Attribute Based Document Annotation Using Big Data Framework

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ABSTRACT

Technology and its advantage of using in the modern age of Information Technology, where the content based document annotation keep on changing. In the context of the structured and unstructured data gives us the most significant information, but in order to process the data of the content structured would be useful. In this Paper, we try to give the most significant glimpse of the big data based information in the Human Interface of the UI. Technologically its process of facilitation optimized way to the data can be made search. In order to such trend we need protocol of User interface before submitting the data making in the format the query based structured or unstructured approach. In this one we have used the UI based framework which in turn uses the approach of the content in the document in order to facilitate the process of the QTP and the big data makes the sense protocol of the category.

Keywords : Document Annotation, Adaptive Forms, Collaborative Platforms, Hadoop Analytics

I. INTRODUCTION

The challenge of automatically annotating documents with structured semantic big data has been addressed in previous projects by BBC Research and Development, including work on automated concept tagging and document linking. However to date, this work has consisted of using supervised learning models which require a training set which must be compiled by hand in advance, or substituted by some heuristic or external source of information which serves as a suitable proxy for ground truth. A thorough, empirical analysis of the effectiveness of active learning techniques already published in the literature, including a comprehensive appraisal of different query strategies and error measures, as well as a comparison to established supervised and semi-supervised learning algorithms. By combining active learning approaches to inference with models that reflect the structure of the topic space in question, we hope to make a novel contribution to the field of automated topic modeling and classification. Specific approaches could include the use of query-by-committee to estimate classification variance in a model where computing such statistics directly would be intractable, combining active learning with complementary semi-supervised and unsupervised learning techniques, and the use of active learning to infer a topic distribution over documents, by defining a topic model over users of the system and propagating this to documents via their training decisions.

II. RELATE WORK

In addition to different goals and different prediction aims, two more criteria must be considered in the design phase of an adaptive component. First, in some cases, very detailed information about the users of the system is available for instance, in cases where the same course has been conducted several times and analyses of usage data have shown that users' behavior changes only marginally across various semesters, or in cases where users have already taken several different courses on the platform, whereas in other cases the system does not know anything about its users.
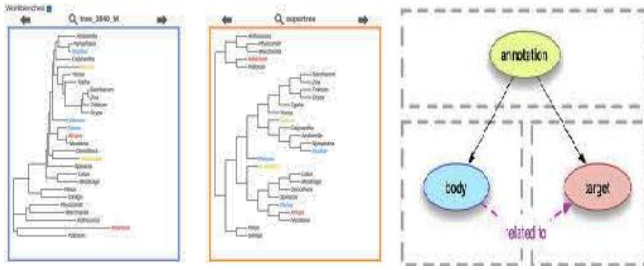
Figure 2.1. Related view of the Document Annotation

This can crucially influence the decision on how usage data is analyzed and evaluated. The modeling step aggregates usage data by bundling data instances based on their relations to each other. The outcome is a new data instance which can be passed over to the analysis unit responsible for prediction. The modeling approach again depends on the nature of the data and the prediction aims. If usage data comprises information of different tools and users, it might be interesting to find out how users are related to each other, or how tools are used in combination. If usage data comprises data of only one tool that can be used in different ways, it might be interesting to find out in what order the different activities happened. The combination of students and problems can help to not only find out which approach a student shows, but also if the approach deferrers for different types of problems. Both entropy indices, however, tend to naturally increase as the number of clusters increases in the concrete scenario, and are, therefore, not sufficient in themselves for characterizing the results of the clustering process. This increase originates, in this case, from clusters often being homogeneous along one dimension but inhomogeneous along others. For instance, regarding the distribution of students to clusters, we have to consider that problem-solving behavior consists of several components that could influence the assignment of a student's problem-solving sequence to a cluster. The more clusters are introduced; the granularity of the analysis, and the more factors could end up being emphasized by the representation in a cluster. Thus, it is practically impossible to receive the optimal cluster setting mentioned before. However, a good cluster setting would be able to group a student's problem solving sequences into the same cluster if they are similar at least along one dimension.

III. PROPOSED METHODOLOGY

In the Era of technology, the individual cluster setting evaluation metrics were introduced are the student entropies, the problem entropies, the variance, and the expected prediction error. The entropy based metrics aim at capturing intra-personal similarities and the effectss of problem types on the behavior of learners. Regarding student entropies, patterns are indicative of students showing stable problem solving behavior. Regarding problem entropies, recognized patterns are either indicative of problems of the same structure or of independent approaches people share. The expected prediction error can be assessed in a way similar to what was described for variance. Generally, a low value for the expected prediction error is good. However, if the number of clusters becomes too high, thus minimizing the number of data instances in a cluster and thus also the expected prediction error, the resulting clusters are not informative in any way anymore. Thus, again, the value for the metric should not be a certain threshold. It should be assured that adaptations based on predictions are in general potentially reasonable. For instance, if the system recognizes a pattern in the current live graph based on the users involved, how would a subsequent adaptation look like? For example, to recommend collaborators for future activities, an ideal system would strive to take into consideration any observable extrinsic factors that may have a effect collaboration. Summing up, the described approach could potentially provide valuable results regarding predictions and subsequent adaptations if specific conditions are held. If this is not the case, the approach's success can only be measured after practical implementation.
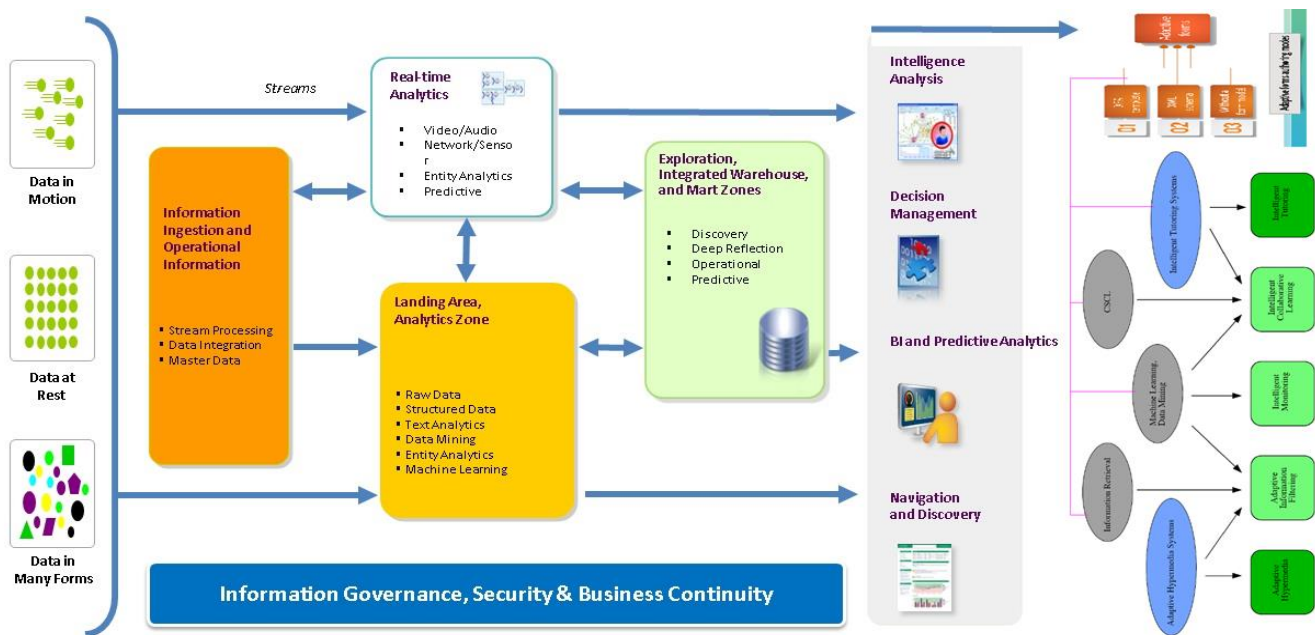
**Figure 3.1.** Model Retrieval annotation Big data System Architecture

The general idea of using detailed, reliable information about an individual in order to infer the behavior in a group is a promising one of big data analytics are currently bound by significant latency perceived by end users. Almost all widely used Big Data technologies are not suitable for real time analytics. Task is as difficult as finding needle in haystack in no time. Problem further exacerbates when data can be linked with other data Consistent Governed: centralized and managed usable: by any business to consume analytics Relevant: connected to all the data users need to do their jobs well Accurate: data quality is paramount Timely: Provide real time data and agile content development Engaging: Offer a social or collaborative component Deployed widely across the organization Yet, the intermediate step required here would lead to inaccurate models and subsequently also to inaccurate predictions. Generally, the approach first splits incoming data and organizes it into sites / tools. As not all activities which occurred in the same site and tool, are potentially related, criteria to determine the probabilities for relations must be defined. These criteria can be different for different tools, e.g. for an asynchronous communication tool, the time frame in which related activities can occur is much longer than in synchronous communication tools. Thus, we find a default setting for splitting tool activities into time slots. As classification should be performed on the basis of interrelated activity sequences, the activities cannot be sent through the classification process. Another approach would be to include several items' data as features in a data set which then goes to the classifiers. However, as the number of items in every time slot can different drastically, classification on the basis of time-slot-data is not possible. Yet, a fixed number of items can be used for one data set and include the corresponding time slot index as an additional feature in the feature set for classification data. Another possibility is to build the feature set based on the metrics described before, i.e. activity data will not be sent through the classifier in its original form, but be preprocessed first, creating a new data set for e.g. every time slot, containing elements like mean, standard deviation, variance, minimum and maximum, number of elements in this time slot, etc. Furthermore, standard matrix and graph metrics like scarcity or connectivity can be included. Given the results of the classifiers, one can extract information about what leads to successful

collaboration and what does not seem to influence the success of a group at all. This information can then be used to add contextual information to the knowledge gained by classification of independent activities. Furthermore, it could potentially reveal new information about collaboration in general and collaborative learning in specific.

IV. EVALUATION AND ANALYSIS

The expected prediction error can be assessed in a way similar to what was described for variance. Generally, a low value for the expected prediction error is good.
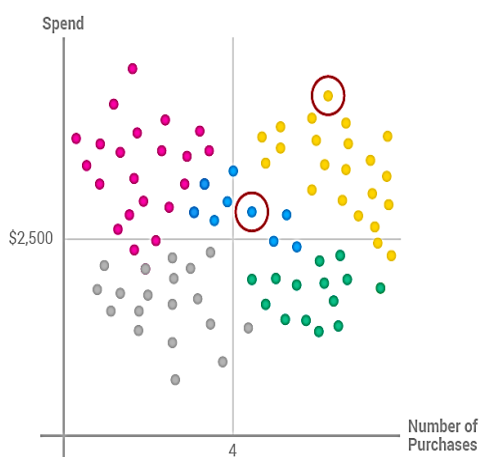
Figure 3.1.1. Comparison of the cluster based Analytics attribute Spend with Purchases

However, if the number of clusters becomes too high, thus minimizing the number of data instances in a cluster and thus also the expected prediction error, the resulting clusters are not informative in any way anymore. Thus, again, the value for the metric should not decree a certain threshold.

V. CONCLUSION AND FUTURE WORK

Several alternatives to representing sequences have been considered and evaluated, concentrating on the interwoven questions of comparability. Hadoop is the most widely accepted and used open source framework to compute big data analytics in an easily scalable environment. It's a fault tolerant, reliable, highly scalable, cost-effective solution that's supports distributed parallel cluster

computing on thousands of nodes and can handle petabytes of data. Two main components HDFS contribute to the success of Hadoop. Specifically, a formalism should be found, that would allow for the comparison of activity sequences that might differ only little, but also for comparing sequences with only small amounts of overlap. In general, the modeling of sequential data faces the challenge of not losing information about relations and dependencies between the individual items.

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