A Distributed Intelligent Agent Approach to Context in Information Retrieval

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Abstract. Information retrieval across disadvantaged networks requires intelligent agents that can make decisions about what to transmit in such a way as to minimize network performance impact while maximizing utility and quality of information (QOI). Specialized agents at the source need to process unstructured, ad-hoc queries, identifying both the context and the intent to determine the implied task. Knowing the task will allow the distributed agents that service the requests to filter, summarize, or transcode data prior to responding, lessening the network impact. This paper describes an approach that uses natural language processing (NLP) techniques, multi-valued logic based inferencing, distributed intelligent agents, and task-relevant metrics for information retrieval.

Keywords: Intelligent agents ·Natural Language Processing· Fuzzy Logic · Quality of Information;

1 Introduction

Network science focuses on complex networks, studying the relationships between social networks and communications networks, as well as the information networks that overlay them.[2] Disadvantaged networks, with constraints on bandwidth, topology, connectivity, and otherwise limited network resources, have additional challenges in comparison to commercial networks.

This paper describes an approach that uses natural language processing (NLP) techniques, multi-valued logic based inferencing, network status checking, and task-relevant metrics to deal with information retrieval challenges for disadvantaged networks. We designed, implemented, and conducted experiments with distributed intelligent agents to show the efficacy of this approach for making quality assessments that kept network performance at optimum levels.

2 Method

Our approach was to modify the information nodes into task-aware intelligent agents, distributed across the network, which can infer the appropriate quality in response to queries. These agents would need to be more than reactive agents, which automatically send responses based on physical measurements, thresholds, or triggers.

We selected a multi-valued, fuzzy logic approach because of the need to apply a graduated scale of assessments on quality, depending on differing tasks and network conditions. In a distributed agent environment, it is efficient to separate the types of intelligent agents that provide services and collaborate on user tasks. Sycara et.al. organized their framework into agents that interact with the user, agents that perform tasks, and agents that provide access to information sources. [5] Our experimental network contained two types of intelligent agents attached to information nodes: resolver agents and responder agents. *Resolver* agents are responsible for processing the incoming unstructured query from the user and, using the inferencing rules within its knowledge base, determine the task that is implied. *Responder* agents are responsible for transmitting information across the network in response to an incoming task from another information node.

Unstructured text as input is usually handled by keyword searches or query expansion using lexical resources (vocabularies, word banks, databases, etc.). These "bag-of-words" approaches lose some of the context of the original query, for example that which could be derived through word order. Another issue is that sometimes the literal meaning of the words doesn't reflect the underlying intent of the question. A technique called example-based NLP (EBNLP) has been used in machine translation (MT), to improve the accuracy and precision when dealing with unstructured, non-standard text. A bi-lingual corpus of data is used to extract examples, consisting of sentences and their corresponding parses, to handle complicated linguistic phenomena such as polysemy and unique idiomatic phrases that don't have literal translation. As described by Sumita [4], this technique was very effective for improving the accuracy for English-to-Japanese MT engines, but required a large corpus of training data. In our EBNLP algorithm, we create exemplar sentences for each task and then compare the input sentence against a list of example sentences, organized by task. The sentences are compared lexically (word for word) and structurally (by part of speech).

Comparing the sentences structurally required a part-of-speech (POS) tagger. In this instance, the POS tagger used the Penn Treebank, a widely used lexical resource, to assign tags to English text. [6] The tagger applies a bigram (two-word) hidden Markov model to assign probabilities to the appropriate POS tags for a word. Given both the lexical and structural information available in tagged sentences, a text similarity algorithm was used to compare the string to the exemplars. Text similarity is a technique for quantifying the sameness between strings. Text similarity was computed by searching for literal word token overlaps. [3] It was important to determine the number of word tokens that are identical between the two strings, as well as calculate other metrics, such as number of shared words, phrasal matches, edit distance, and relative string length.

Much of the existing work with quality of information (QOI) methods for data transmission focuses on optimizing intrinsic quality attributes or measurable network states such as bandwidth, latency, fan out, number of concurrent users, or other resource utilization costs. Task-aware extrinsic features that change based on context needed to be incorporated into an overall quality metric. A fuzzy logic engine was used to quantify and combine the attributes into one overall quality metric. There were two intrinsic attributes (*bandwidth level* and *improvement*) and one extrinsic attribute (*responsiveness*). *Improvement* and *responsiveness* attributes are derived from mapping functions that use object size, while *bandwidth level* is a directly measured quantity. The resulting QOI quality metric is a combination of all three attributes.

The information objects being retrieved across the networks were images with embedded metadata. Generally, image data transmission has a more significant network impact than document retrieval, unless the number of documents being retrieved is very large. The images were retrieved using embedded metadata in the images, such information as description, caption, time stamp, camera focal length, longitude, latitude, description, caption, orientation (rotation), x-resolution, y-resolution, and numerous other generated or manually entered attributes.

Determining the appropriate quality to send was based on the choice from transcoded images, which were variants of the original image. These transcoded options were pre-processed, minimizing latency due to image processing time. This assumption would coincide with a standard operating procedure that required the phone automatically create the transcoded versions upon taking a photograph, to speed up quality functions. Among the transcoded options were: original, compressed, reduced resolution, grayscale, monochrome, and thumbnail.

The distributed agent framework was evaluated in an experiment using simulated network traffic. The purpose of the experiment was to use the quality metric to establish a baseline for image retrieval across a disadvantaged network with fluctuating bandwidth in order to gauge the quality improvement given agent-based assessments of what to send. There were three possible tasks that could be performed based on the requested image data: identification, detection, and inventory. An example text string for each type of query task was selected for input to the resolver agent. Dynamic network traffic was simulated using a sine wave.

3 Results

The results for the identification task are shown in Figure 1. The Y-axis on the left depicts the available bandwidth on a scale of 0 to 200 KBps. The Y-axis on the right shows the predicted quality metric value on a scale of 0 to 10. The X-axis shows the experiment duration, in seconds, and also indicates the time step of the sampling points. The red line is the bandwidth. The green line on the chart is the baseline condition, when there is no quality assessment of the images prior to transmission. In that situation, all the original images in the result set are sent. The purple line is the experimental condition, where the responder agent uses QOI assessments to determine the transcoded option.

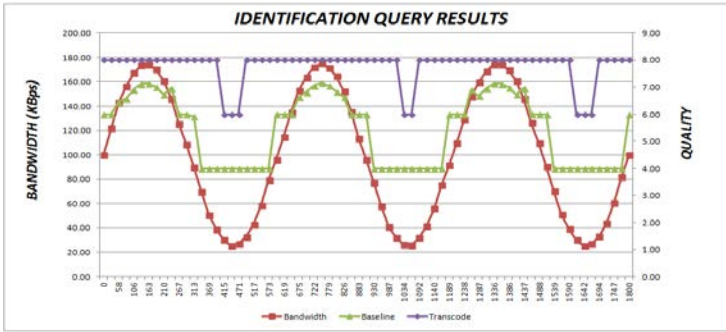

Fig. 1. Experimental Results for Identification Task

The quality values distribution of the experimental runs for the detection and inventory task are similar to this example, but not nearly as high, because the result sets are moderate to very large in size, respectively. Over all task categories, there is a significant improvement in quality, approximately 25% with respect to the baseline.

4 Conclusion

This paper described an approach that used NLP techniques, intelligent agents, multi-valued logic based inferencing, network monitoring, and task-aware metrics for information retrieval. We successfully defined and validated a quality metric based on intrinsic and extrinsic quality attributes. Through the use of a simplified technique, example-based NLP, we were able to use text similarity to capture intent from unstructured queries. Distributed intelligent agents used fuzzy logic inferencing to identify tasks and to determine what form of information object to retrieve. The experiment with this QOI agent framework showed the efficacy of this approach for making quality assessments that kept network performance at optimum levels.

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