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Research Article

Context Aware Question Answer Analysis For Student Education Using Sentiment

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ARTICLE INFO **ABSTRACT**

The currently available approaches for making recommendations based on content have two significant drawbacks. In the first place, the suggestion results are quite limited because of flaws in both the objects themselves and the algorithms that match user models. The second issue is that the recommendation system isn't aware of its context since the situation isn't given much thought. Increasing customer enjoyment via the provision of high-quality suggestions is an essential need. This study aims to improve recommendation performance by analyzing and expanding two state-of-the-art recommendation systems. The first method incorporates context information into the suggestion process; it's called the context-aware recommender. The second method considers domain semantics; it's called a recommender based on semantic analysis. The issue lies in combining them in a way that will completely take use of their potential, despite the fact that they are compatible with one another. An strategy based on Spark and MapReduce has been suggested for the context-aware recommendation system. In this work, we suggested a context aware similarity aware strategy utilizing Matlab to evaluate its accuracy, precision, recall, and F-score. Specifically, we looked at these metrics.

Keywords — Big Data, Context Aware Recommendation, Question and Answering and Semantic Analysis

I. Introduction

Users' preferences can be used in conjunction with data from content-based recommender systems (abbreviated as CB) to narrow down the search results that are relevant to individual users. However, the traditional CB method focuses primarily on finding matches between user profiles and item descriptions without taking into account the fact that context might play a role in shaping user preferences. As a result, it is unable to reach a high level of accuracy when predicting consumer preferences. Research questions and hypotheses are developed and tested as an integral aspect of human-centered application development and design. Earlier or baseline MoJo technologies are expanded upon by these hypotheses and queries. By developing and testing primary algorithmic backend services grounded on solid semantics in this setting, we are able to provide convincing proof of concept for the suggested architecture. The proliferation of location-based social networks and the meteoric rise in the volume of data generated by online social networking systems have led to an uptick in interest in location recommendation research from both public and commercial sectors. Nevertheless, the issue of data scarcity continues to provide a significant obstacle for the location suggestion algorithms that are now in use. In addition, one of the most important aspects that plays a role in determining how a user checks in, the extraction and modeling of many contextual pieces of information presents a significant barrier for the methodologies that are currently in use. When it comes to modeling user check-in habits, many of the currently available location suggestion systems have a poor level of accuracy since they only employ a small amount of contextual information. The learning management system, often known as LMS, is a piece of e-learning software that helped to pique the attention of various groups of learners. Learners, on the other hand, have a tough time locating learning resources that are suited to their preferences in the most effective method and at the appropriate time. Utilizing different contexts and learning styles, such as tailoring different areas of one's education, can help make the learning process more productive and enjoyable for the student. To ensure the success of cutting-edge big data applications like entity reconstruction and information enrichment, we emphasize relation completion, or RC for short. When given the semantic relation R, RC will try to find pairs of entities in two lists that are related by it. The Open

Mobile Network, a semantic framework for mobile network topologies, is built upon Linked Data. By connecting the Open Mobile Network to the Linking Open Data Cloud, new semantic context-aware services (CAS) may be built. Not only do these CAS take their cues from more conventional context data (like location), but they also include semantically-derived information. Thus far, this open-source project has just provided triplified data on network topology from open-source cell databases like as OpenCellID and OpenBMap, which is very static. Retailers have a huge chance to create demand-side optimization (DSM) schemes and customized pricing schemes for different types of consumers with the fast growth of smart metering information on smart grids. This is made possible by the fact that there are more smart meters than ever before. Traditional relational data interfaces necessitate the use of exact structured queries which may or may not involve sophisticated schemas. Non-expert users, who often lack linguistic competence and are unfamiliar with the nuances of the schema, have challenges when attempting to use these rigorous data retrieval procedures because they create obstacles. Query by Example (QBE) techniques give an alternative methodology. With these methods, users supply samples of the output they wish their queries to produce, and the QBE system is tasked with inferring what the users' intended queries are. On the other hand, these methods center their attention on the instances' structural similarities while ignoring the more nuanced context that is provided by the data. As a consequence of this, the queries that they generate are generally too generic and fall short of adequately capturing the user's intent.

II. REVIEW OF LITERATURE

The foundation of the project in [8] will be a recommendation engine, with a focus on digital media content like movies and web shows. The foundation of our study will be a methodology called collaborative filtering. We will use spark (MLib), the ml-25m dataset, matrix factorization concepts, and the ALS method to create this model. By using Deep Learning, Spark's distributed computing design will enhance the system's scalability and speed while facilitating the efficient analysis of large datasets.

In this era of big data, semantic web, data-driven narrative, and crowdsourced soundscape heritage, the purpose of studying how to improve the Mobile Journalism (MoJo) paradigm for management is given by [9]. From several vantage points, soundscapes and the meanings attached to environmental noises impact cultural heritage, which in turn affects the standard of living for humans. This position proposes that cutting-edge machine training and deep learning technologies, when combined with location- and context-aware mobile applications, can provide multilayer semantic analysis for the purpose of monitoring sound-related heritage. These utilities may provide new light on long-term strategies for sustainable development in urban as well as rural areas. The multimodal preservation and auralization of open historic theaters with peculiar acoustic behavior and unique soundscape regions are also highly prioritized since they are great cultural artifacts. This part of the process is called auralization. Creating and studying a ubiquitous computing platform to apply and assess the suggested MoJo technique is one way to accomplish this goal. Central to this concept is the use of client-side and cloud-based semantic analysis services.

In [10], Multi-Context-aware Location Recommendation using Tensor Decomposition (MCLR-TD) is introduced as a way to simulate user check-in behavior by using multiple types of context information at different levels of granularity. We utilize a tensor with four modes to depict the link between people, places, time, and weather. We continue to construct four feature vectors that, in conjunction with the tensor, are used in a collaboration decomposition approach to address the issue of data sparsity. Extensive trials using two real-world datasets from Foursquare along with Yelp show that our strategy works.

This article presents a novel data-driven method for discovering student characteristics using activity trace mining in [11]. The method is based on the Felder-Silverman Learning Style Model (FSLSM). One hundred fourteen students from three separate agronomy classes at IAV HASSAN II were surveyed for this study, which took place in the winter semesters of 2019, 2020, and 2021. Students are categorized with an unsupervised clustering algorithm based on their preference for sequential or global learning styles. Following the training of a need-specific classifier model, we supplied the learner with a learning item recommendation list that took into account both their chosen learning technique and the current operational environment. Given that the majority of students preferred an international approach to learning, the findings showed that students' performance was improved by more than 96% when contextual variables derived from their adaptable near environments were used. The LS identification was successfully accomplished using the k-means algorithm.

A method for making suggestions about IPE resources based on collaborative filtering (CF) is detailed in the article [12]. Recommendations for educational materials are provided to users according on their interests, surfing habits, and history. By tracking users' actions on the site, a reliable recommendation system may learn what they're looking for and provide better content recommendations. This research found that the political and ideological education precision recommendation system outperformed the traditional algorithm by 16.75% in terms of accuracy. Educators may access students' data stored in numerous locations online, get real-time insight into their current situations, and tailor their lessons to each student's unique requirements by leveraging big data technology and the intelligent ideology modes.

To improve the efficiency of mining Distributed Utility itemsets in respect to huge data, an optimized approach termed IDUIM is proposed in [13]. A number of improvements have been made to the Distributed

Utility item sets Mining (DUIM) method, which this approach augments. Information management and decision-making systems that operate in near real-time rely on the valuable insights provided by IDUIM, which efficiently mines item sets of large datasets. Results from experiments show that the approach performs similarly to IDUIM and other state methods such as DUIM, PHUI-Miner, and EFIM-Par. In comparison to other state-of-the-art algorithms, the findings show that the IDUIM method is both more efficient and executes better.

A hybrid data-driven approach to customer load profile clustering and retail plan optimization is suggested in [14] study for energy retailers. Incorporating user-side data into the risk-aware decision-making framework, specifically using the conditional value-at-risk (CVaR) demonstrating method, allows the retailer to direct customers' energy consumption behavior in a way that ensures cumulative revenue without harming their benefit. Conditional value-at-risk (CVaR) modeling might be the key to making this happen. The vast array of demand response alternatives accessible to customers would more than compensate for a little increase in the quantity of money that consumers may be obliged to pay, according to large-scale experiments. Retailers stand to gain between 33% and 34% in profit and 49% to 51% in revenue if they use demand response technologies.

Bilateral Generation (BiG) is a novel and simply implementable data augmentation technique proposed in [15] to enhance the effectiveness of rating question answer pairs utilizing existing labeled data. As a training goal, BiG is contrastive. Using two pre-trained generation models, one for question creation and another for answer production, we generate pseudo-positive QA pairs rather of the original negative QA pairs due to the limited amount of positive QA pairings in the initial data set. In order to learn how to rank question-and-answer pairings, we use the enhanced dataset to create a contrastive training goal. By maximizing the use of pre-existing labeled data, our approach considerably enhances ranking model performance and is readily applicable to other ranking models, as shown experimentally on three benchmark datasets.

III. Proposed Model

A. Overview

Within the scope of this study, contextual information is regarded as an essential source of data for the purpose of furnishing users with pertinent recommendations that help them acquire a deeper comprehension of the situation in which they find themselves. Through the provision of QA item recommendations, the system that has been made available serves as an important instrument in the fulfillment of user knowledge. In subsequent studies, the primary focus will be on building some natural expansions of the current idea as well as minimizing some of the limitations posed by the current approach. They will put their attention on: In order to include the information offered by the present context into the recommendation strategy, we are proposing methods for gauging its quality. These methods will take as their point of departure several notions that have been created in the past, such as relevant contextual information..

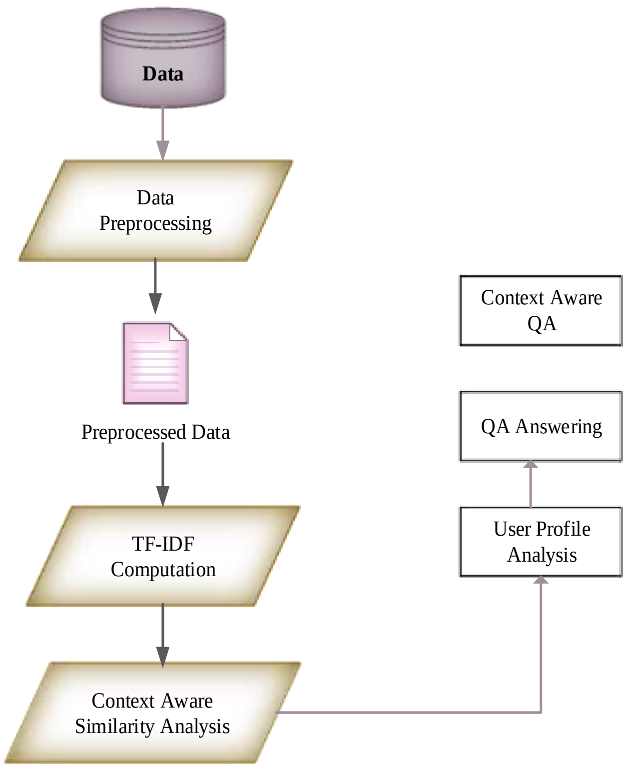

Fig.1. Context Aware QA Analysis

- Because it incorporates contextual information into the model that is created by the recommender system, the model that has been provided is suitable for use with the CA approach to contextual modeling. Figure 2 depicts the overall plan for the proposal, which is called LSAContextCluster. The plan is divided into five stages, which are as follows:Analysis of the QA domain's semantics: The dimensionality of the term-document matrix is decreased as a result of the application of LSA.Create a profile of the user's preferences: It does an analysis of the user's tastes and creates a profile for each user based on the profiles of the documents that the user has previously indicated that they have enjoyed reading.Build context model: It performs an analysis of the context, which is comprised of a stream of status updates occurring within a specified time period, using clustering in order to divide the numerous topics that the context includes, and creates feature-space profiles for each subject included within the context.Contextualize user profiles by choosing the context subject that is most appropriate to the preferences of the target user and then combining the preference-based user profile with the context topic profile to produce the contextualized user profile.In order to make a prediction, it examines both the document profiles and the user profile that has been contextualized.
- The following is a list of important CR-QA terminologies:A question and its accompanying response are what is known as a QA item, and this pair makes up the textual item that should be suggested. - Term: A single term that can be found within a document that is being referred to as a QA item here. Characterizing objects and using them as a foundation for suggestions are the two main functions of features in content-based recommendation. The use of suggestions based on features is on the rise. To find the set of characteristics (or characteristic space) that are most relevant to the current collection of QA items (or documents), this research use the LSA approach. This is achieved by feeding it the words from the relevant set of QA elements in the form of their TFIDF matrix.Overview of the document: The vector profile _dLSA, which is associated with the feature space generated by the LSA method, represents the quality assurance items, sometimes called documents.Profile of the participant: In the feature space, a vector profile LSA represents the use profile. All of the quality assurance elements that show up in the profile _dLSA after a user has shown interest in a document by writing, commenting, or voting on it combine to form this vector profile LSA.A user-supplied, unstructured text input that is linked to a specific information source (here, Twitter) is known as a status update. inside the scope of this study, the context is defined as the collection of status changes that occur inside a certain time range. Here, this collection of updates is handled in a manner that is analogous to the processing of the document profile in order to acquire the context model profile e_cLSA, which will be utilized in the stages that come after this one.The feature vectors that reflect the phrases that are associated with the context profile _cLSA are clustered in order to group them into the categories that are the most relevant to each other. After that, a context topic profile c_(c_i)LSA may be recognized as belonging to any given cluster.
- The profile that results from merging the user profile (u_uLSA) and the profile (c_i iSA) is known as the contextualized user profile."involved with" "a chosen context" topic content.

Table 1. Different Types of Contexts

Domain of Context	**Incorporated Contexts**
Travel and Tourism	Considerations such as time, company, place, neighborhood, recent events, social connections, goals, seasons, nationality, finances, and areas of specialization are all important.
Places	Considerations include the following: time, place, partner, distance to an accessible point of interest, purpose, nationality, activity, weather, user mood, social connections, personal preferences, as well as societal impact.
Multimedia	Who, when, where, what, place, time, crowd, mood, companion, social, mental stress, weather, orientation, age, sensory data, gender, and a user profile are some of the things that need to be considered.
e-Documents	Factors such as activity, background, location, technology, environment, device, URL, gender, time of day, age, prior logs, ISBN, title, manufacturer, author, keyword, abstract, introduction, major theme, conclusion, paper type, and language Considerations such as activity, technological advances, location, environment, backdrop, device, gender, age, time of day, and prior logs are included.
e-Commerce	Details such as gender, age, place of residence, category, closeness, mood, season, present budget, previous logs, time, mental strain, planned store, as well as intent to buy are included.
Others	Time, seasonality, sequentially, role, geographical location

B. TF-IDF Matrix

Our idea is based on the assumption that the QA dataset includes textual information of the questions as well as their associated replies. For the purposes of this proposal, the questions and all of the responses to those questions make up the document, and the terms refer to the words that appear inside that document. The

Porter Stemmer method was used to perform the stemming on the words. Following the process of stemming words, the TFIDF document profiles profile _dTFIDF are constructed in accordance with Equation 1.

The dimensionality of the matrices is reduced by performing LSA after the TFIDF document profiles have been constructed. Success of LSA has been shown by describing articles and words in an area of features with a small number of attributes. In this step, we look at Equation 3 to determine how to decompose the original word-document matrix into three parts: a word-features matrices U, a singular value vector s, and a document-features matrix V.

The estimated decomposition of the TFIDF matrix is constructed using Singular Value Decomposition. Reducing the original matrix's size while preserving its top-f singular values is possible with this strategy. For this reason, the QA domain semantic framework relies on two matrices, U and V, to provide the feature space word and document profiles:

$$\begin{aligned} \text{profile}_d^{LSA} &= \{u_{d,1}, \dots, u_{d,f}\} \\ \text{profile}_t^{LSA} &= \{v_{t,1}, \dots, v_{t,f}\} \end{aligned} \qquad (1)$$

TABLE 2. Consumers' inclinations toward products, the evaluation grid.

	d_1	...	d_k	...	d_n
u_1	r_{u_1,d_1}	$\cdots$	r_{u_1,d_k}	$\cdots$	r_{u_1,d_n}
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
u_j	r_{u_j,d_1}	...	r_{u_j,d_k}	...	r_{u_j,d_n}
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
u_m	r_{u_m,d_1}	...	r_{u_m,d_k}	...	r_{u_m,d_n}

C. BUILDING USER PREFERENCE PROFILE

Now that LSAContextCluster has built a model, it contains word and document profiles. The ability to provide customers with tailored recommendations depends on building user profiles using a common feature space. Whether a user demonstrated interest in a certain document (see to Table 2) by writing it, talking on it, or voting on it is indicated by a binary matrix stored in the LSAContextCluster. This table displays the set of articles that user u has shown interest in, as:

$$R_u = \{d \text{ s.t. } r_{u,d} \in R\} \qquad (2)$$

The user's profile, which details their preferences within the feature space, is constructed using the profiles of the files that are part of R_u:

$$\text{profile}_u^{LSA} = \sum_{d \in R_u} \text{profile}_d^{LSA} = \{\sum_{d \in R_u} \text{profile}_{d,1}^{LSA}, \dots, \sum_{d \in R_u} \text{profile}_{d,f}^{LSA}\} (3)$$

Since the user's profile will be compared to other profiles with the cosine correlation coefficient, which only considers the angle of the vectors being compared, normalizing it is unnecessary. It is possible to divide the semantically enhanced CF into three components.Using ontologies for user modeling: Model the user's and neighbor's preferences using the semantically upgraded CB approach.During the neighborhood generation process, the k closest neighboring objects may be chosen by calculating the semantic match, which is a match between two users' models.Find a ballpark for R (u, i) using the tried-and-true method of user-based score prediction.

This work is focused on expanding RS by combining information about the area and the context into suggestion in order to further improve the efficiency of recommendation and overcome the limitations. For the purpose of describing the properties of an object (for example, the categories of books), the ontology or other analogous representations are utilized. A set of ontology-based (or comparable) observable properties, such the time or position within a day, are expressed using the context information. One approach that might work is an integrated method that takes into account both the heuristic CB-based semantic and the context information.

D. BUILDING ON THE CONTEXT MODEL

It is necessary to construct the context model in order to include contextual information into the process of making recommendations. As part of this plan, one of our goals is to encourage the submission of questions that are pertinent to recent events. In this way, our concept takes use of the fact that status updates on

microblogging sites like Twitter are a great place to find out about the latest trends. Status updates, in a formally speaking sense, are just user-generated, free-form text inputs that have a timestamp and some other meta-data attached to them. After analyzing the status updates, LSAContextCluster builds an image of the context to inform the profile adjustment process. The overarching strategy for the time being while the context architecture is being constructed is shown in Figure 3.
In this proposal, the context is defined as the status changes that were generated during a specified time range of 24 hours; however, this may be adjusted to suit different needs by modifying the context model. The given time period is used to construct the context, which consists of status updates. Starting off, we have stemmed every single term that is part of the current context's status updates. After that, the LSAContextCluster tool examines all of the terms that are present in the context and removes any terms that are absent from the QA semantic model that was produced in the first step (for more information, see Section III-A).
Since the context consists of many status updates, a wide range of topics may be covered. The proposal uses a fuzzy clustering method to identify the subjects in the context by analyzing the words used inside. Fuzzy c-means clustering then sorts the words into categories based on their _tLSA feature vector profiles. The definition of the phrase is this. To find the distance between the several words used for clustering, the cosine correlation coefficient is used. The final product is a collection of clusters, where each cluster identifies a unique context topic (c_i).
The current context's words will be grouped into themes, and then the proposal will construct a profile for each subject by combining the profiles of the keywords in each group. With the help of the QA domain's feature representations, LSAContextCluster generates a profile for every topic in the context (for more on this, see Eq8). At this point, LSAContextCluster has built a model of the context out of several context profiles, with one profile corresponding to each clustered topic in the context.

$$\mathrm{profil}_{c_i}^{LSA} = \sum_{t\in c_i} \mathrm{profile}_t^{LSA} = \left\{\sum_{t\in c_i} \mathrm{profile}_{t,1}^{LSA}, \dots, \sum_{t\in c_i} \mathrm{profil}_{t,f}^{LSA}\right\} \quad (4)$$

E. USER PROFILE CONTEXTUALIZATION

Now we can create contextualized and personalized recommendations by merging the target user's preference profile with the context model. To achieve this aim in a user-specific way, LSAContextCluster selects the context topic profile that is most close to the user's preferences profile from all of the ones held by the context model. Therefore, the topic c_i in the context that best fits the target user's preferences is used to update the user's profile. Consequently, each user's choices are taken into account while contextualizing their profiles.

$$\underset{c_i}{\mathrm{argmaxcosine}} \left(\mathrm{profile}_u^{LSA}, \mathrm{profile}_{c_i}^{LSA}\right) \quad (5)$$

In order to create the contextualized user profile, the profile of the chosen context topic c_i is combined with the user's preference profile after this step. Because of this, we use the convex combination. You may do a weighted combination using this setup, where the argument specifies the weight. In the complemented user profile, the preference profile of the user takes precedence over the profile of the given context topic when for is larger. As the value of rises, this happens. As is reduced, the weight given to the selected context problem profile for the creation of suggestions grows.

$$\mathrm{profile}_{C,u}^{LSA} = \alpha * \mathrm{profile}_u^{LSA} + (1-\alpha) * \mathrm{profile}_{c_i}^{LSA} \quad (6)$$

In subsequent research, more complex methods, such as matrix factorization, will be investigated to see whether they can be used to integrate contextual data into the content-based recommendation model that was developed initially. For the sake of this research, we will disregard this issue as our main goal is to show that the recommendation performance may be directly affected by adding information to the original model. In next works, our primary focus will be on improving integration of this kind in order to achieve maximum accuracy in our recommendations.

F. PREDICTION

In order to align the aspects with their relevant opinion information, we first use inter-sentence attention to capture the interactions among the question and response phrases given a QA pair. The feature representation is then fused and refined using a self-attention layer and a controlled fusion layer. After that, we use self-attentive encoding to emphasize the emotion in the response and summarize the conveyed perspective. Next, in order to keep the emotion consistent, a local context encoder is used. Lastly, the unified tagging technique is used to forecast the tag sequence using the improved question representation. An auxiliary aspect term extracting (ATE) assignment, which utilizes the attended data from the response to aid extract the discussed aspect, is trained alongside our model to develop a better aspect-aware issue representation.
After the contextualized user profile has been created, we will be able to make a prediction regarding the appropriateness of a certain item in relation to the profile. The advice is organized as a list of papers based on $p_{u,d}$:

$$p_{u,d} = \text{profile}_{C,u}^{LSA} * \left(\text{profile}_{d}^{LSA}\right)^{T} \quad (7)$$

For the purpose of obtaining contextualized word representations, we use BERT as our backbone network. We use BERT to convert every token in w_i to its word vector given a query Q and an answer A $h_i \in \mathbb{R}^{d_h}$ where d_h occupies the unseen space. Our notation for the changed sequences is as $H^q = \{h_1^q, h_2^q, \dots, h_m^q\}$ and $H^a = \{h_1^a, h_2^a, \dots, h_n^a\}$ where m and n denote the lengths of their respective sequences. In keeping with this standard practice, we will use capital letters like H^q to represent the array of the whole sequence, and matching lowercase letters like h_i^q to designate the depiction of the i-th token from now on. The next step is to apply self-attentive encoding to the response text in order to highlight the most crucial section of it, making the emotion polarity in the answer phrase more apparent:

$$\alpha_i = \frac{\exp\left(w_s^T \tanh\left(W^s \bar{h}_i^a\right)\right)}{\sum_{k=1}^{n} \exp\left(w_s^T \tanh\left(W^s \bar{h}_k^a\right)\right)} \quad (8)$$

where $w_s \in \mathbb{R}^{d_o}$ and $W^s \in \mathbb{R}^{d_a \times d_h}$ α_i represents the weight for the i-th response token, and these parameters may be trained. A fixed-size response representation $\bar{p}$ is then calculated in the following manner:

$$\bar{p} = \sum_{i=1}^{n} \alpha_i \bar{h}_i^a \quad (9)$$

which summarizes the main opinion information in the answer. A linear transformation is further applied to obtain a more condensed representation $p \in \mathbb{R}^{de}$. We add it to every question token to make the sentiment data bigger, and we label the updated question as $\bar{S}$ where $\bar{s}_i = [s_i; p]$, and $[;]$ performs the procedure of joining.

Using the combined representations as input, we train a convolutional neural network (CNN) with a kernel size of one to focus on the individual question tokens and improve their features. To prevent conflicting sentiment predictions for the same aspect, we build an additional CNN layer on top of it, this time with a bigger kernel size, to use the surrounding data for each token and regulate the consistency of sentiment:

$$O = \text{ReLU}\left(W^l * \text{ReLU}\left(W^t * \bar{S} + b_t\right) + b_l\right) \quad (10)$$

where W^l and W^t represent the parameters that may be trained for two convolutional kernels, and * denotes the operation that does the convolution. $O \in \mathbb{R}^{m \times d_u}$ is the last representation of features for the whole set of questions.

IV. EXPERIMENTAL RESULTS

The largest Chinese e-commerce portal, Taobao2, provided us with the QA pairings that we used in our research. The three product categories included in the dataset are Electronics (ELEC), Beauty (BEAUTY), and Bags (BAGS). An annotation consisting of one or more tuples: (aspect term, polarity) is appended to each QA pair. The aspect phrase is a span of the question text. We eliminate the mis-annotated data and eliminate the duplicate QA pairings from the original corpus. We used a random 8:2 split for each product category's data to create a training set and a testing set. While training, we choose a random 20% sample to serve as development data for hyper-parameter tuning and use the remaining 80% for training. In Table 3 we can get a summary of all the dataset statistics, including the amount of QA pairs as well as aspect terms.

Table 3: Statistics of the datasets of three domains

Dataset		Train	Test	Total
ELEC	# QA pair	3639	909	4548
	# aspect	4071	1018	5089
BEAUTY	# QA pair	3577	894	4471
	# aspect	3887	964	4851
BAGS	# QA pair	3620	904	4524
	# aspect	4228	1035	5263

In these trials, we examined a few different CR techniques that were based on LSA and information from their environment. In order to carry out the experiment, the technique that was suggested was carried out, but with certain alterations to account for knowledge regarding the experiment's environment.

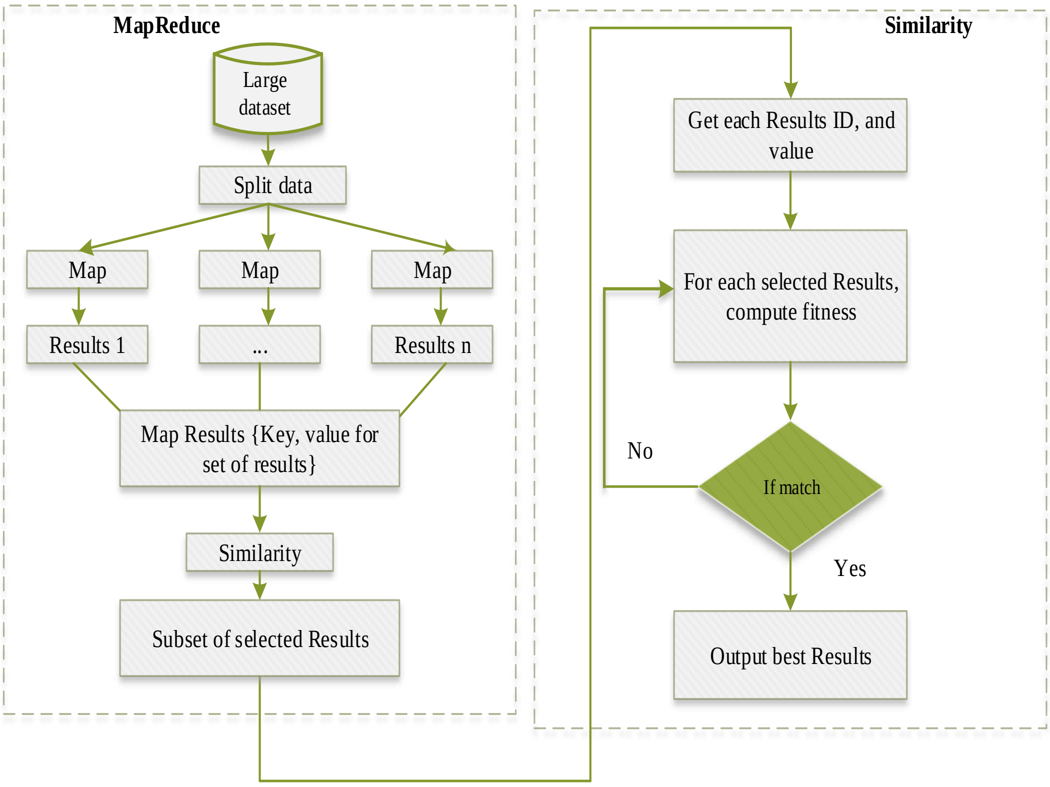

Fig.2. Spark MapReduce

Make two sets of data: one for training and one for testing. Use 5-cross-validation as a method to partition the dataset according to the obtained quality assurance items. One often used approach for evaluating recommender systems is five-fold cross-validation, which we would like to bring to your notice. As a part of this method, the initial set of data is separated into k folds. The model is trained using data from the other folds (a total of k-1) and verified using data from the fold that was used for validation. Each of the k subsamples is used as test data exactly once throughout the k-times cross-validation phase, while the remaining subsamples are utilized for training. After the completion of the very last stage of this process, the last step involves reporting the performance of the k assessments on an average scale. Construct the model using the individual training data received in the phase before this one. The model should be built of QA items obtained from real-world tweets in the amount of 6500 Create a profile for each individual user, making sure to include any relevant contextual information. This piece of contextual information was taken from tweets and consists of those tweets. To eliminate the possibility of any bias in the partitioning process, this entire method was carried out twenty times. The experimental procedure was created inside the MapReduce methodology using the big data framework Spark. Spark is capable of processing enormous volumes of data and provides abstractions for distributed computations.

Apache Spark was initially released as a component of the Hadoop Ecosystem. It provides users with access to a set of in-memory primitives that are designed to supplement those provided by MapReduce and that are appropriate for iterative workloads. It is built on something called Resilient Distributed Datasets (RDDs), which is a structure that saves data in a way that makes it simple to parallelize later calculations over a network of computers. RDDs enable the caching and redistribution of intermediate results, which makes it possible to create pipelines for the processing of data.

We use two libraries within Spark: MLlib and Spark Streaming. To take use of Spark's strengths in iterative tasks, the scalable machine learning library MLlib was created. Classification, optimizing, and data preprocessing are just a few of the machine learning methods it provides. For regression and clustering, in particular, we make advantage of the tools that MLlib makes available to us. Spark Streaming offers a scalable method of managing data that is generated at a rapid pace, which enables us to handle the data that is supplied by microblogging systems and to calculate the context model.

On the test set, we put the model that performed the best on the growth set to the test. In addition to reporting the associated recall (Rec) and precision (Pre) scores, we use the F1 score as our primary assessment measure. When both the retrieved span and the anticipated emotion are accurate, the prediction is considered accurate according to the exact match metric. Results are presented as the average of five runs with varying random initializations. Using the dataset, this part evaluates the learning models. In order to do this, a number of course assessment questions, including those concerning the quality of instruction and the course material, are developed and submitted using Google Forms. Nevertheless, the dataset is divided into sets for training and validation so that the student comments may be analyzed. Additionally, the following measures are used to evaluate the efficacy of learning models:

The precision: When comparing the total amount of rows in the dataset to the number of valid predictions generated by the model, accuracy is expressed as the ratio. True positives (Tp) and negatives (Tn) are represented in equation 1, whereas false positives (Fp) and negatives (fn) are displayed in equation 6, respectively.

$$\text{Accuracy } = \frac{Tp+Tn}{Tp+Tn^{+P_p+F_n}} \qquad (11)$$

One definition of precision is the percentage of right predictions to total predictions made by the system. Equation 7 shows the formula that may be used to compute it.

$$\text{Precision } = \frac{Tp}{Tp+Fp} \qquad (12)$$

The recall measures how many true and incorrect emotion labels there were relative to the overall number of right predictions provided by the model. Equation 8 shows the formula that is used to calculate recall.

$$\text{Recall } = \frac{Tp}{Tp+Fn} \qquad (13)$$

When it comes to multi-class classification tasks, F-Measure is another popular statistic to utilize. The geometric mean of recall and accuracy is what it is called. As stated in equation (9), the F-measure is a useful statistic for evaluating the model's performance.

$$F- \text{ score } = \frac{2^{*} \text{ Recall} * \text{Acc}}{\text{Recall} + \text{Acc}} \qquad (14)$$

Table 3. Evaluation metrics.

Evaluation Metric	**Condition**	**Merits**
Precision	To evaluate the proportion of retrieved files that are relevant	It denotes the system’s ability to reject any non-relevant document in the retrieved set.
Recall	To measure the proportion of relevant documents that are retrieved	It determines the system’s ability to find all the relevant documents.
F-measure	To measure the harmonic mean of recall and precision	It expresses the balance between precision and recall.
Mean Absolute Error (MAE)	To measure the accuracy of rating predictions	It evaluates the deviation of recommendations from the user-specified ratings.

Table.4 Performance Analysis for the ELEC Dataset Proposed vs. Existing Approaches

Method	Precision	Recall	F1-Score	Error Rate
Logistic Regression	0.95	0.95	0.94	0.2
CNN	0.96	0.95	0.95	0.155
LSTM	0.96	0.95	0.95	0.124
PROPOSED	0.98	0.96	0.975	0.1

Table. 5 Performance Analysis for the BEAUTY Dataset Proposed vs. Existing Approaches

Method	Precision	Recall	F1-Score	Error Rate
Logistic Regression	0.95	0.95	0.94	0.2
CNN	0.96	0.95	0.95	0.155
LSTM	0.96	0.95	0.95	0.124
PROPOSED	0.98	0.96	0.975	0.1

Table.6 Performance Analysis for the BAGs Dataset Proposed vs. Existing Approaches

Method	Precision	Recall	F1-Score	Error Rate
Logistic Regression	0.95	0.95	0.94	0.2
CNN	0.96	0.95	0.95	0.155
LSTM	0.96	0.95	0.95	0.124
PROPOSED	0.98	0.96	0.975	0.1

Measuring the forecast accuracy relative to the rating deviation is the usual practice. In contrast, the methods under consideration do not forecast ratings but rather provide a number that stands in for how well objects fit the user's profile. Because of this, the types of measurements that may be employed are ones related to the retrieval of information, such as recall and precision. Researchers have made the observation that, despite their usefulness, they are not logically sound with regard to the categorization of the things that recommender systems perform. In general, the purpose of this work was to offer a strategy that takes into account the part that the context plays in quality assurance recommendations. In particular, we proved that QA items are a major case where content could be crucial when it comes to making suggestions for quality assurance. It should be noted, however, that our approach is broad enough to be applied to any textual element and may even serve as a way to combine two separate data sources for better recommendation performance. We consider this to be the most significant benefit of our proposal since that is the case.

However, our concept still has significant shortcomings, which will need to be addressed by doing more study. In this case, a restriction is associated with the fact that there are occasions when making use of the context results in a detrimental influence on the performance of the advice. Even if this sort of conduct is to be anticipated, further study is required in order to make the most accurate detection of situations of this kind.

V CONCLUSION

We explored the possible uses of contextual data in quality assurance domain suggestion as part of this effort. At its outset, ContextClustering builds the LSA model associated with the QA domain. The next step is for it to combine the user's choices with the QA profiles to build the user profile. Several clusters are formed by building the context profiles simultaneously; thereafter, a context profile is built for every one of these clusters separately. Following this, the user's choices should be combined with the context profile that best fits their situation. One way to do this is to discover the cosine coefficient that connects the two profiles. The system can learn the user's tastes and incorporate contextual data into its suggestions thanks to this integrated profile.

Within the Spark big data framework, we conducted experiments and a case study to assess the effectiveness of the different implementations of the suggested strategy. Based on our research, we determined that selecting words with the highest membership value across every group in the researched QA area is the best way to create a profile for every scenario cluster. Furthermore, we demonstrate that the proposed approach yields superior outcomes in comparison to the standard operating procedure (LSA).

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