Розглянут проблем проектув н-ня інтелекту льної системи комерційного поширення інформ ційних продуктів із з стосув нням персон лізов ного підходу до відвідув чів н основі к тегорій т тегів цік вого відвідув ч м контенту. Розроблен з г льн типов рхітектур відповідної системи з використ нням методів т з собів персон ліз ції в Інтернет-середовищі із ядром втом тичного рекомендув ння тегів (к тегорій) у вигляді нейромережі з контрольов ним н вч нням. Персон лізов ний підхід до користув ч с йту призводить до більш високого коефіцієнт прод ж. Розроблен систем н основі суч сних методів SEO-технологій з вр хув ння метрик оцінюв ння роботи інформ ційно-пошукового модуля системи дозволяє підбир ти релев нтний контент згідно інтересів персон лізов ного користув ч . Систем володіє кл с ми т підкл с ми, до яких н леж ть ре льні комерційні інформ ційні продукти, між якими побудов ні логічні зв`язки, з допомогою яких відбув ється інтелекту льн под ч контенту н основі персон ліз ції потреб т з цік влень користув ч . Т кож н основі суч сних методів Machine Learning розроблен систем н вч ється уточнюв ти результ ти пошуку з требув ного контенту згідно персон ліз ції вподоб нь користув ч . Алгоритми персон ліз ції дозволяють пов'яз ти кожного користув ч з списком продуктів, які н йімовірніше його з цік влять, т кож можуть прогнозув ти те, що клієнти можуть хотіти б чити, н віть якщо ще не зн ють про це. Метою інтелекту льної системи е-комерції є под ч унік льного контенту н основі підходу персон ліз ції т використ ння тегів. Окрім звич йного текстового введення к тегорій т тегів н основі зобр жень т опису продукту, розроблений процес втом тиз ції визн чення тегів т к тегорій тов ру. Розпізн в ння контексту з допомогою глибоких нейронних мереж тепер з безпечує технологію втом тичного дод в ння тегів в описи тов ру с йтів е-комерції. Методи можн використовув ти для кл сифік ції міміки і розпізн ння емоцій

Ключові слов : комерційний контент, персон ліз ція, Machine Learning, SEO-технологія, метрики пошуку, електронн комерція, NLP

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DESIGN OF THE ARCHITECTURE OF AN INTELLIGENT SYSTEM FOR DISTRIBUTING COMMERCIAL CONTENT IN THE INTERNET SPACE BASED ON SEO-TECHNOLOGIES, NEURAL NETWORKS, AND MACHINE LEARNING

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1. Introduction

Recent years have witnessed the increasing effectiveness of search features and navigation as regards the Internet e-commerce [1]. It is an important component of successful strategy of e-business [2]. Companies increase their own investments into the personalization of the Internet content, because they recognizes a series of advantages of this effective technology for e-business [3]. Search keywords from consumers ensure, in real time, a deeper understanding of the behavior of the target audience and provide the company with invaluable data for future research and use [4]. The information on behavior of the target audience, if successfully applied, is very valuable because it increases sales volume and the number of loyal customers [5].

Personalized approach to the Internet-resource user greatly increases sale coefficients [6]. That is, those clients that cannot find the required information leave a Web-resource unsatisfied and would probably never visit it again, given the extremely competitive Internet market [7]. Paper [3] found that up to 40 % of visitors usually use the search feature on a Web-resource, thereby demonstrating their intentions to buy a product using its title or code [8]. The home page and search page on a Web-resource are the best positions to place blocks with recommendations [9].

Therefore, obtaining the required results from personalized search and further analysis by means of artificial intelligence based on SEO technologies, neural networks, and Machine Learning, is essential for the successful development of e-business [10]. E-commerce employs Machine Learning to improve recommendations for consumers as the regular/potential visitors of a Web resource [11]. The methods of Machine Learning significantly improve analysis of results from the previous personalized search each time the user visits a Web resource. Generating a search topic rating makes it possible for a Web-resource to sort out results for estimated relevance. This estimate takes into consideration specific search terms, as well as the specific features of the respective user's profile (such as age range, gender, previous orders, preferences and previous search terms). The personalization algorithms make it possible to associate each user with the most probable list of goods/services according to his needs and interests. These algorithms also make it possible to predict customer wishes, even if they are not aware of them or have no idea at all [12]. In addition to the usual text entry of categories and tags based on images and description of goods/services, a more viable option is to add automation processes and decision making systems for the identification of wishes by the user of a Web resource [13]. Scientific advances concerning the recognition of context using deep neural networks now provide the technology of auto-tagging the descriptions of goods on the Internet e-commerce site [14]. In addition, these methods are used to categorize facial expressions and emotion recognition of Web resource users [15]. The purpose of an intelligent system of e-commerce is to provide unique content based on user personalization and on applying the appropriate tags for training a neural network.

2. Literature review and problem statement

Twiggle uses natural language processing to improve search results for buyers of goods on the Internet. Clarifai in the United States also improves the search process in e-commerce [16]. The project uses visual search elements and the so-called artificial intelligence with a prediction. The latter makes it possible for developers to create intelligent applications that "see the world as you", thereby making it possible for companies to develop customer-oriented experience through advanced image recognition and video [17].

By using the technology of Machine Learning, software employs artificial intelligence to automatically adds tags, organize and search content, by marking the properties of an image or a video [18]. Referral process is widely practiced in e-commerce to help clients find the best solution [19]. For example, Amazon generates personalized recommendations to users depending on their activities at the Internet-site and previous purchases [20]. Netflix creates personalized content for tv and the movies based on the interaction between the user and a genre [21]. Providing personalized recommendations help users find an object of search, saving their time and resources, as well as creating an atmosphere of trust and personal attention to each visitor of a Web-site [22]. This makes it possible to increase the volumes of visitors and expand the circle of loyal consumers of the relevant e-commerce.

The effectiveness of implementing artificial intelligence to personalize the prediction of user wishes in the results of searching for a product heavily depends on the operation of an information retrieval system embedded to a Web-resource. A standard assessment of information-retrieval systems includes such components [23] as a collection of:

– content of the Internet e-commerce site [24];

– test informational needs in the form of queries by users [25];

– estimated relevance, represented in the form of binary assertions on relevant/non-relevant relative to each pair request-content (reference (gold standard) relevance assessment) [26].

An approach to evaluating information-retrieval systems is based on the concept of relevant/non-relevant content according to the end user personalization [27]. According to the informational needs by users, content from a test collection undergoes binary classification: relevant or non-relevant [28]. Relevance (from English: relevance) is the degree of conformity of the result obtained to the result desired [29]. That is, it is a measure of compliance between the results of query from the personalized user [30]. A collection of test content and queries must be of a sufficient size: the larger the test sample, the more accurate the evaluation of quality of operation of the personalized search algorithm [31]. To assess the quality of work of an information-retrieval system, different estimates are used [32]. In this case, the best algorithm is the one for which the personalized output of search results, generated by the system, are close to the user's conclusions [33]. The most commonly used metrics for evaluating the operational quality of systems based on user needs are [34]:

– recall [35];
– precision [36];
– average precision [37];
– precision at the level of 5 content articles [38];
– precision at the level of 10 content articles [39];
– R-precision [40];
– 11-point matrix (TREC) [41];
– modified 11-point matrix (RIRES) [42].

To categorize information-retrieval systems, most often used are recall, precision, accuracy, error, and F-measure [43]. Most of these metrics are explored in detail [44]. However, the interpretation of these estimates often varies [45]. Therefore, we shall provide a detailed description of each metric within the personalized search when applied to a single query (category). Next, by averaging the metrics to obtain the integrated quality indicators for search/classification. Most metrics, when estimating the content-based search, are based on the matrix of classification given in Table 1 (Fig. 1), where a is the amount of content found by the system and which is relevant to the user; b is the amount of content found by the system, but non-relevant to the user;

c is the amount of relevant content, not found by the system;
d is the amount of non-relevant content, not found by the system [46].

Table 1

Main document categories

Amount of content	Relevant	Non-relevant
provided for a query	a (correctly provided content)	c (provided content, non-relevant for a given category)
not provided for a query	b (incorrectly provided content)	d (not-provided and non-relevant content)

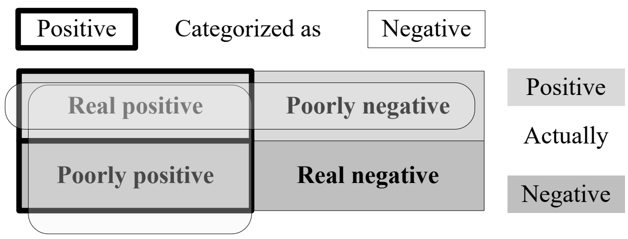


Fig. 1. Content categories

We shall consider each metric in detail.

Recall is calculated as the ratio of the found relevant content to the total amount of relevant content [47]. This is the capability of the system to find the content desired by user, but it does not account for the amount of non-relevant content provided to the user. For example, if *Recall*=50 %, then half of the relevant content was not found by the system [48].

$$Recall = \frac{a}{a+c}.$$

Precision is calculated as the ratio of the found relevant content to the total amount of the found content [49]. This is the capability of the system to produce only the relevant content in the collection of results. For example, if *Precision*=50 %, then a half of the found content is relevant and a half is not relevant [50].

$$Precision = \frac{a}{a+b}.$$

Accuracy is calculated as the ratio of decisions, correctly made by the system, to the total number of decisions [51]. Since it is assumed that the system makes a decision on that each content within a collection belongs to a given category. Thus, the denominator does not depend on a given category. When calculating an estimate, the denominator used is the total amount of content, which was estimated for at least one category [52].

$$Accuracy = \frac{a+d}{a+b+c+d}.$$

Error is calculated as the ratio of decisions, incorrectly made by the system, to the total number of decisions [53]:

$$Error = \frac{b+c}{a+b+c+d}.$$

F-measure is used as a unified metric that combines *Recall* and *Precision* in a single metric for this query (category) [54]:

$$F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} = \frac{2 \cdot \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}.$$

Main features in the metric F for $0 \le F \le 1$ [55]:
– if r=0 or p=0, then F=0;
– if r=p, then F=r=p;
– $\min(r,p) \le F \le \frac{r+p}{2}$.

A general formula for the F-measure is calculated from [56]:

$$F_\beta = (1+\beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}.$$

In the case of classification and filtering, the text search employs a method for **averaging multiple metrics**.

1. Macroaverage: compute metrics for each query separately and then average them [57]. Characteristic of evaluating search tasks [58], in which an important result is based on average for the query, regardless of the power of a response to this query [59].
2. Microaverage: find the total amount of content based on a category from Table 1 and calculate the desired metric [60]. Characteristic of evaluating the categorization and filtering where the volumes of queries are considered [61].

Metrics for a collection of content, sorted by relevance, take into consideration not only the fact of the presence of content in the list of that found, but its position in the collection [62].

Precision of content at level *n* (*precision n)* is defined as the amount of relevant content among first n of the provided content divided by n [63]. If the system provided $k>n$ content, then *precision* (n)=*Precision* of the system based on first n of content for query results [64]. If the system provided $k<n$ content, then *Precision* at level of n content would not exceed the system's *Precision*. *Precision* of content at level n describes the capability of a system to produce relevant content at the beginning of results collection [65]. For example, if the system provides <10 content at the first page, *precision* (10) reflects the quality of the system's results, which are obtained at the first page. This metric has a series of disadvantages. In particular, for different queries, the metrics of *precision*(n) are not comparable. For example, for a system that produces relevant content only, *precision*(100)=0.2 for the query which has 20 relevant content, and *precision*(100)=0.3 for the query that returned 30 relevant content. Despite the shortcomings, precision at level is an indispensable metric for search systems since it makes it possible to estimate the usefulness of the first page in the system's response to a personalized user [66].

R-precision equals precision of content at level n for n equal to the amount of relevant content for a given query [67]. This metric replaces precision at level in those cases when it is necessary to account for a big difference in the amount of relevant content for different queries [68].

Average precision for a query is defined from [69]: let a query returns k relevant content. Precision at the level of the i-th relevant content *prec_rel*(i) equals *precision*(*pos*(i)), if the i-th relevant content is in the query results on position *pos*(i). If the i-th relevant content is not found, then *prec_rel*(i)=0. The average precision for this query is equal to the average value for magnitude *prec_rel*(i) for the entire k relevant content [70]:

$$AvgPrec = \frac{1}{k}\sum_{i=1}^{k} prec\_rel(i).$$

Basic features of metric *average precision* [72]:

– $AvgPrec \le$ recall;

– if relevant content is only at the beginning of the collection of results, then $AvgPrec \approx$ recall;

– if relevant content is evenly distributed in the collection of results, then $AvgPrec \approx$ precision·recall;

– the amount of content ranked below the last relevant does not affect the values (the "tail" is truncated).

Average precision makes it possible to evaluate operational quality of the system, taking into consideration the priority of highly ranked content against those documents that are at the end of the collection. In contrast to the metrics *precision*(n) and *R-precision*, the average precision takes into consideration the entire found content [72].

Using the personalized recommendations on a Website based on the results of relevant, topical, and precise search instead of standard navigation would be of interest to modern average consumer in order to return to such a convenient service when time saving is quite a significant indicator for the informatization of society. If a use, while making a purchase with specific intentions and needs, is given an automatic service for quick and easy orientation in the collection of goods/services in accordance with his history of requests and previous purchases, then he is more likely to return and recommend this Web-resource to others. If the user at the beginning is presented with novelties from the categories of interest to him in the form of a conveniently arranged content modules for viewing, the chances to draw attention dramatically increase. Every new purchase from a particular Web-resource provides the system with better personalized information about the consumer, for example, categories of products/services, criteria for purchasing/ordering, price range, size, form of delivery, etc. By using Machine Learning, the system learns from a specific consumer to recommend him, during his next visit, a collection of goods/services better adapted to him.

Each user has different requirements for content regarding a query. However, typical search engines return the same result for the same request from different users. Intelligent search engines take into consideration the so-called cookies in the users' browsers thereby refining the result of relevant content. However, this will not solve the task for e-commerce, as HTTP-Cookies contain either too much or too little information so that the user could place an order not from his computer. To solve the problem of information overload and to provide users with relevant information, Web-personalization is applied. It increases the accuracy of a search engine at the Internet e-commerce site, simplifying the process of individual search, saving time, and providing users with relevant content. Personalization creates a sense of individuality and uniqueness. Customers feel special and important, as if a company does care about them. By segmenting and targeting different buyers, personalization meets different needs by each client, thus optimizing the user experience, as well as the average experience for all. The object of this study is the application of neural networks for creating tag-recommendations and using personalization tools available in the market. The subject of this research is the automation of the process for forming personalized recommendations to the end regular user of the Internet e-commerce site.

3. The aim and objectives of the study

The aim of this study is to design an architecture of the intelligent system for distributing commercial content in the Internee space based on SEO technologies, neural networks, and Machine Learning.

To accomplish the aim, the following tasks have been set:

– to define general functional requirements to the architecture of the system for distributing commercial content in the Internet space;

– to construct a method of personalization of commercial content according to the needs of the user;

– to develop software support for distributing commercial content in the Internet space based on SEO technologies, neural networks, and Machine Learning;

– to analyze results from experimental testing of the proposed method for the personalization of commercial content according to the needs of the user.

4. General functional requirements to the architecture of an intelligent system for distributing commercial content according to the needs of the user

Personalization can be improved in two stages.

1. Generate the most relevant collection of content.

2. Classify the appropriate content for the needs and desires of the user and demonstrate it in a convenient form in the process of flipping through the pages by a user to avoid selecting non-relevant content or losing time searching for relevant personalized content.

A Web resource user uses e-commerce service to make purchases for convenience, to save time and effort. Improving the conditions of cooperation with each end user would make it possible to significantly simplify the process of doing business and could reduce the effort required from the user to search for what he needs.

The most common activities by a user of the Internet e-commerce site are reviewing products, making purchases, and registration of clients (Fig. 2). A unit that registers customers makes it possible to get discounts or invitations to closed sales. A unit for viewing the goods includes adding the search tags. The client can also search for products, view a product list, view recommendations, add products to a shopping cart or a wish list.

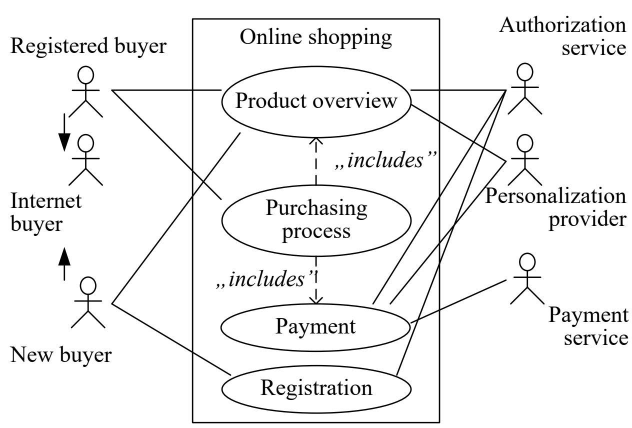


Fig. 2. Use case diagram for the Internet e-commerce site

A unit for adding the search tags is expandable using the automated generation of recommended tags, and includes forming a product (Fig. 2). A unit for client authentication includes a unit to view recommended products and those added to a wish list, because both require the authentication of a client. At the same time, a product can be added to a shopping cart without checking the authenticity of the user. A decision-making system for the Internet e-commerce site ensures that adding each new product by a content-moderator provides rendering of the expanded description of products. In addition, it yields appropriate recommended categories and tags using synonymic options. A synonymic series is determined through a neural network and the Machine Learning algorithms. An example of application is the implementation based on .Net CMS Sitecore, which has personalization tools that can be extended, as well as to add new rules, based on available core-functionality.

A home page at Fig. 4 includes units with typical content: video, courses, books, published articles. It is extended with a personalization unit, which includes various versions of the aforementioned content and thus includes the unit "changed content at the home page". In addition, a unit of the personalized content is extended with a unit of saved tags in Sitecore, because these tags underlie the execution of personalization rules. A personalization unit is also extended with specified units of categories and subcategories that are also stored by the CMS Sitecore and are related to the unit "tags saved in Sitecore".

A unit to add a product is extended with a description of this product (Fig. 5). A product description is extended with the unit "neural network of recommended tags".

The purpose of the diagram essence–relation is the introduction of certain general data for the Internet e-commerce site: client, Web-user, account, cart, product, categories, tags, as well as relations among them (Fig. 6). Each client has a unique identifier that is associated with exactly one account. A customer can sign up as a Web user to purchase goods on the Internet. A Web-user has a login name, which is a unique identifier as well. A Web-users can exist in several states: new, active, temporarily blocked. A client can have no orders, not the history of previous searches or page views. Customer orders are sorted and are unique.

Products have tags that define them, as well as categories to which they belong. Each product may refer to a single category and have many tags.

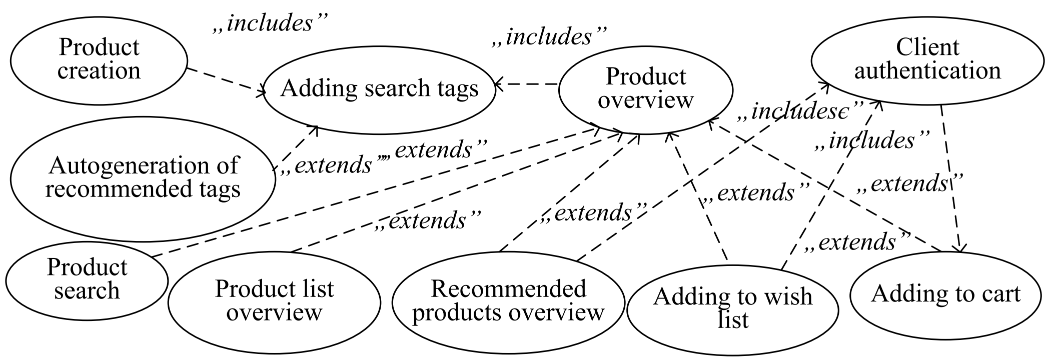


Fig. 3. Use case diagram for a product overview unit

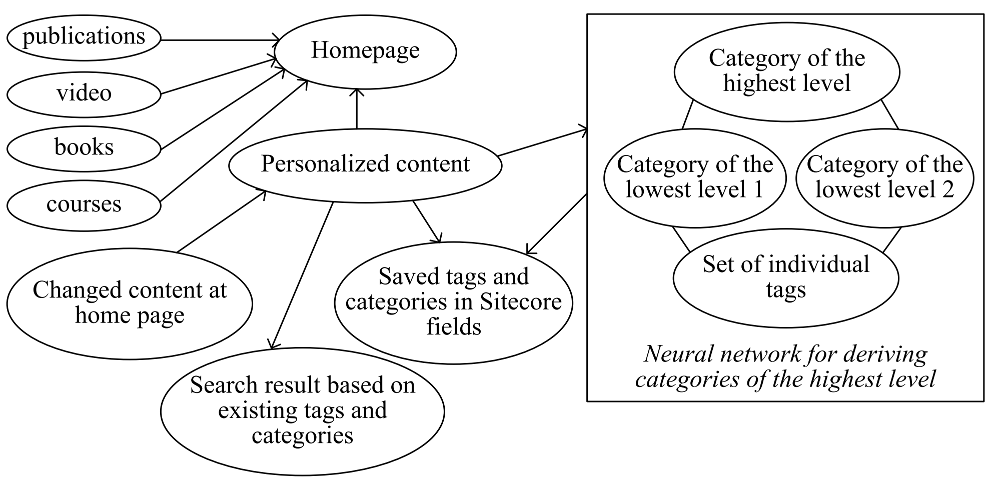


Fig. 4. Use case diagram of the content personalization process

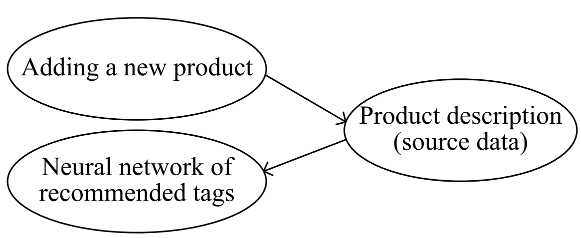


Fig. 5. Use case diagram of the process to add a product

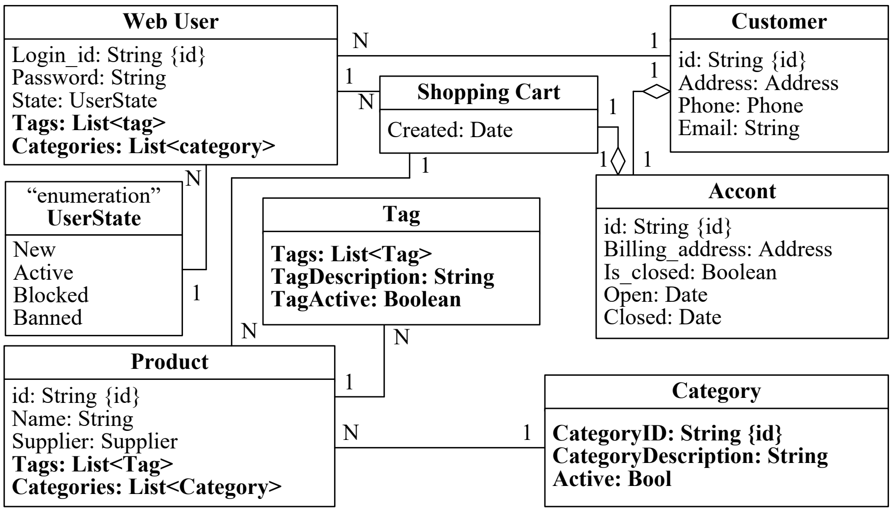


Fig. 6. ER-diagram for the Internet e-commerce site

5. Method of content personalization according to the needs of the user

Personalization is a method for displaying targeted, relevant content to users, taking into consideration their characteristics and behavior, such as location, gender, content, or previous visits. By using personalization, one can confirm that the required content reaches appropriate users, for example, showing, hiding, or customizing the content. Personalization is used to:

– display different content for users based on geolocation;

– hide a registration form for the users who filled out the form previously;

– change a banner text on a Web-site by linking it to the site of the user.

Conditional visualization is a piece of content that is displayed when a condition is defined in advance. One can use conditional shades to control the way customers view and interact with a Web-resource.

Conditional representation is often used as a synonym for personalized content. This, however, is not synonymous with personalization. Personalization refers to a broad process of delivering targeted, relevant content for appropriate users (Fig. 7). Personalization includes:

– adaptive (a dynamic change in the content on a Web-resource based on user's behavior);

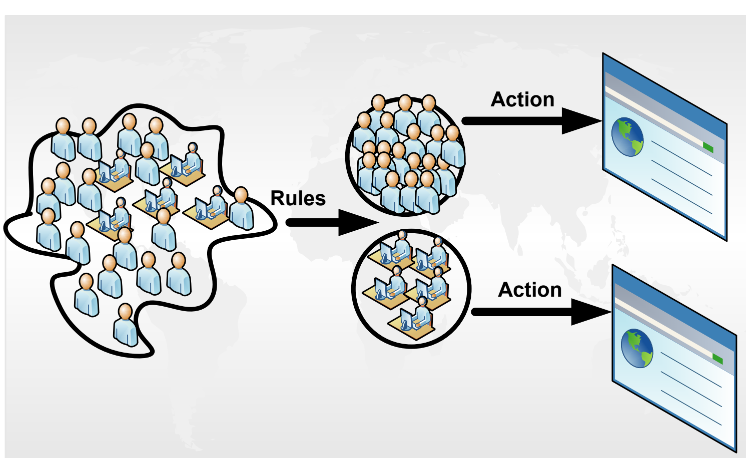


Fig. 7. Personalized content for users

– based on the creation and implementation of rules for conditional representation.

Sitecore sets conditions for conditional visualization in the rules editor based on logic to determine the validity of condition. One also defines activities as a conditional rendering that takes effect when the condition holds or a certain event takes place. A condition that is associated with action is the rule. Access to the rule code editor is derived from the editor of activities. Access to it is also obtained by using a content editor and marketing control panel. Typically, conditional correction is carried out and moderation is performed in the experience editor.

Content profiles are the categories for tracking user behavior when navigating the Internet e-commerce site. It helps better understand the behavior, actions, and interests of users. The content of profiles consists of:

– profile's keys (attributes of categories for tracking);

– values for a profile (numeric values assigned to different keys of the profile);

– profile's cards (stored combinations of profile's keys and values that are used for content).

Sitecore is also used to create personal properties to represent typical users who are also assigned with profile's cards. Users are used to implement the personalization of rules. They create profiles of content, keys to the profile, profiles and persons at the center of marketing. The elements' profile is compiled in the experience editor. Profile's keys describe various aspects of profiles. They assign numerical values of the profile for the profile's keys, and then use the value of the profile to track the interaction between users and the Internet e-commerce site. Sitecore has some predefined profiles that have the assigned profiles. One can also create own keys to the profile. When users navigate at a Web-resource, they are assigned the values of the profile's content, which are defined for each visited element. These values are accumulated at repeated visits to a Web resource by user. They help create a contact profile for regular users. Information about users' activities – browsed pages, the goals accomplished and the way they navigate a Web-resource, etc. – defines those sections at the Web-resource that must be improved. It is also used for the segmentation of users and to create personalization rules for selling. For example, if a user often navigates certain categories or reached a high profile, he is a potential client of this direction. Then he is added to a CRM system as a potential buyer or sent an e-mail message.

Profile's cards contain the saved keys to the profile and values of the profile. Profile cards are used for assigning standard values of profiles for the Web resource elements. Conditional persons are created when setting the content profiles. These are fictional characters as certain types of users within a target demographic group. Persons describe life, age, habits, prerequisites, interests and a profession of the fictional character who can use the Internet e-commerce site in a certain way. They create profile cards that describe the way a person consumes the content of a Web resource.

Users profiles' source data on a Web resource in Sitecore are the input data for a neural network in Machine Learning for personalization when forming recommendations to the end customer of e-commerce. Neural networks are formed from layers of similar neurons. Most neural networks have at least an input layer and an output layer. Input template is given in the input layer. Then the output template is returned from the output layer. Processes between the input and output layers is a black box, for example,

– input to a neural network: [–0.535, 0.383, 0.1];

– output from a neural network: [0.383, 0.645].

There are many different architectures that define processes between the input and output layers. A neural network has three neurons in the input layer and two neurons in the output layer. The number of neurons in the input and output levels does not change. The number of elements in the input and output templates for a specific neural network can never change. To use a neural network, it is necessary to state the task so that the array of numbers has a floating point. Similarly, solutions to the problem must be an array of floating-point numbers. They take one array and convert it to another. Neural networks recognize patterns.

Entering a text to a neural network is especially complicated. There are certain challenges that must be overcome. Individual words have different lengths. Neural networks require a fixed input and output size. Should letters "A"–"Z" be kept in one neuron or in 26 neurons, or otherwise? Using a recurrent neural network, such as neural network by Elman, solves part of the problem. Let us create an Elman neural network, which has enough input neurons to recognize Latin letters. It will use a context layer for remembering the order. Text processing employs one long thread of messages. Each entry is the quantity of one particular word. The entire input vector contains one value for each unique word, such as "with and without trousers", "two sports trousers", a "dark tracksuit" and "trousers and black trousers". There are such unique words that form the dictionary of keywords.

– Input 0: *and;*

– Input 1: *dark;*

– Input 2: *suit;*

– Input 3: *sports;*

– Input 4: *without;*

– Input 5: *trousers;*

– Input 6: *black;*

– Input 7: *with;*

– Input 8: *two*.

Lines are encoded in the following way, by filling the missed words with zero:

– "with and without trousers"
[0 4 5 7]→[1, 0, 0, 0, 1, 1, 0, 1, 0];

– "two sports trousers" [1 5 8]→[0, 1, 0, 0, 0, 1, 0, 0, 1];

– "dark tracksuit" [1 2 3]→[0, 1, 1, 1, 0, 0, 0, 0, 0];

– "trousers and black trousers"
[0 5 6]→[1, 0, 0, 0, 0, 2, 1, 0, 0].

Now there is a constant vector length. Nine is the total number of words in the dictionary. Each component's number in the vector is an index in the dictionary of available words. Each vector component keeps the count of the number of words for this dictionary. Each row usually contains only a small subset of the dictionary. As a result, most vector values are zero. One of the most difficult aspects of programming in Machine Learning shifts the problem to an array of the fixed quantity of floating-point numbers.

6. Methods and means to implement the architecture of an intelligent system for distributing commercial content according to the needs of the user

Processing of the Internet e-commerce sites makes it possible to receive operative and objective data about the functioning of e-business and in order to assess the level of competition in the segment of financial Internet market of commercial content. As well as to evaluate the level of competitors and measures of their competitiveness in the financial market for distributing commercial content (Fig. 8).

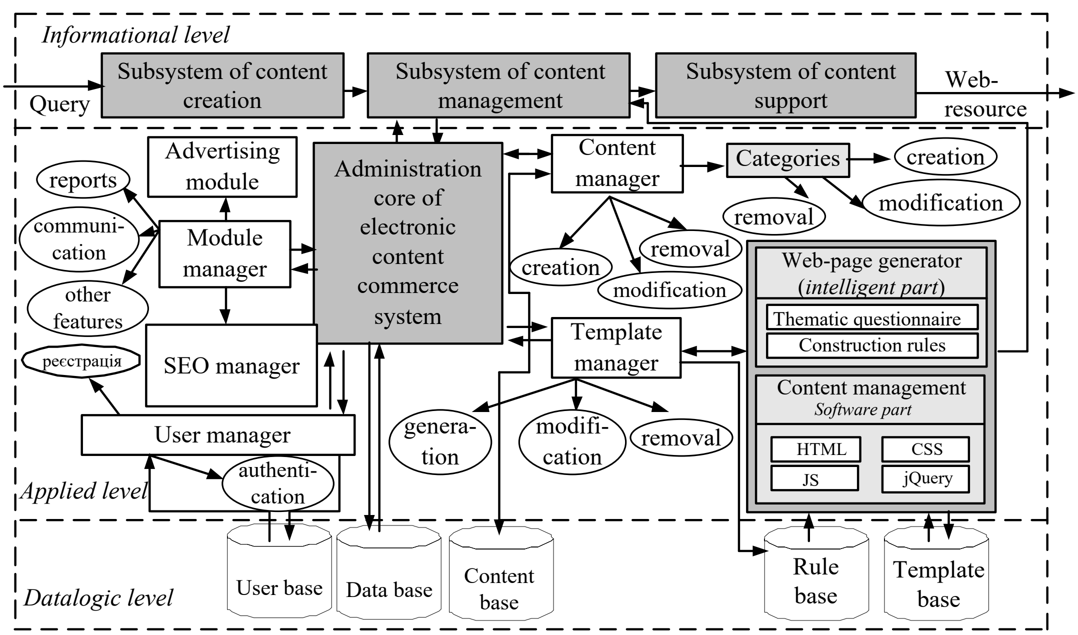


Fig. 8. Structure of e-commerce system

Main classes of users/characters of the Internet e-commerce sites (clients, task force managers and administrators) define the design of the site and the process of decision approval. The Internet e-commerce site mandatorily includes a Web-display (informational resource) with a directory of commercial content (with the ability to search) and the necessary interface elements for entering registration data, order formation, payments through the Internet, delivery type (e-mail/on-line), obtaining data on the company, as well as on-line support (Fig. 9).

Registration/authorization of a regular user is carried out when processing order or when entering the system. To protect, the interaction is carried out over a secure SSL channel. The entire process of content management is registered when supporting personalized content for compiling statistical data on the functioning of a Web-resource and personalized proposals in the form of a list of popular topics related to content to form the content. Fig. 10 shows a detailed diagram of the process of processing a Web resource. By identifying priority topics in the content and their relationship to main classes of users, they create the architecture of a Web-resource system, the hierarchy of content, the ways to display it and the interaction between each class of users (for example, themes and agenda or sessions, planning these issues). The process of processing Web resources is made up of subsystems for the creation of content (collection/creation, systematization and dissemination of personalized content); content management (editing, processing, and submitting personalized content).

I. A subsystem of content creation is realized in the form of content-monitoring over collection of content from a source during data integration (Fig. 11).

The subsystem of content creation is provided with the construction of a database of content according to the needs of regular/potential users: *moderator→content creation→database→content systematization→database→distribution of content→editor, or Web-resource (a source)→collection of content→database→content systematization→database→distribution of content→moderator*. The result of collection (Fig. 12) and primary processing is that the content is brought to a unified format, classified according to the defined rubricator and is assigned with descriptors with keywords. The subsystem ensures constant updating of the database with content, effective simultaneous access to the database by users, convenient search tools for the required content. Creation and management of the Web-resource is performed by information system depending on the activities of users and moderators of the system, as well as personalized commercial content.

Such an information system that supports the process of processing a Web-resource makes it possible to maintain a rapid growth rate of demand in the distribution of content; constant interaction between users and the system; a possibility to increase the target audience of existing/potential clients, increasing the rating of content and the Web-resource; improvement of e-business via better understanding of a client. The subsystem makes it possible to save on resources involved in the administration of information system and processing a Web-resource; to keep anonymity; not to overload the Internet traffic; to self-scan the Internet.

II. A content management subsystem consists of the following relationships: *User→content processing→database→content analysis→database→content display→user*. Analysis of content and a Web-resource, modeling and display is one of the most informative methods for quantitative examination of the dynamics of thematic flows of personalized commercial content.

A display subsystem (Fig. 13) generates a page with content requested based on the content from the database. The dialog box of database access enables viewing, search, and content representation, a possibility is given to refer to the originals of content on the Internet. Content in the database is changed using the edit module. Pages are created anew by a server for each request, which increases the load on the system's resources. The load is reduced when using caching tools of modern Web servers (Fig. 13). The task on a full-text search in a large array of content is inefficient. The issue of accuracy is resolved by a search among the annotated content. Instead of searching the full content, it is appropriate to search based on annotations – search images of content. Quasi-abstract for large content is the formation that remotely resembles the original content and most often is not perceived by humans. However, the search image of such content with weighted keywords and phrases leads to quite adequate results during full-text search. Quasi-abstract is constructed from fragments of content with the largest weight values. The benefits of caching pages with content are: a display subsystem generates a page once (Fig. 13); a page in the cache exists time Δt– until the content is relevant; a ready page is loaded faster from cache; the cache is updated periodically manually/automatically: at the end of time Δt; when modifying an informational resource or content.

III. A content support subsystem includes the following integrated sequential processes: *User→content structuring→database→content moderation→database→content generalization→moderator*. The problem in content support is the lack of general approaches to automated analysis of the functioning of the system of electronic content-commerce. In order to attract more clients to a Web-resource, they add the options for content analysis (ratings, reviews, and comments) about content (Fig. 14). A Web-resource with reviews of the content attracts more visitors. This functionality does not include moderation and leads to redundancy of data on a Web-resource. The user is forced to segment a constructive content, which requires efforts and diverts a prospect. The content that gets on a Web-resource is not filtered, that is the interaction between users and a portal is one-sided. The component Ratings/Reviews reflects the results of evaluating the rating of the content based on the scale defined in advance (Fig. 15).

Many business areas are trying to find new ways of personalization and creation of recommendations to the end user. They come up with new tests for such systems and Web solutions. However, designing those that will increase the real value of e-business is a very long and difficult process.

Consider four examples where different types of e-businesses obtained considerable and fast results through testing or personalization. Each of these methods is a possible approach to personalization. Each of these approaches is based on customization by available tools from Personalization Sitecore.

1. *Testing the result.* It specifies a message about a proposal, which would have the greatest impact. The problem is in that the tests, developed by a team, are rather basic, and typically do not contain enough information on individual segments. Thus, the team returns to the built-in test A/B Sitecore for a better understanding of which content best fits the business results. Next, one needs to check several messages about a proposal from a home page and obtain the results, the example is shown in Fig. 16.

The same proposal changes dramatically when the display path is changed. In the end, the winner is ahead by a large margin, making it possible for the company to initiate a strategy to change a proposal for other content with high profitability. It also gives an idea for forming future proposals at different channels to maximize the impact of personalization.

2. *Personalization based on geolocation.* An example is the personalization of the audience, depending on its whereabouts. They create individual components at key pages for the western, central, and eastern regions. This is a simple example, but it is also one of the easiest ways to get a quick win. The location of visitors can be tracked in real time.

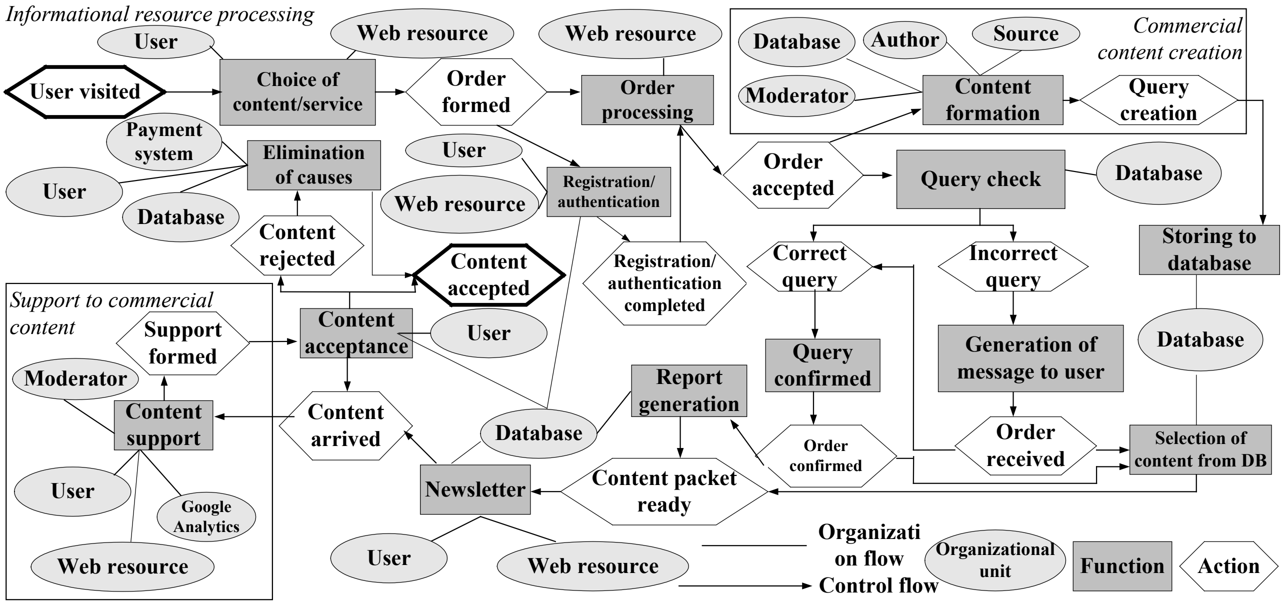


Fig. 9. Diagram of informational flows during content processing

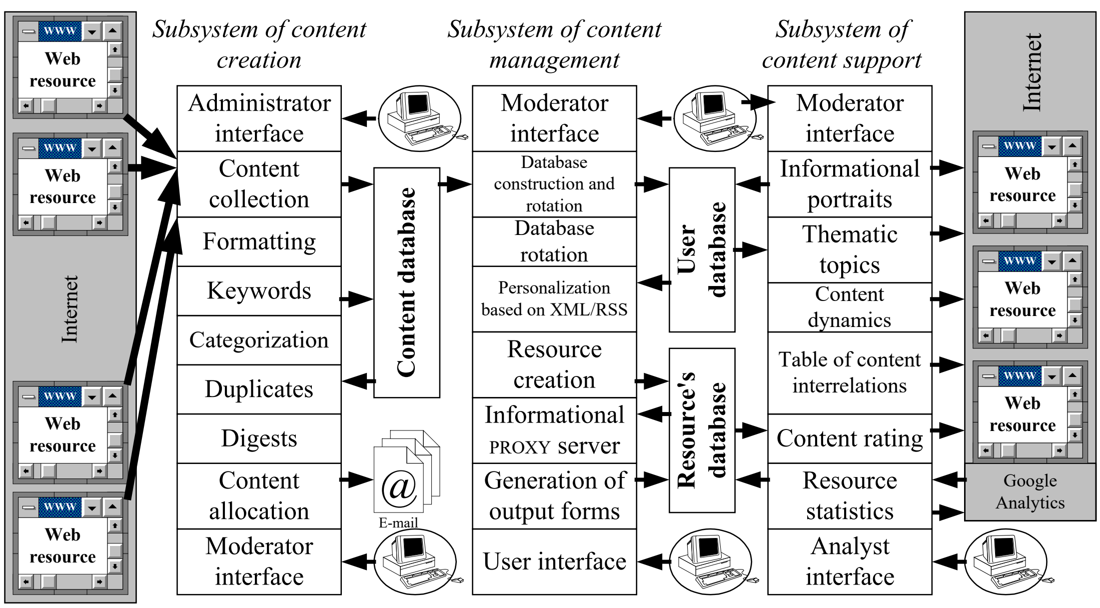


Fig. 10. Schematic of processing a Web-resource

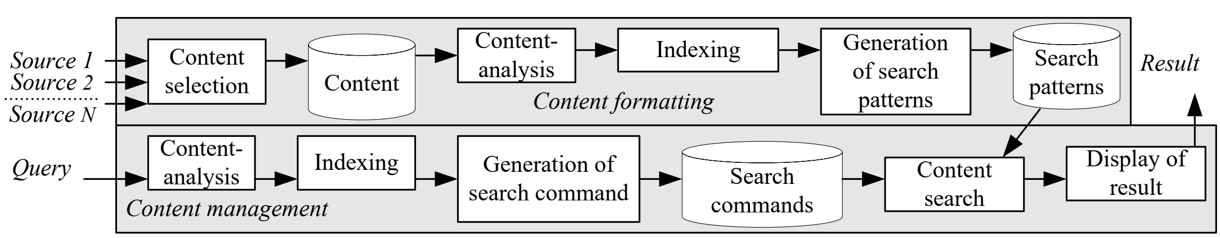


Fig. 11. Structural diagram of the process of content-monitoring of data

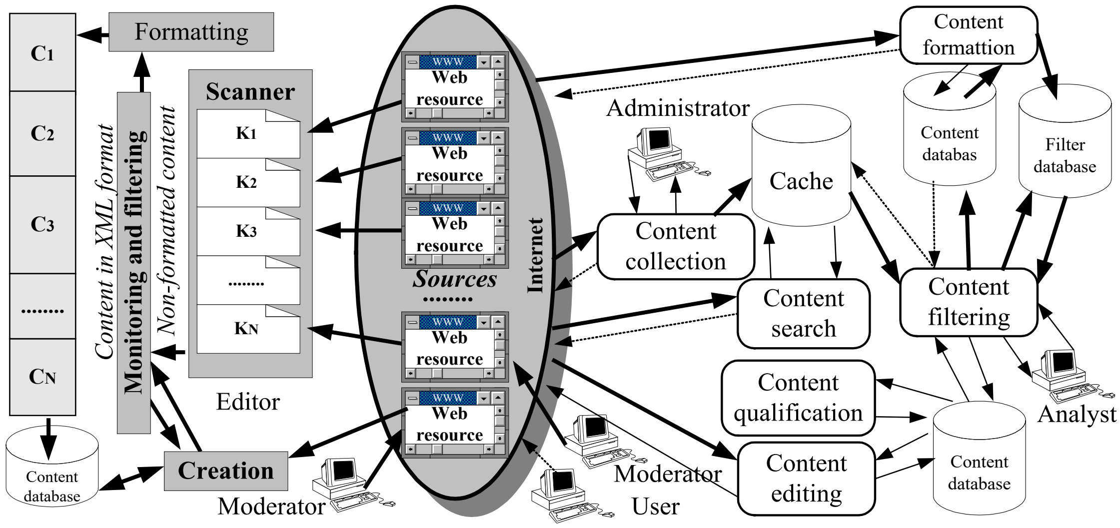


Fig. 12. Schematic of the personalized content creation

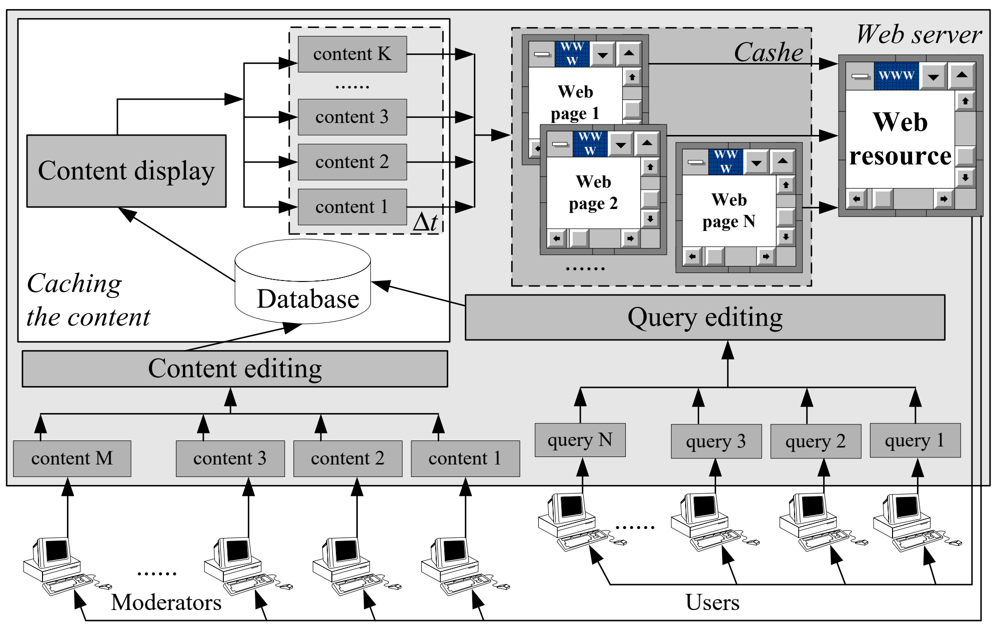


Fig. 13. Schematic of caching the generated pages of a Web-resource

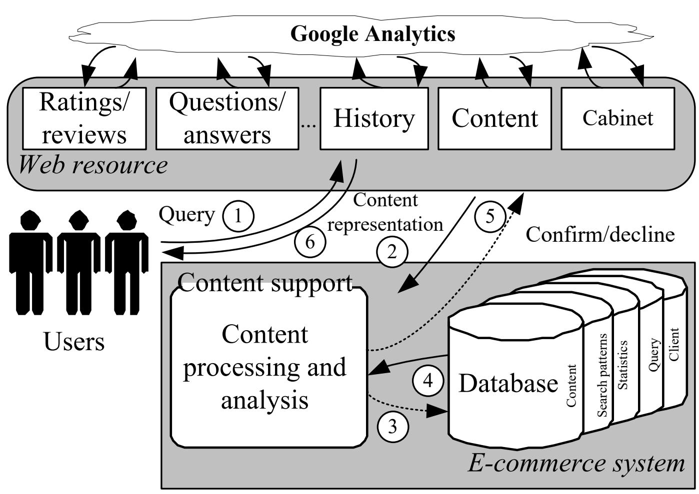


Fig. 14. Structure of the subsystem of commercial content support

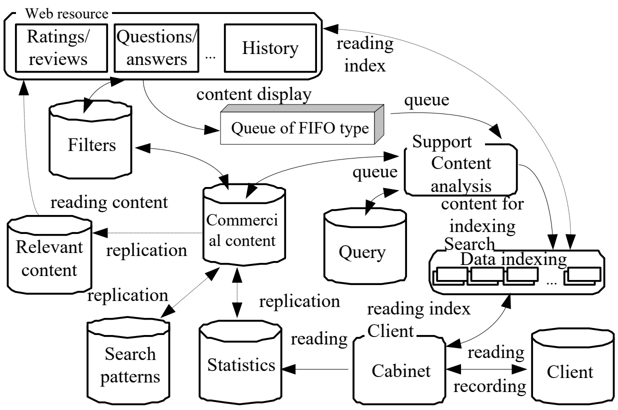


Fig. 15. Data flow diagram in the commercial content support subsystem

Position 3	Position 1
	Winner
Below the level of conversion by 18.37 % below the third best	21.43 % better than the preceding one and 9.76 % better than the last one

Fig. 16. Personalized content for users

3. *Personalization based on the visitor's profile.* E-business can see that the Web-resource is visited by different types of users. Thus, the team sets up the profiles and uses the predefined categories to determine to which group a visitor belongs. The built-in algorithms capture the intentions of individual visitors in real time when navigating through the content of a Web resource. Next, using the intelligent personalization of the home page for each category of user, they change the image of a banner and call for a response, to focus on performance, as a company with a personal touch. These changes not only provide the team with more potential clients, but also new defined categories. In addition, they help focus its strategy for personalization on the rest of the Web-resource.

4. *Personalization based on the stage of flipping through content.* It is required to register the movement of users within a Web resource on the eve of a big event. It is necessary to track the movement of early visitors, tracking everything from electronic chapters, which were of interest, before they confirmed their registration for the event. Next, the types of interests that predated the registration must be divided into categories. Thus, there forms a clear idea about which areas of the Web-resource are weak, which left the visitors interested, but failed to inform, and which informed, but did not motivate. This approach is used for the creation of clear strategies of personalization based on how close a visitor to the registration.

After collecting the personalized user data, we build a neural network using the example of a hash table in conventional programming. A hash table is used to represent keys to values. Somewhat similar to a dictionary, for example,

– "*listen*"→"*perceived by ear*";

– "*run*"→"*move faster than walk*";

– "*write*"→"*represent symbols at the surface with a tool (for instance, pen)*".

This is representation of words and the definition of each word. This is a hash table. They use the key of the row for another value of the row. The appropriate key from the dictionary returns the value. Most neural networks function in this way. A single neural network is the bi-directional associative memory, that is it also makes it possible to transmit the value and receive the keys.

Hash tables in programming use keys and values. For example, the pattern that is sent to the input layer of the neural network is very similar to the process of typing a key to a hash table. Similarly, the value that is returned from a hash table as a template is similar to the one returned from the output layer of the neural network. However, the process of functioning of a neural network is much more difficult than working with hash tables. Neural networks do not return the empty result NULL but find the closest value. Therefore, if one completes the "introduction" to the above neural network, he would probably get what is expected at "output". Not enough data for a neural network to change the response, since there are only three examples. Thus, probably, we shall obtain at the output one of other keys. To begin with, consider the operator XOR as if it would be a hash table. *Truth table* for XOR is as follows.

– False XOR False=False→ – [0.0, 0.0]->[0.0];

– True XOR False=True→ – [1,0, 0,0]->[1.0];

– False XOR True=True→ – [0.0, 1.0]->[1.0];

– True XOR True=False→ – [1.0, 1.0]->[0.0].

These representations show the input and the best ideal expected output for a neural network. If one sets the perfect result, this is a *controlled training*. If one does not provide the perfect results, then it is the *uncontrolled training*. Supervisory training trains a neural network to produce a perfect output. Uncontrolled training usually teaches a neural network to group the input data into multiple groups, defined by the original number of neurons. Supervisory and uncontrolled training is an iterative process. For a controlled training, each learning iteration computes how close the actual result is to the perfect output. This closeness is expressed as a percentage error. Each iteration modifies the internal matrices of weight in a neural network to obtain an error at the low level. Uncontrolled training is also an iterative process. However, the calculation of error is not that simple. There is no expected output, so one cannot measure how close the uncontrolled neural network to the perfect output, because there is no a perfect output. Often, they repeat several iterations, and then use the network. If additional training is needed, then it is learning. Another very important aspect of the above-specified training data is a possibility to use them in any order. The result "0" XOR "0" will always be "0". This is not the case for all neural networks. For the operator XOR, they probably used a type of the neural network *feedforward*. A tagger in Machine Learning automatically assigns four bogus tags, two at the beginning and two at the end, to a target expression. Then the neural network learns to automatically assign the morpho-syntax descriptions, taking into consideration the context, that is, the two previously assigned tags and possible tags for the current and the next two words. One word is characterized by a vector that encodes its morpho-syntactic description. To encode possible morpho-syntax descriptions, we use $P(a|w)$, where every possible attribute has a single corresponding position inside the encoded vector.

$$P(a|w)=\frac{C(w,a)}{C(w)}.$$

Vectors are used to encode the possible syntax-morpho descriptions for the current and the next two words. While training, we also compute a list of suffixes with proper morpho-syntactic descriptions that are used at run time to create a possible morpho-syntactic vector for unknown words. When such words are found in the data for testing, we approximate their possible morpho-syntactic vector using a variant of the method proposed by Brants. When a tagger is used to a new expression, the system iteratively computes the original morpho-syntactic description for every single word. After the tag was assigned to a word, the vector, associated with this word, changes so that it accepts a value of 1 for each attribute, present in its newly designated morpho-semantic description. As a result of encoding each attribute separately for morpho-syntax descriptions, a tagger assigns new tags that were never associated with the current word in the learning process. Although it is a good practice to work with unknown words, it often refers to that it assigns the value of an attribute that are not valid for the wordform. To overcome these types of errors, we use an additional list of words with their permitted morpho-syntactic descriptions. For a word, a list is calculated as the combination of all morpho-syntactic descriptions that appear with suffixes that are used to this word. When a tagger assigns a morpho-syntactic description of a particular word, it selects one of the morpho-syntactic descriptions of possible word forms in the list with the word using a simple function of distance:

$$\min_{e\in P}\sum_{k=0}^{n}|o_k-e_k|,$$

where P is the list of all possible morpho-syntactic descriptions for a given word; n is the length of encoding the morpho-syntactic descriptions (110 bits); o is the output of a neural network for the current word; e is a binary encoding for morpho-syntactic descriptions in P. A WordNet project homepage, http://wordnet.princeton.edu, is a linguistic database that includes a large number of interrelated synonyms. We shall use them for the work of a neural network. The lexical database WordNet is a current research project, which includes the multi-year efforts by professional linguists. Proper use of WordNet over the past ten years is simple, mostly using the database to identify synonyms (synsets in WordNet) and examining possible parts of a word. We shall use the open utility libraries Java WordNet. There are also good client-side applications with open source software for viewing the lexical database WordNet, the links to which are available at the Web site of WordNet.

7. Results of research into implementation of the system for distributing commercial content in the Internet space according to the needs of the user

As an example, we shall use approaches 2 and 3 and define in Sitecore CMS the following rules for the system. To this end, we shall apply Sitecore Rule Set Editor. It is a tool that employs the rules of logic to manage the content. The rule set editor is used to create conditional visualizations for personalization and contact management. The correct set editor has three main elements: conditions, actions, and rules.

The rule set editor combines conditions with actions to create rules that can be used to implement personalization, to launch scripts, to create steps in the plans of interaction, etc. (Fig. 17).

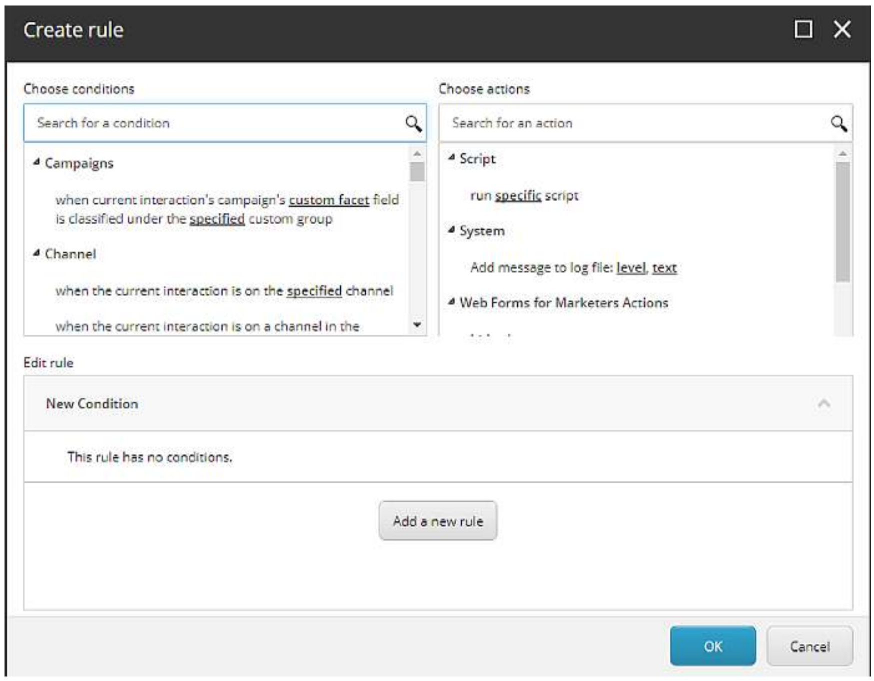


Fig. 17. Creation of conditions for personalization rules in Sitecore CMS

– *Conditions* consist of logical assertions that determine whether the condition is true. Sitecore has a series of default conditions that one can use, but one can also employ own conditions. We shall use a condition for the location of the user, to define a country of origin.

– *Actions* are the logical steps that are performed when one or several conditions in the rule are true. For example, one can introduce a condition for the registered contacts, which hides a registration form filled previously. They usually create actions that implement a conditional representation of a Web resource for contacts that meet the criteria. In addition, they indicate the actions that hide or show content if the condition holds. Sitecore has a series of actions by default, but one can also implement own actions. For example, let us create a rule about changes to content units at a homepage. And, based on this and the previous element, we shall create a rule (Fig. 18).

– *Rules* associate one or more actions with one or more conditions. To this end, one needs to define own conditions and actions prior to introducing a rule. In addition, the logical operators are used, such as *and* and *or* to create combinations of several conditions and actions. For example, we shall create a rule that hides a certain element in the content from contacts from a particular region. The conditions for this rule check the geographical location of contacts; if appropriate, respective pages in a Web-resource will not be displayed.

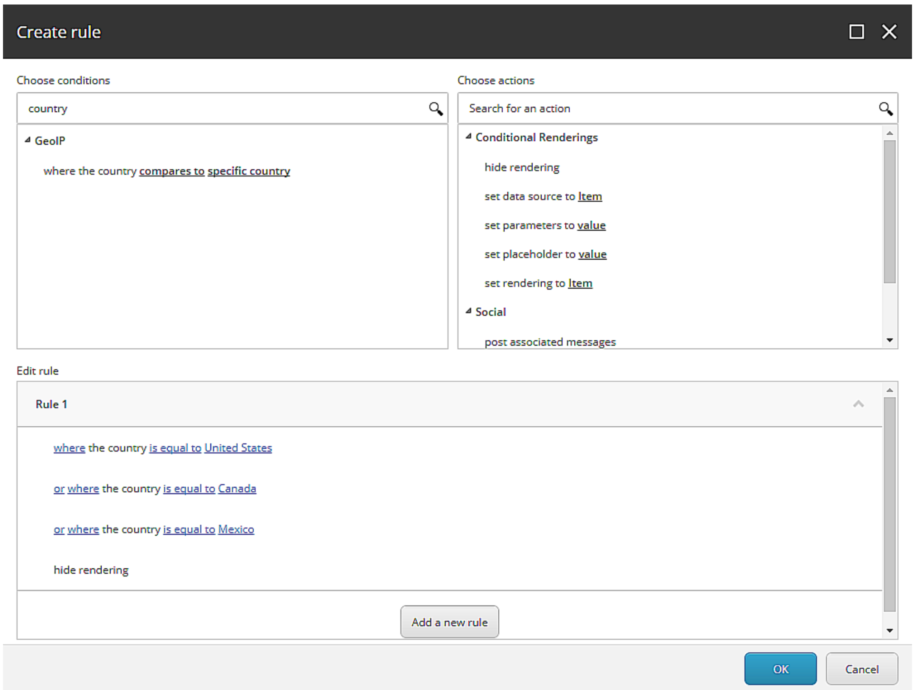


Fig. 18. Example of a rule in Sitecore CMS regarding the place where a user lives

8. Discussion of results of studying the automated distribution of commercial content based on SEO technologies and Machine Learning

A path analyzer shows a digital track (or sequence) of users by displaying it visually in the manner that is easy to use. These visual paths reflect life perceptions in order to identify opportunities. If, for example, many visitors stay at certain pages led by clicks, without conversion, it may mean that something is not working. A path analyzer would give an idea of what has to be started independently or follow the advice from Sitecore. After several test runs on the Web-site, one can see the representation of navigation through the pages in the diagram shown in Fig. 19.

The possibilities of *creating profiles* are theoretically unlimited. After using the Chrome browser as a unique customer, and performing a consumer activity on the Web-site, we shall consider the obtained results for a user profile in Fig. 20.

To summarize the received user profile details:

– surfing behavior: new visitors vs. returning visitors, websites visited, etc.;

– purchasing behavior: popular brands, price ranges, related products, etc.;

– geographical data and demographics: age and gender;

– sociological data: family situation, profession, interests, etc.

In general, if you chose to define these profiles, it strongly depends on the sector. One needs to constantly ask questions regarding customers that is functionally possible and practically possible. Using a practical example, all the above-described takes the following form. We shall provide an example of a short article for training a neural network for the Internet e-commerce site from the industry of Internet newspaper or Internet magazine (to define recommendations – which articles would the user wish to see in the first place (Fig. 21).

Run the console program for training a neural network in order to receive the output data in the form of a table of the most probable content tags according to the list assigned by the user in the Internet e-commerce site (Fig. 22).

Estimate the output data shown in Fig. 23.

The result provided a set of keywords to the user profile based on which the system would offer him, the next time he visits, the relevant ranked content – articles about data management have the advantage over articles on big data and risk, while the latter have priority over those on compliance and administration, etc.

During subsequent visits by this user, the system would learn taking into consideration not only the navigation on the Web-resource, but while reading specific articles. A client-oriented search using modern information retrieval metrics greatly improves the process of personalization of recommendations to the regular end user of the Internet e-commerce site.

However, at present there are no common standards and functional requirements to the development of a typical system for creating referrals based on the personalization of needs and wishes of the end regular user. All projects that were successfully implemented and are actively exploited are closed non-permanent commercial projects. And we can only guess which principles and approaches underlie their work and promote the successful development of e-business. The application of modern methods of SEO technologies makes it possible to gather up-to-date information about the user. Application of artificial neural networks will make it possible to train the system to make personalized recommendations to the end user. The application of Machine Learning methods makes it possible to refine personalized recommendations to the end user during subsequent visits to the Internet e-commerce site. From a scientific standpoint, this segment of IT is not explored in detail. Each separate project is implemented almost from the beginning, actually based on own ideas and solutions. The scientific literature contains limited information about theoretical substantiation, research, conclusions, recommendations, generalization for the design of typical systems and for processing Web resources in such systems. There is a need for analysis, generalization and justification of existing approaches to the implementation of e-commerce and to construction of intelligent systems for distributing commercial content based on the personalization and geolocation methods. It is a relevant task to create a complex of technological means based on theoretical substantiation of methods, models, and principles of processing Web resources in such systems, built on the principle of open systems, which make it possible to control the process of improving the distribution of commercial content.

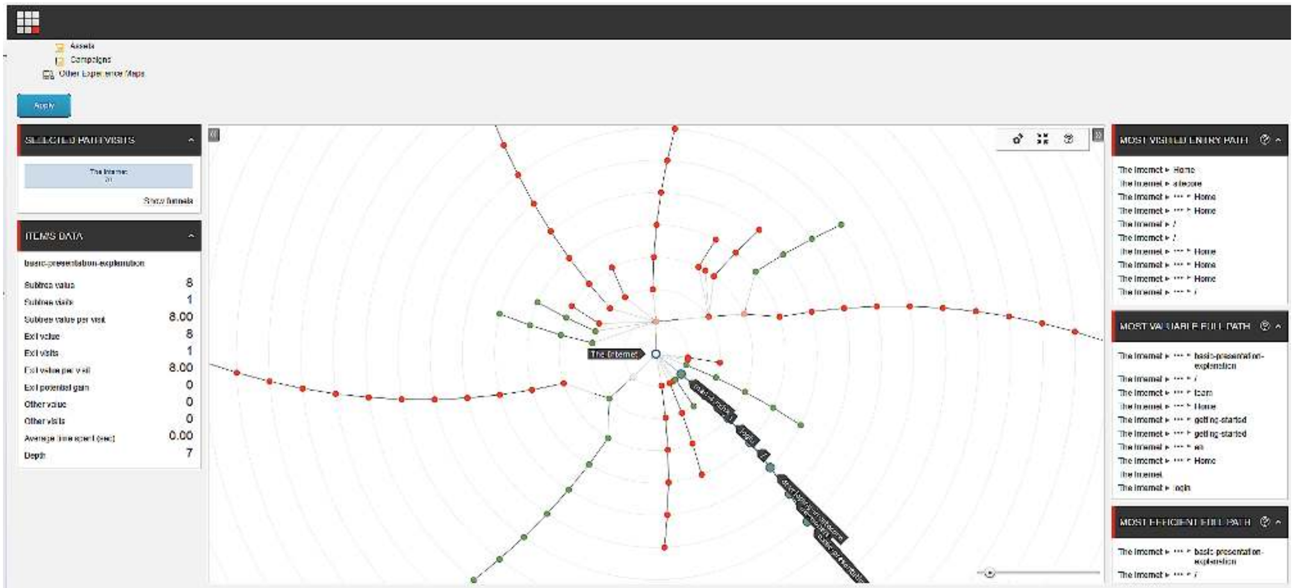


Fig. 19. Output of statistics on gathering information based on the user profile and his navigation on a Web-resource

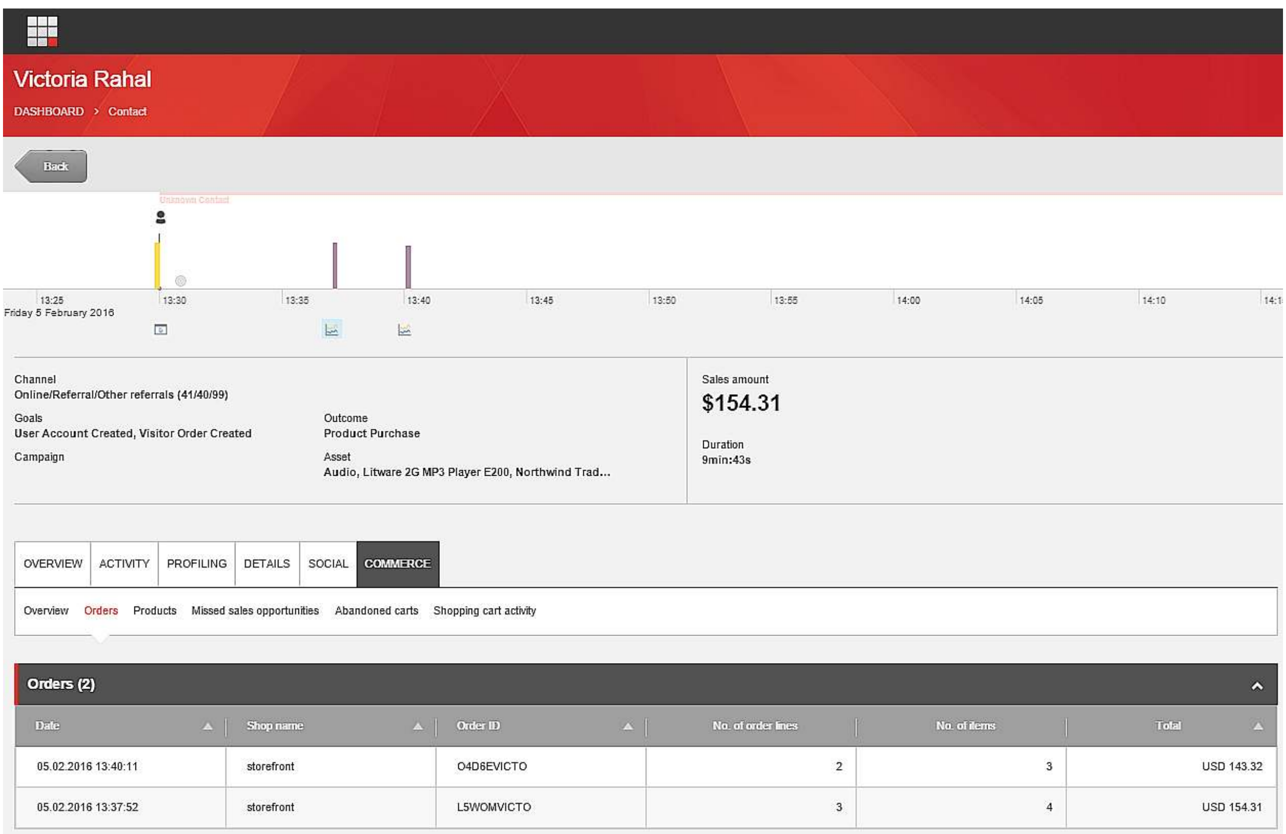
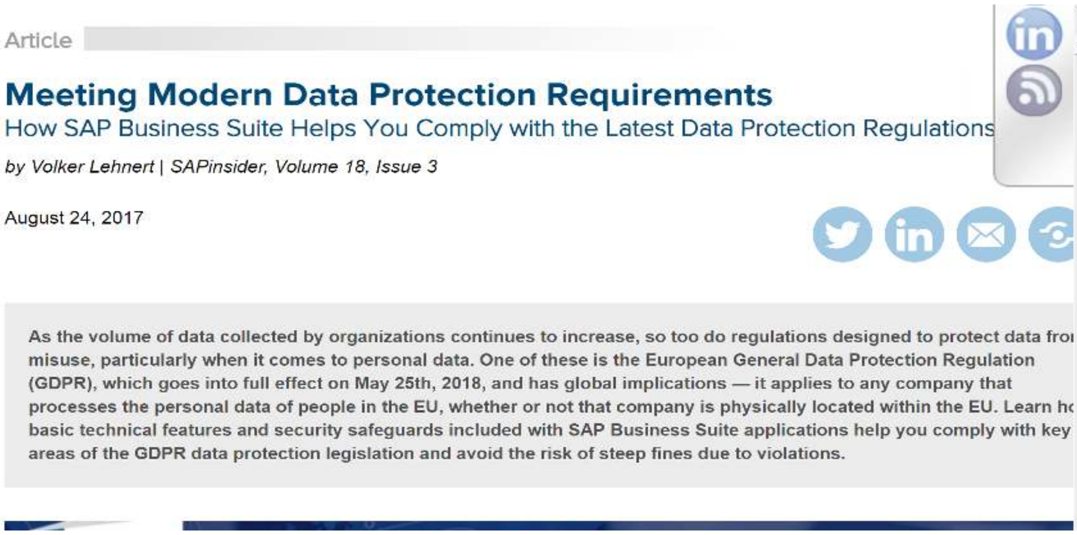


Fig. 20. Output of statistics on the activity of a user profile

The use of artificial intelligence gives companies a competitive advantage, and it is available for developers or enterprises of any size or budget. An excellent example is the recent update suggested by Pinterest to its Chrome extension, which allows the users to select an object from any photo on the Web, and then, by using Pinterest, to look for similar objects using software for image recognition. It is not only Pinterest that provides new search experience using artificial intelligence. New software platforms that manage e-commerce create innovative opportunities for visual search. As well as search for relevant products; the artificial intelligence makes it possible for buyers to find additional products, whether it is the size, color, shape, fabric or even a brand. Visual capabilities of such software are really great. By initially receiving visual cues from the uploaded images, the software successfully helps the customer find the required product. In other words, owing to visualization and the artificial intelligence algorithms the user easily find similar and required goods/services via the Internet e-commerce site.


Article

Meeting Modern Data Protection Requirements

How SAP Business Suite Helps You Comply with the Latest Data Protection Regulations

by Volker Lehnert | SAPinsider, Volume 18, Issue 3

August 24, 2017

As the volume of data collected by organizations continues to increase, so too do regulations designed to protect data fro misuse, particularly when it comes to personal data. One of these is the European General Data Protection Regulation (GDPR), which goes into full effect on May 25th, 2018, and has global implications — it applies to any company that processes the personal data of people in the EU, whether or not that company is physically located within the EU. Learn h basic technical features and security safeguards included with SAP Business Suite applications help you comply with key areas of the GDPR data protection legislation and avoid the risk of steep fines due to violations.

Fig. 21. Example of an article for training a neural network

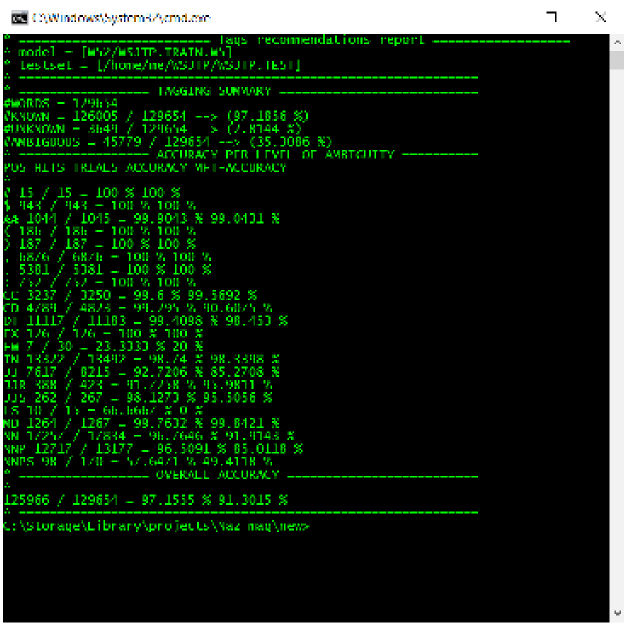


Fig. 22. Intermediate results from training a neural network

```
# single output
{
    'governance': 0.00004324968926091062,
    'risk': 0.007702528578033991,
    'compliance': 0.0002575132225946431,
    'risk management',
    'data management': 0.2071775132225946431,
    'big data': 0.008160047807935744,
    'administration': 0.00015069427192724994
}
```

Fig. 23. Output data on training a neural network according to the input data

Indeed, receiving optimal results from adding tags and categories is an important issue because recent research has shown that it significantly affects the behavior of consumers and the profit of enterprises. At first glance, this seems to be a trivial problem; given the set of goods, simply place them in decreasing order, but of great importance is that consumers should receive the appropriate products at minimal cost. However, the difficulty is in determining the proper correspondence between each content and each individual user. If users' preferences are similar, we have a generally correct sequence of the selected content for a given request, which makes the problem of sorting easier. However, if users' preferences are different, that is, if two users submit the same query and search for different data, the problem becomes much more difficult. A user who is looking for Java can search coffee, but finds information about the programming language Java or a vacation on the islands of Java. The corresponding features of content depend on a specific user. For example, a coffee house is relevant to a user who is looking for coffee but not for those looking for holiday tours. An optimal order should be individual. A potential solution to this problem is to personalize the content sequence. Indeed, all major search engines have experimented and, in some cases, did add their personalized content selection algorithms, even for users who visit a Web-site for the first time.

Some researchers even doubted the importance of personalization of search results, not only in the context of search engines, but also under other conditions. In fact, this discussion about search results personalization is part of a larger discussion about the results of personalization in the context of marketing-mix variables. As regards privacy, consumers and administrators should understand that keeping the long histories of users helps reveal situations when personalization helps.

This paper considered content personalization using sorting, that is, an optimal customized sorting of content sequence for getting the required results. The goal is to build a structure to display personalized content and to evaluate personalization in general.

In the process, we sought to identify the role of users and the level of queries in personalization. This is a difficult problem due to three reasons.

First, one needs a structure with an extremely high accuracy of prediction. The problem of personalized content in the system is one of the predictions – which result or content will be the best for the user? To organize a list of selected results so that the top part displays the most optimal options for each user. Traditional econometric tools that are used in the literature on marketing are not suitable to answer this question because they are designed for causal conclusion to derive the best objective assessments, and not for the prediction. That is, they generate inaccurate predictions.

Objective assessment are not always the best indicators, because they tend to have high variance, and vice versa. Thus, the problems on forecasting and on causal conclusion are fundamentally different and often conflicting. Thus, a methodological framework is needed, optimized for the accuracy of prediction.

Second, they need to include a large number of attributes, and allow complex interactions between them. The standard approach to modeling in the marketing literature is to accept a fixed functional form to model an output variable, include a small set of explanatory variables, allow several interactions between them, and then to specify the settings related to the predefined functional forms. However, this approach has poor predictive ability.

Third, the developed approach is an effective and scalable. Efficiency concerns the time of the execution and deployment of a model, which is as short as possible, at minimal loss of accuracy. Thus, an effective model loses a small amount of accuracy, but leads to huge gains during use. Scalability and efficiency are necessary to run the model in real time. To solve these tasks, we refer to the methods of Machine Learning. They ensure the extremely high precision of work with a large number of data attributes, as well as effective scaling.

9. Conclusions

1. We have considered a task on designing an intelligent system for commercial distribution of information products using the personalized approach to visitors based on the categories and tags for content that is interesting to visitors. We have designed a general standard architecture of the corresponding system using methods and means of personalization in the Internet environment with a core that automatically recommends tags (categories) in the form of a neural network with controlled training. Providing a convenient Internet site is essential, since the Internet e-commerce site help clients find a desired product in a more universal way. That makes it possible for visitors to manage their own experience of buying, which helps increase the loyalty of customers and makes them more prone to return to the Web resource for more purchases, which in turn would greatly contribute to e-trade. Artificial intelligence technologies will provide clients with the best services, and individual experiences. They will also maximize the marketing efforts of a company, minimizing the need to spend money on ineffective advertising campaigns.

2. We have developed a method to personalize commercial content according to the needs of the user. The personalized approach to a site user leads to a higher coefficient of sales. The personalization algorithms make it possible to associate each user with a list of products that are most likely to be of interest to him, and can predict what customers may want to see, even if they are not aware about it. However, at present there are no common standards and functional requirements to the development of a typical system of recommendations based on the personalization of needs and wishes by the end regular user. All projects that were successfully implemented and are actively exploited are closed non-permanent commercial projects. And we can only guess which principles and approaches underlie their work and promote successful development of e-business. The application of modern methods of SEO technologies makes it possible to acquire up-to-date information about the user. Application of artificial neural networks will make it possible to train the system to offer personalized recommendations to the end user. Application of the Machine Learning methods makes it possible to refine personalized recommendations to the end user when he revisits the Internet e-commerce site.

3. We have developed the intelligent system for distributing commercial content in the Internet space based on SEO technologies, neural networks, and Machine Learning. We have also stated general functional requirements to a system for distributing commercial content in the Internet space. The developed system, based on modern methods of SEO technologies with consideration of the metrics for evaluating the work of information-search module within a system, makes it possible to select relevant content according to the user's personalized interests. The system has classes and subclasses that include the real commercial information products, which are interconnected by logical links, using which performs the intelligent presentation of content based on the personalized needs and interests of the user. In addition, based on modern methods of Machine Learning, the designed system learns to refine search results for popular content according to user preferences and personalization.

4. We have analyzed results from experimental testing of the proposed method for the personalization of commercial content according to the needs of the user. The purpose of the intelligent system of e-commerce is to supply unique content based on a personalization approach and the use of tags. In addition to a standard text entry of categories and tags based on images and description of a product, we have developed an automated process for defining tags and categories of goods. Context recognition that uses deep neural networks now provides a technology for auto-tagging the descriptions of product at the Internet e-commerce sites. The methods can be used to classify facial expressions and emotion recognition. The system is designed for the distribution of information technology products (publications, books, courses, videos, files, etc.) via the Internet. Implementation of this system would make it possible to access a particular kind of content by a wide audience of users, because the site would be posted on the World Wide Web, on the other hand, another part of the purpose for creating this system is a commercial component, namely ensuring profits for the owner or administrator of the intelligent system, through the mechanisms of e-commerce. Our project, when completed, has practical application and could be used as one of the systems of e-commerce on the Internet, provided it is filled with actual goods and services. If we are to evaluate the degree of its readiness for implementation, then of course one must first conduct a relevant study into demand for, and proposal of, services available in the market prior to running the entire cycle of works related to e-commerce. Success will depend not only on the literacy and quality in the design of a Web-resource, but also on interest in the proposed services, on advertising and awareness about the resource.

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