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TOPIC MACHINE: IDENTIFYING KEYWORDS USING LTM

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Abstract – Search Engine Marketing (SEM) manages thousands of search keywords for their clients. Using dashboards, users had created test variants for various bid choices, keyword ideas, and advertisement text options. And then, they used controlled experiments for selecting the best performing variants. Campaign management can easily become a burden on every advertiser. In order to target users in need of a particular service, advertisers have to determine the purchase intents or information needs of target users. Once the target intents are determined, advertisers can target those users with relevant search keywords. In order to formulate information needs and to scale campaign management with increasing number of keywords, we propose a framework called topic machine, where we learn the latent topics hidden in the available search terms reports. Our hypothesis is that these topics correspond to the set of information needs that best match-make a given client with users. We foresee, the advertisers can view a topic by a campaign management to thousands of keywords comfortably with the use of topic machine while at the same time optimizing for conversions. Topic machine's internal model can be used to reduce dimensions of the search term space.

Keywords: Internet advertising, Search Engine Marketing, Topic machine

1. INTROUDCTION

The Internet has fostered on the ability to search the content people produce on the Web and find those pages that are highly relevant to a given query. Lucrative markets are created out of the information-seeking behavior of billions of people traversing the Web. Consider a do-it-yourself (DIY) social network creation platform that sells subscription based services. There are two options for the company to market their services: - Launch a marketing campaign for displaying ads to the full set of Internet users. Next, employ what is known as precision targeting as in "show my ad to any user who enters the query 'create my own social networking site' ". If a user types into a web search engine "create my own social networking site", then we may infer that this user wants to create a social network, and is potentially willing to pay for the provided service. There could be many such users browsing the Web. An advertiser can create an online advertisement that speaks exactly to the market segment containing these users or in other words create an advertisement to the specific purchase intent in question. This new type of advertising is attractive to both advertisers and customers at the same time.

2. SCOPE OF THE PROJECT

In this concept, we working in a frame work called Topic Machine. In Topic Machine, we learn the latent topics hidden in the available search terms reports. Our hypothesis is that these topics correspond to the set of information needs that best match-make the client with its users. For this, we use a Latent Dirichlet Allocation (LDA) topic model.

3. EXISITING SYSTEM

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Topical structure changes across time, predict conversion performance, capture trends between topics and conversions, and generate search terms that conform to a particular topical distribution campaign.

Even more difficult to manage multiple campaigns consisting of a wide array of continuously evolving sets of keywords.

3.1 EXISTING TECHNIQUES

TOPICAL STRUCTURE: The topic structure consists of the topics themselves, per-document topic distributions, and per document per word topic assignments. The topic structure is the hidden structure.

3.2 DISADVANTAGE

It is difficult to maintain keyword coherence within a campaign.More difficult to manage multiple campaigns consisting of a wide array of continuously evolving sets of keywords.

4. PROPOSED SYSTEM

Here we proposed a framework called TopicMachine. TopicMachine uses an LDA-based topic model. Since information needs may change over time or drift in concept, we learn dynamic topic models by sequentially chaining model parameters in a Gaussian process across a well-defined epoch.We assessed the quality of the models learned in TopicMachine by showing the predictive power of the framework.

4.1 PROPOSED TECHNIQUE

TOPIC MACHINE: TopicMachine uses an LDA-based topic model. Since information needs may change over time or drift in concept, we learn dynamic topic models by sequentially chaining model parameters in a Gaussian process across a well-defined epoch. We assessed the quality of the models learned in TopicMachine by showing the predictive power of the framework.

4.2 ADVANTAGE

TopicMachine provides an interface to capture similar trends in between topics, and between topics and total conversions. TopicMachine can be used to visualize topical structure at a given epoch.

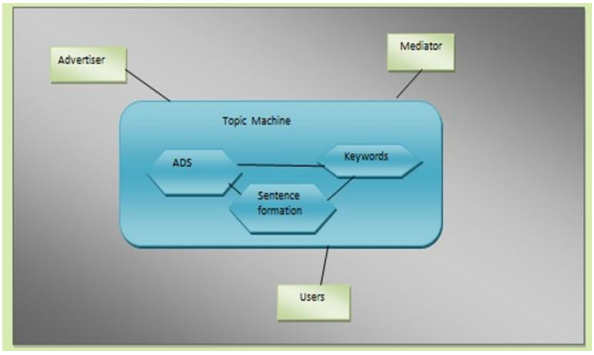

Figure 4(a) System architecture

5. GIVEN INPUT AND EXPECTED OUTPUT

Mediator

AUTHENTICATION:

Input: Provide username and password to get permission for access.
Output: If authorized person to request and process the next.

DATASET COLLECTION

Input: Insert the keywords in Data Base

Output: It will be stored in Data Base

DATA SET ANALYSIS

Input: Analysis the keywords through Data Base

Output: It will be saved in Data Base

TOPIC MACHINE

Input: combining the sentence like a frame work.

Output: Saves all the details in Data Base.

Users

SEARCH TOPIC

Input: Users types a sentence.

Output: Gets the details from topic machine.

View Topic machine
Input: response from topic machine.

Output: views all the information.

Advertiser

New Advertising
Input: Pay amount to view his AD.

Output: Response from mediator.

6. ALGORITHM USED

Latent Dirichlet Allocation (LDA)

Topic Machine uses a technique Latent Dirichlet Allocation (LDA)-based topic model. Since information needs may change over time or drift in concept, we learn dynamic topic models by sequentially chaining model parameters in a Gaussian process across a well-defined epoch. LDA effectively provides a mechanism to reduce dimension within a given text corpus. With a K-topic LDA model learned over the corpus, each document is expressed as a K-dimensional feature vector of probability values.

7. FUTURE ENHANCEMENT

In Future, The insights driven from structural trends, and target new market segments. All such management operations should be feasible while the underlying set of keywords scales to millions.

8. CONCLUSION

TopicMachine uses an LDA-based topic model. Since information needs may change over time or drift in concept, we learn dynamic topic models by sequentially chaining model parameters in a gaussian process across a well-defined epoch. We assessed the quality of the models learned in TopicMachine by showing the predictive power of the framework. We measured how well the conversions can be predicted with features extracted from TopicMachine model. In experimental results, TopicMachine term space, we foresee that advertisers can scale their campaign management to thousands of keywords comfortably with the use of TopicMachine while at the same time optimisingforconversions. Outperformed its closest competitor with an improvement of 41% in predictive R2 performance. Since TopicMachine's internal model can be used to reduce dimensions of the search.

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