm is superseded by speed at the expense of the fact that direction of further search of optimum is defined in every local point. In result, the algorithm cannot assure finding of a global optimum and more, the result depends on a choice of the initial point.

Development and discussion.

Quality criteria of graph partitioning. Semantic cohesion and respectively optimal partitioning for semantic cohesion are not the determined concepts and cannot be strictly defined because of subjectivity of concept of meaning of a word per se. But solving the problem demands to determine some, though subjective, quality measure of optimal graph partition.

Some requirements for graph partitioning may affect properties of this subjective quality measure. These requirements can be formulated as follows:

- Graph vertices inside a cluster must be bound more strongly than vertices from different clusters.
- Clusters have not obligatory equal sizes, the more so the themes corresponding to clusters can contain different quantities of concepts.
- Quantity of clusters is not known in advance.

Nevertheless, there is need in some reasonable expectations about quantity of clusters. The matter is that all the concepts are connected somehow or other and, therefore, all of them have to be united in the only cluster. On the other hand, every concept differs from others and, therefore, has to be contained in individual cluster. These are extreme two cases of the choice of threshold value of cohesion at which concepts are united in a cluster. Obviously, the value of threshold cohesion affects quantity of clusters, i.e., scale at which all the system is considered. It is clear as well that a single objective function, suitable for all possible cases, cannot exist and that the objective function has to depend on the parameter which determine where is the boundary between different themes (and corresponding clusters). Evidently, this parameter has to be chosen on the basis on the characteristics of specific problem.

Some arbitrary threshold value of cohesion measure can be used in certain situations. But such an approach has an obvious disadvantage: the value is not absolute and can be determined in different ways, not to mention that the unit of measurement of this threshold value cannot be clear defined.

Another approach is to use as a threshold parameter one of interdependent values, namely, the quantity of clusters and average size of a cluster. Both of the values are intuitive, are measured absolutely and defined uniquely. Of these two, usage of the quantity of clusters is more convenient, as this value does not depend on the quantity of graph vertices.

Existing methods of graph partitioning. Actually, there exist different methods of graph partitioning, the best known are Kernighan-Lin algorithm, multilevel algorithms and spectrum algorithms.

- Kernighan-Lin algorithm [2] is used for partitioning a graph into two subgraphs of the same size. The main feature of this algorithm is minimization of sum of the weights of "disrupted" edges between the subgraphs. Fiduccia-Mattheyses algorithm is an improved version of Kernighan-Lin algorithm in case of hypergraphs.
- Multilevel algorithms are based on the idea of the graph simplification, allocation features of the largest possible size and finding solution at this level with further detailed specification of it. This idea allow speed-up versus brute-force search at the expense of inaccuracy caused by neglecting the details. One of examples of such algorithms is METIS [3].
- Spectrum algorithms are based on analysis of quantity of edges with certain weight and divide all the edges into two groups: the inner edges of the cluster and the edges connecting vertices that belong to different clusters. In fact, these algorithms are very similar to graph partitioning using histograms.

Nevertheless, any of the above-mentioned algorithms cannot be used for solving the task. The main reason is that all these algorithms demand to determine in advance the quantity of future subgraphs. For some of the algorithms the quantity of resulting parts have to be set immediately, other allow to determine it in a few iterations by serial bisection. Realization of the last schemes also leads to that the sizes of resulting clusters are the same or, even if they are not the same, they cannot depend on cohesion of vertices inside the clusters.

Thus, the existing algorithms are insufficiently flexible for partitioning a graph into not equal or somehow preliminary restricted parts, but in some more or less natural way. It leads to necessity to propound another algorithm for the problem of semantic graph partitioning.

Description of the algorithm. The algorithm, as well as other existing algorithms of graph partitioning, is not precise. In the framework of propound approach, the problem is defined as optimization problem with some target function which is the quality measure of partitioning of graph into subgraphs. The algorithm is sequential and action that is made at each step of it is chosen as an operation that maximally changes the target function towards its optimum value. The algorithm is stopped when there is no operations that tends the target function towards the optimum. So, it is obvious that during evaluation the algorithm the local optimum matters and the system as a whole not necessarily reaches the global optimum, but the result depends on the choice of initial state of the system.

As a trivial example of the initial state of a system can be used the state when each vertex is considered as a self-sustained cluster.

The algorithm as a whole consists of the following parts:

- moving the vertices between the clusters. This action can be possibly applied to all the vertices in graph, if it leads to optimizing the target function;
- merging the clusters. This step is useful in case when relocation of a single vertex does not tend the target function towards the optimum, but relocation of a set of vertices do it;
- deleting the zero-sized clusters that appeared because of different relocations.

This algorithm can be generalized for applying in the case when the whole data is not known immediately, but appears gradually. Then graph partitioning is made in the above-described manner with initial state of data, and after appearing a new portion of data the clusterization is repeated in the same way with the new data included in the system.

Such gradual partitioning allows considering changes in data in less time than solving the problem from the very beginning for each portion of new data. This variation of algorithm has certain inertia and is also useful in a situation when sharp change in way of partitioning the whole graph into clusters, which can be caused by re-partitioning the graph from the very beginning at each addition of new portion of data, is unacceptable.

Target function. As it was mentioned above, the quality of partitioning is a subjective value, which cannot be strictly defined. Because of this fact, the choice of target function was made on the base of quality, not necessarily precise and unconditional, considerations. As a target function in this paper we use the following function:

$$F = -Qf \cdot \sum_{i=1}^{N_c} \sum_{j=1}^{S_i} \sum_{k=1}^{S_i} A_{jk} + \sum_{i=1}^{N_c} S_i^2 + Sf \cdot N_c \ , \qquad (1)$$

where N_c is a quantity of clusters, S_i is a quantity of vertices in the *i*-th cluster, A is the adjacency matrix of the graph, Qf and Sf – some parameters, described below. We also use minimum of the function F as an optimal value of the target function, and measure of cohesion between the vertices connected by an edge as the weight of this edge. Due to the statement of the problem the weights of the edges should be nonnegative.

Nonnegative parameters Qf and Sf are necessary for adjusting the contribution of every of the three terms of target function (1). The third possible parameter is excessive because of existing possibility of normalization the function, as all that matters for the problem solution is the fact that the target function reached its minimum, and the specific value of this minimum is inessential.

The term $\sum_{i=1}^{N_c} \sum_{j=1}^{S_i} \sum_{k=1}^{S_i} A_{jk}$ is the sum of weights of inner edges of a cluster. It corresponds to the requirement for internal connections between vertices of the cluster to be stronger than external connections. This term is proportional to the measure of cohesion between vertices inside the cluster. The sense of this term and minus sign before it is what determines that optimum of the target function (1) is its minimum value. Hence, the parameter Qf determines the importance of cohesion of vertices inside a cluster with respect to other terms of the target function.

But all the foregoing does not allow accounting the second part of the requirements, namely, the weak coupling between clusters. And obviously, in the case of existence of only the first term in the target function the optimal value is reached as long as the entire graph is the only cluster. Another disadvantage of hypothetical target function in the form of only the first term is that dependence of this term on the size of clusters is quadratic, as the quantity of possible edges, excluding loops, in case of undirected graph is $\frac{1}{2} \cdot S_i \cdot (S_i - 1)$), and it also results in achieving the optimal value of this hypothetical target function in case of the only cluster.

The term $\sum_{i=1}^{N_c} S_i^2$ is introduced to eliminate above-mentioned issues. So, the term $\sum_{i=1}^{N_c} S_i^2$ is the total quantity of possible edges in all the clusters (up to a factor and considering loops). This term counteracts to quadratic increase of the first term, representing total cohesion, as negated to it.

The third term in (1) is introduced for regulation of an average size of a cluster, and parameter Sf represents the ideal desirable size of a cluster (detailed explanation can be found below).

For investigation of characteristics of the target function let assume that $Qf = 0$. Then the target function takes the form

$$F = \sum_{i=1}^{N_c} S_i^2 + Sf \cdot N_c \, . \qquad (2)$$

As in specified case the role of cohesion between vertices in the clusters is neglected, it is possible to consider the case of equal size of all the clusters without loss of generality. If $\overline{S}$ designates the size of a cluster in this case, then quantity of clusters of the entire system will be $N_c = \frac{N}{\overline{S}}$, where N is the total quantity of graph vertices. Then the target function can be transformed to the form

$$F = N_c \cdot \left(\frac{N}{N_c} \right)^2 + Sf \cdot N_c \, , \qquad (3)$$

and it reach its minimum value at

$$N_c = \frac{N}{\sqrt{Sf}} \qquad (4)$$

(discreteness is neglected here). At non-zero value of parameter Qf the real quantity of clusters can differ from (2), because increase of the level of cohesion inside clusters can require increase or decrease quantity of clusters. Thus, it can be said that parameter Sf determines recommended size of a cluster, but rigidity of this recommendation is regulated by correlation of parameters Sf and Qf.

Thereby, existence of all the three terms in (1), as well as parameters Sf and Qf give desired flexibility to proposed algorithm in contrast to mentioned known algorithms. This flexibility allows us to apply algorithm described in this paper for so poorly formalized problem as construction of connections between words.

Usage of the target function in the form (1) is impractical. The reason of it is the fact, that in this form the target function depends not only on the injected parameters but also on the size of the system under consideration, and this dependence results in instability of ratio of terms contribution in the ending value of the target function. Evidently, it leads to inconvenience at choosing parameters values.

For stabilizing the ratio of terms contribution regardless of size of the system it is appropriate to multiply parameter Qf to the minimum value $F_{min} = 2 \cdot N \cdot \sqrt{Sf}$ of the target function (3) in case of $Qf = 0$.

Thus, finally the target function takes the following form:

$$F = -Qf \cdot 2 \cdot N \cdot \sqrt{Sf} \cdot \sum_{i=1}^{N_c} \sum_{j=1}^{S_i} \sum_{k=1}^{S_i} A_{jk} + \sum_{i=1}^{N_c} S_i^2 + Sf \cdot N_c \, . \qquad (5)$$

Implementation and usage. For experimental approbation of foregoing considerations there was created the program in C++ language. The program is serial but it can be simply parallelized. For the system containing approximately 17000 words (i.e., $N \approx 17000$) the performance of the algorithm on a single core processor Intel Xeon E5620 is about 20 minutes, memory consumption is about 1,2 GB. The choice of C++ was caused by significant resource consumption of the problem. It results in good performance of the program relative to other higher-level programming languages but required more time for the program development. Nevertheless, due to good performance the time required to conduct experiments for the selection of the target function and its parameters was reduced.

As it was mentioned in the introduction, the Internet was used as a source of texts. But loading all the existing pages from the Internet and construction on its base the adjacency matrix for all the words is too difficult both from a technical point of view and in terms of the resources. That is why services of existing search providers [4] were used as a filter for limiting the huge volume of information.

Conclusions.

- Algorithm of partitioning a graph into subgraphs can be realized through optimization of some target function.
- The proposed target function allows taking into account reasonable factors of constructing the clusters of related concepts.
- The proposed algorithm of partitioning a graph into subgraphs allows to solve the problem of finding the clusters of related concepts in an acceptable period of time.
- Texts available on the Internet can be used for grouping semantically connected concepts.

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КЛАСТЕРИЗАЦІЯ ПОНЯТЬ З ВИКОРИСТАННЯМ МЕРЕЖІ ІНТЕРНЕТ

У роботі розглянуто підхід до аналізу текстової інформації з використанням даних із мережі Інтернет на прикладі кластеризації понять. Задачу кластерізації понять зведено до задачі розбиття графа на підграфи з невизначеною наперед кількістю підграфів. Запропоновано алгоритм розбиття графа на підграфи шляхом оптимізації цільової функції. Запропоновано вигляд цільової функції для опису кластерізації понять. Результати перевірені на експериментальних даних

Ключові слова: кластеризація, аналіз тексту, розбиття графа на підграфи, оптимізація

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КЛАСТЕРИЗАЦИЯ ПОНЯТИЙ С ИСПОЛЬЗОВАНИЕМ СЕТИ ИНТЕРНЕТ

В работе рассмотрен подход к анализу текстовой информации с использованием данных из сети Интернет на примере кластеризации понятий. Задача кластеризации понятий приведена к задаче разбиения графа с изначально неизвестным количеством подграфов. Предложен алгоритм разбиение графа на подграфы путём оптимизации целевой функции. Предложен вид целевой функции для описания кластеризации понятий. Результаты проверены на экспериментальных данных.

Ключевые слова: кластеризация, анализ текста, разбиение графа на подграфы, оптимизация.

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OUT-OF-PLANE ANGULAR DEPENDENCE OF FERROMAGNETIC RESONANCE OF PERMALLOY THIN FILMS

Out-of-plane ferromagnetic resonance (FMR) spectra of Permalloy films 25, 50, 75 and 100 nm thick were measured. The angular dependence of FMR was analyzed using Landau–Lifshitz–Gilbert (LLG) equation. With increasing film thickness, the contribution to linewidth of two magnon scattering increases.

Key words: ferromagnetic resonance, Permalloy, thin film, linewidth.

Introduction. Improving the technology of thin magnetic films allows their use in spintronic devices and microwave technology. Therefore there is an interest in their studies. As a powerful technique, ferromagnetic resonance (FMR) has been employed to study magnetic anisotropy, interlayer coupling, magnetic relaxation, film quality, and so on [1, 2]. Three mechanisms have been considered to contribute to the linewidth [3–4, 7–9]. As the first contribution, intrinsic Gilbert damping, resulting from a combination of the exchange interaction and the spin–orbit coupling, exists in all magnetic materials. The second contribution to the FMR linewidth arises from the broadening induced by magnetic inhomogeneity, such as the spread of the magnitude of the magnetization or the internal static magnetic field, and the orientation of the crystallographic axes or magnetic anisotropy axes. This part strongly depends on the preparation condition and thus the film quality [5]. As the third contribution to the linewidth, the so-called extrinsic magnetic relaxation has been argued to originate from the coupling between the uniform resonance modes and degenerating spin waves through structural inhomogeneity. This phenomenon is called two-magnon scattering process [6]. Since the contributions of the intrinsic damping effect and the extrinsic magnetization relaxation, and the inhomogeneity originate from different mechanisms, they have different out-of-plane angular and microwave frequency dependence. Therefore, they should be able to be analyzed and discerned from the measured FMR linewidth.

Experimental results and discussion. The samples were prepared by Electron Beam Evaporation (EBE) and have 100, 75, 50 and 25 nm of thickness. FMR measurements were carried out at room temperature using a Bruker E580 EPR spectrometer, with a fixed microwave frequency of 9.45 GHz. The goniometer was used to vary the angle. Thus the angular dependence of the resonance field and the linewidth were obtained.

Figure 1 shows the sample oriented relative to some right-handed *X-Y-Z* frame such that the sample normal is parallel to the *Z* axis. External magnetic field H_{ext} and magnetization M_s lies in ZY plane. θ_H is the angle between H_{ext} and the sample normal Z, θ_0 is an angle between M_s and Z. The angle θ_H changes in range of 0^o – 90^o.

The angular dependence of FMR spectra can be obtained by using the LLG equation[1]:

$$\frac{\partial \vec{M}}{\partial t} = -\gamma \vec{M} \times \vec{H} + \frac{G}{\gamma M_S^2} \vec{M} \times \frac{\partial \vec{M}}{\partial t} \quad (1)$$

Here M_S is saturation magnetization, $\gamma = g\mu_B / h$ and G are the gyromagnetic ratio and the Gilbert damping coefficient, respectively. Using this equation, the resonance conditions can be written follow:

$$\frac{\omega}{\gamma} = \sqrt{H_1 H_2}\ , \quad (2)$$

$$H_1 = H_{res}\cos(\theta_H - \theta_0) - 4\pi M_{eff}\cos(2\theta_0)\ , \quad (3)$$

$$H_2 = H_{res}\cos(\theta_H - \theta_0) - 4\pi M_{eff}\cos^2(\theta_0)\ , \quad (4)$$

where H_{res} is the resonance magnetic field, $4\pi M_{eff} = 4\pi M_s - H_A$ and H_A are the effective demagnetizing field and anisotropy field.

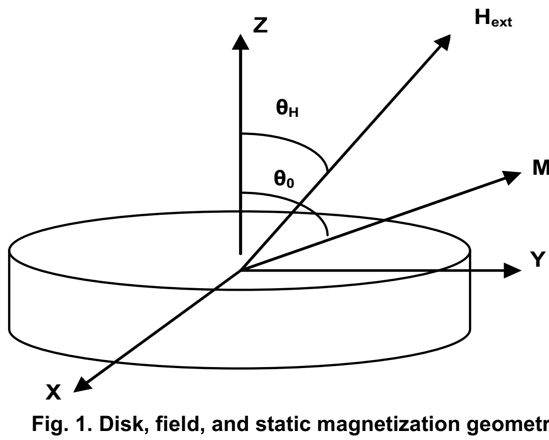

Fig. 1. Disk, field, and static magnetization geometry for the static equilibrium and FMR analysis

The condition for static equilibrium is found if the net torque on M_S is set equal to zero. The net torque is a result of the external field, the demagnetization field, and the anisotropy which acts to pull the magnetization into an easy direction. This condition yields an expression which relates the field and magnetization angles θ_H and θ_0:

$$2H_{res}\sin(\theta_0 - \theta_H) = 4\pi M_{eff}\sin(2\theta_0) \quad (5)$$

Values of the effective magnetization $4\pi M_{eff}$ can be determined from (2) attached to normal film orientation.