A Big Data based Smart Evaluation System using Public Opinion Aggregation

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Abstract: Assessing service quality proves very subjective, varying with objectives, methods, tools, and areas of assessment in the service sector. Customers' perception of services usually plays an essential role in assessing the quality of services. Mining customers' opinions in real time becomes a promising approach to the process of capturing and deciphering customers' perception of their service experiences. Using the US higher education services as an example, this paper discusses a big data-mediated approach and system that facilitates capturing, understanding, and evaluation of their customers' perception of provided services in real time. We review such a big data based framework (Qiu et al., 2015) in support of data retrieving, aggregations, transformations, and visualizations by focusing on public ratings and comments from different data sources. An implementation with smart evaluation services is mainly presented.

1 INTRODUCTION

Service quality is well recognized as the overall perception of the services that results from comparing the service provider's performance with the general expectations of customers of how the service provider in that industry should perform. Challengingly, assessing service quality proves very subjective, varying with objectives, methods, tools, and areas of consideration in the service sector. Regardless of how service providers think about their provided services, frequently to a customer, it is the encounter of a service or 'moment of truth' that defines the service. In other words, it is the experience that customers perceived from their encountered services subjectively defines service quality (Qiu, 2014). Therefore, customers' perceptions of experienced services play an essential role in assessing the quality of consumed services. Correspondingly, mining customer or public opinions in real time becomes a promising approach to the process of capturing customers' perceptions of their service experiences (Meyer and Schwager, 2007; Labrecque et al., 2013).

Education has been one of main services in the US service sector for many decades. Ensuring that the US education service performs well is one of top nation's priorities. The higher education particularly draws much attention from a variety of stakeholders, from students, parents, employers, the government, to college administrators and boards of directors. Hence, finding a reliable method of knowing how the US higher education as a whole or an individual college is performing is necessary. Over several decades, there have been a variety of ranking systems that in different perspectives provide assessments of education services on higher education nationally or internationally (Harvey, 2008; Bergseth et al., 2014). A few well known ranking systems include the US News & World Report (USNWR), the Times Higher Education (THE) from the United Kingdom, and the Academic Ranking of World Universities (ARWU) from China's Shanghai Jiao Tong University (SJTU) (Huang and Qiu, 2016).

Regardless of ranking system or metrics, it is typical to utilize service quality factors that are subjectively selected and weighted. As a result, the provided rankings' objectivity and impartiality become worrisome and sometimes confusing and misleading (MIT, 2011). To some extent, a quantitative and model-driven method to

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computationally generate ranking factors' weightings in a ranking system can help address the objectivity and impartiality issues in its enabled rankings (Huang and Qiu, 2016). The method bears an acronym of HESSEM, i.e., Higher Education System oriented Structural Equation Modeling. Because selecting ranking factors for a ranking system is also subjective, thus it is desirable for a ranking system to allow ranking factors to be easily adjusted, i.e., removed from or added into the ranking system. Promisingly, HESSEM allows ranking factors to be easily changed whenever needed. However, it is never easy to identify new factors impacting on rankings and then capture sufficient data for the identified factors (Qiu et al., 2015).

Gathering customers' perceptions of their experienced services is still the most pervasive and dominative means for service organizations to decipher the quality of services provided by the organizations although there have been a lot of changes in terms of tools and instruments used in capturing and understanding customers' perspectives over the years. Periodically conducting customer surveys and interviews has been popularly adopted in the fields of marketing and after-sale services, aimed at enhancing product designs, prioritizing engineering and marketing efforts, and improving after-sale services. Today, with the help of digital media, mobile and pervasive computing, and significantly enhanced tools and methods to capture and understand customer interaction and behavior in its deepen and refined granularity, traditional approaches have been evolved and substantially augmented by incorporating social data along with traditional data sources to provide a complete picture of customers (Ahlquist and Saagar, 2013; Labrecque et al., 2013; Qiu, 2014; Qiu et al., 2014). As a result, capturing and understanding not only cross-sectional and longitudinal but also real time and comprehensive customers' perceptions of services become practically implementable.

"People-centric sensing will help drive this trend by enabling a different way to sense, learn, visualize, and share information about ourselves, friends, communities, the way we live, and the world we live in." (Campbell et al., 2008) Thus, it is worthy to explore a way to collect and aggregate public opinions to enhance assessment of service quality (Qiu et al., 2015). This paper uses the US higher education as a service example to show how big data-mediated public opinion aggregation can be well applied to augmenting the assessment of service quality. Please keep in mind, a system of computing rather than a service quality modeling approach is presented in the remaining paper.

The remaining paper is organized as follows. Section 2 briefly reviews a framework for capturing and visualizing public options that has been used to develop a ranking module, part of the Leveraging Innovative Online Networks to Learn Education Networks and Systems (LIONLENS) research project by the authors. Section 3 then discusses how the LIONLENS enables the core and fundamental computing supports necessary for the realization of aggregating and visualizing public opinions and sentiment trends on the US higher education in its ranking module. Finally, a brief conclusion for this paper is given in Section 4.

2 A FRAMEWORK FOR CAPTURING AND VISUALIZING PUBLIC OPINIONS

To the service provider of a service system, capturing, understanding, and controlling the interaction among all the stakeholders of a service system plays an essential role in designing, developing, and managing the service system (Qiu, 2014). A ranking system undoubtedly is a service system. Thus, real time capturing and understanding public perceptions or opinions become necessary for the development of a desirable and reliable ranking system, which would not only meet the needs of the public but also be well aligned with the long-term goals of ranking service providers. Bearing this understanding in mind, a framework for developing the LIONLENS including capturing and visualizing public opinions has been proposed (Qiu et al., 2015), which is graphically illustrated in Figure 1. Technically and financially, the proposed framework allows the LIONLENS to be modularly and then gradually developed while evolving over time (Qiu, 2014).

As shown in Figure 1, the emerging big data technologies, widely adopted mobile computing, and social media can be fully applied and leveraged to facilitate the process of monitoring and deciphering the public's acceptance and colleges' performance in real time (Qiu et al., 2015). The highlights of two different perspectives of the proposed framework in Figure 1 can be briefed explained as follows:

- From the systems perspective: an education system consists of people, technologies, resources, and education service products that can generate respective values for all stakeholders through service provision. To evaluate education service quality, different aspects of data on the system and the public perception of its provided education must be captured and deciphered. Indeed, in addition to using traditional data source approaches, distributed and mobile computing systems and applications have been leveraged so that data and information on college education services, students enrollment profiles, faculty performances, school facilities, campus life, etc. can be effectively captured, retrieved, and archived, college by college and/or colleges as a whole. Technically, the implementations of existing ranking systems differs significantly from each other. However, there is no significant difference in terms of data collection tools and methods adopted by existing ranking systems.

- From the analytical perspective: valid and effective modeling methodologies should be applied to not only enable ranking services, but also uncover the insights from the collected data and information and ultimately provide prompt guidance for administrators to take action for positive changes. Ranking systems vary with adopted modeling methodologies, computing technologies and implementations, and operational models. As a result, ranking and administrative services enabled by the ranking systems could be descriptive, predictive, and/or prescriptive.

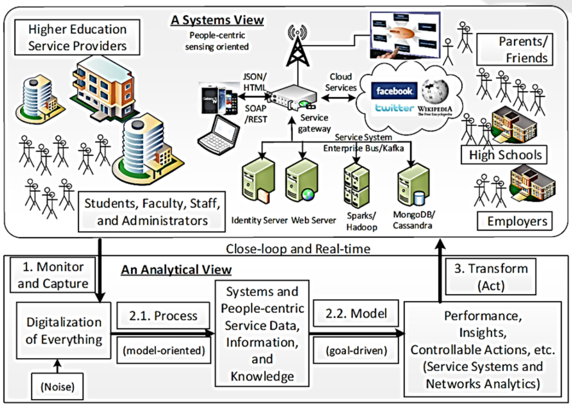

Figure 1: A framework for developing the LIONLENS.

With the advent of the Internet and mobile computing, voluminous and various data on higher education can be retrieved and mined from the Internet and social media. In other words, as such data becomes richer and richer, the list of ranking (or service quality) indicators should become easier to be adjusted (i.e., added or removed) whenever necessary. For instance, the inputs from the public are vital for ranking systems. Therefore, public ratings and comments must be taken into consideration so that a ranking system can evolve to better meet the needs of stakeholders. Figure 2 shows the logic flows of the design and implementation of the ranking module in the LIONLENS, which gets enhanced by incorporating public ratings and comments.

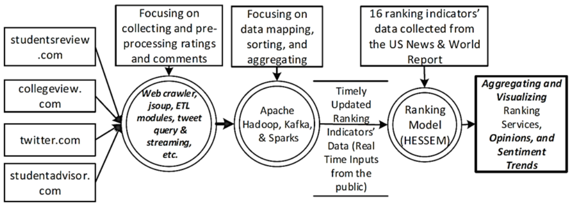

Figure 2: Monitoring, capturing, and visualizing colleges' performance and public opinions.

As discussed earlier, this paper focuses on the discussion of a systems and computing approach to enhancing service quality assessment for the US higher education. In other words, using the systems perspective we aim to show how big data-mediated public opinion aggregation can be practically applied to addressing service assessment problems. In particular, we show how big data technologies, mobile computing, and social media can be fully leveraged to facilitate the process of monitoring, capturing, and visualizing colleges' performance and public opinions on education service quality in real time. As shown in Figure 2, the process of adjusting ranking factors is enhanced by including public opinions' sentiment analysis. In practice, public opinions can be captured, retrieved, and analyzed from websites and online media including twitters.

We have developed HESSEM - a quantitative and model-driven ranking model to evaluate higher education service quality in the US. Using collected data, we applied structural equation modeling to systematically determine ranking factor weights for assessing education service quality and performance of the US higher education (Huang and Qiu, 2016). By extending the brief discussion presented in our previous paper (Qiu et al., 2015), this paper in great detail discusses how the public textual inputs can be captured and filtered, and aggregated to enhance educational service quality assessment. Therefore, in the next section we explain technically and functionally the core computing components and algorithms applied in this study.

3 BIG DATA-MEDIATED FUNCTIONAL SUPPORTS

As mentioned earlier, in this paper we focus on presenting technically and functionally the data flows and computing components deployed in the LIONLENS that support the retrieving and aggregating of the public opinions (Figure 3).

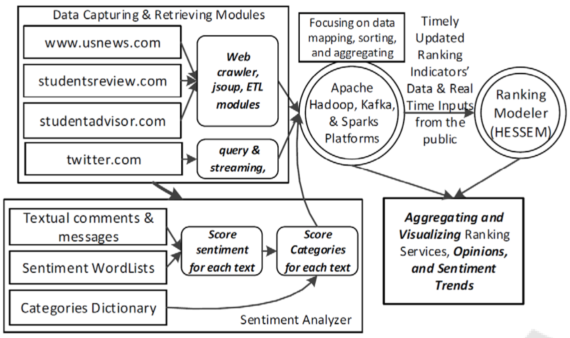

Figure 3: Functional flows and components in support of retrieving and aggregating the public opinions.

As highlighted in Figure 3, five main computing components in support of the ranking services enabled by the LIONLENS, which are briefly introduced as follows:

- Data capturing & retrieving modules: web crawler, data extract-transform-load, and tweets query and streaming modules are applied and developed for retrieving and pre-processing data from different data sources over the Internet.
- Sentiment analyzer: Collected data and information are saved as files that are transformed and analyzed to generate sentiment scores, indicating service performance trends over time.
- Big data computing clusters or platforms: Apache Hadoop & Sparks platform technologies based on Lambda architecture is used to aggregate, consolidate, and archive the captured and pre-processed data.
- Ranking modeler: HESSEM is adopted for generating rankings on a daily basis based on archived and on-going, newly collected and updated data.
- Visualization modules: interactive web interfaces are developed and deployed to allow end users to visualize aggregated public opinions and sentiment trends on the higher education in the US.

3.1 Data Capturing & Retrieving Modules

To demonstrate how data and information on education services can be used to enhance service quality modeling, we developed web crawler, data extract-transform-load, and tweets query and streaming modules to crawl across a list of selected websites and retrieve public comments and tweets. As numerous information retrieval tools and libraries are available over the Internet, these data retrieving modules can be easily customized for other websites. We use the studentadvisor.com as an example to show how public ratings and comments are captured, pre-processed, and utilized in this project.

The studentadvisor.com website allows the public to post their comments and ratings on any colleges in the US. Ratings spanning over 6 categories from overall, academics, campus facility, sports, student life, surrounding area, to worth the money are Likert-scale based, from 1 to 5. Public comments namely 'The Good', 'The Bad', and 'WouldIdoItAgain' are then text based. As soon as web pages are downloaded, the targeted data including ratings and comments are extracted and transformed. To ensure that retrieved data will be readily accepted by the big data platforms, the transformed data for each college is loaded into a corresponding CSV file as illustrated in Figure 4.

URL	PostTime	Overall	Academics	Campus.Fa	Sports	Student.Li	Surroundi	Worth.the	Comment1	Comment2
stanfordu	August 1	5	5	5	5	5	5	5	The Good: The	The Bad: If y
stanfordu	August 1	4	4	5	5	4	5	4	The Good: The	The Bad: The
stanfordu	June 11-	4	5	4	3	5	3	4	The Good: Sicn	The Bad: If y
stanfordu	June 11-	4	5	5	4	4	4	4	The Good: I dic	The Bad: I vi
stanfordu	June 23-	4	5	5	3	4	4	5	The Good: One	The Bad: Bay
stanfordu	July 27- 2	3	3	4	4	3	5	4	The Good: The	The Bad: A l
stanfordu	July 27- 2	5	5	5	5	5	5	5	The Good: The	The Bad: An
stanfordu	July 27- 2	4	5	5	5	5	5	4	The Good: I liv	The Bad: Ou
stanfordu	August 1	4	5	5	4	5	5	5	The Good: Was	The Bad: I ha

Figure 4: *Data sample from* studentAdvisor.com.

3.2 Data Capturing & Retrieving Modules

Recently online social media has undoubtedly become the most popular and convenient means for the public to communicate, exchange opinions, and stay connected. Hence, studying online messages and formed online social networks has received a lot of attention from scholars and professionals worldwide. Sobkowicz et al. (2012) develop a framework using content analysis and sociophysical system modeling techniques, focusing on understanding and visualizing the formation of political opinions and online networks over social media. Farina et al. (2014) present generally a practical, technical solution to extract and visualize massive public messages from different data sources.

To get the general understanding of public comments, we develop a sentiment analyzer to process public comments. The sentiment analyzer tries to answer two questions. First, it would like to determine the sentiment strength of a comment, i.e. quantifying how positive or negative a comment is. Secondly, it would like to understand in which perception areas a user tried to provide his/her comment, i.e. classifying comments.

To quantify how positive or negative a comment is, we extract relevant words based on a well-defined sentiment dictionary. The AFINN is a list of English words that is divided into positive and negative sentiments. Positive words ranges with the strength of from 1 to 5 and negative words ranges with the strength of from -1 to -5. The current version of AFFIN dictionary contains about 2500 words and phrases (Nielsen, 2011). Instead of using 10 levels of sentiment strength, we redefine the dictionary using 4 levels, defined as very positive (5 and 4), positive (3, 2, and 1), negative (-1, -2, and -3), and very negative (-4 and -5), focusing on finding the polarity of words in the text comments.

To support the categorization of words extracted from comments, the General Inquirer Dictionary (Stone, 1997) is then applied. The list of categories includes Academ (academic and intellectual fields), Coll (all human collectivities), Work (ways for doing work), SocRel (interpersonal processes), Place (place related words), Social (social interaction), Region (region related words), Exert (movement categories), and Quality (qualities or degrees of qualities). The occurrences of words labeled in the dictionary in a comment can be simply used as a sentiment indicator of the comment. Thus, the sentiment analyzer computes how many relevant words that appear in a comment. Using "The Good" and "The Bad" comments for Princeton University respectively, Figure 5 and 6 show sample results of sentiment analysis in this study. The method of validating dictionaries and relabeling words and detailed analysis in support of comments' categorization and classification are well presented in Ravi's thesis (2015).

sentence	vNeg	neg	pos	vPos	Academ	Coll	Work	SocRel	Place	Social	Region	Exert	Quality	pos
The Good: Princeton is the crean	0	1	4	1	1	0	3	1	2	1	0	1	0	positive
The Good: High quality of educat	0	0	3	0	4	2	1	1	1	1	0	1	1	positive
The Good: Princeton is one of th	0	0	3	0	1	1	0	0	2	1	0	0	0	positive
The Good: They have great educ	0	0	4	0	1	0	0	1	0	0	0	0	0	positive
The Good: The school is clean an	0	0	3	0	2	1	2	0	1	1	0	0	1	positive
The Good: One of the best colleg	0	0	3	0	0	0	0	0	0	0	0	0	0	positive
The Good: Princeton students ar	0	0	2	0	1	0	1	3	2	1	0	0	1	positive
The Good: The community was v	0	0	3	0	0	2	0	1	0	0	0	0	1	positive

Figure 5: An example of "The Good" comments.

sentence	vNeg	neg	pos	vPos	Academ	Coll	Work	SocRel	Place	Social	Region	Exert	Quality	neg
The Bad: Princetor	0	1	1	1	2	1	2	3	3	2	0	1	1	negative
The Bad: Traffic is	0	1	0	0	2	0	0	1	0	0	0	0	0	negative
The Bad: Princetor	0	4	2	0	5	1	1	2	3	3	0	0	4	negative
The Bad: The price	0	1	0	0	2	0	1	0	2	2	0	0	0	negative
The Bad: The mate	0	2	1	0	2	1	0	0	2	1	0	0	0	negative
The Bad: Tuition is	0	1	1	0	1	0	0	0	1	1	0	0	0	negative
The Bad: Princetor	0	1	0	0	0	0	0	0	2	1	0	1	1	negative
The Bad: I did not	0	1	1	0	0	0	0	0	0	0	0	0	0	negative

Figure 6: An example of "The Bad" comments.

Twitter.com is a very popular online social networking service, which essentially leverages real time push technologies and allows the public to post and read up to 140-characters microblogs called tweets. With the advent of smartphone technologies and services, mobile devices have made microblogging extremely handy and dynamic. Because of the vivid and pervasive, and short, easily understandable nature of microblogs, microblogging has substantially increased its popularity in the public (Yu and Qiu, 2014). Researchers start to pay much attention to understandings of tweets, aimed at getting better and real time understandings of various social behavior and market trends (Wu et al., 2010; Alper et al., 2011; Marcus et al., 2012).

16	massachu	Massachu	42.36364	71.09433	MIT	Researchers discover that aspartate is a limiter of #cellproliferation http://t.co/63MhyJDeOI @MIT
17	massachu	Massachu	42.36364	71.09433	MIT	#NewHorizons data hint at underground ocean http://t.co/Zr0YFsTIRS @MIT
18	massachu	Massachu	42.36364	71.09433	MIT	330 hp! Maximum torque of 410Nm! The #NewAstra speeds up for @TCRIntl! #TCRSeries http://t.co
19	massachu	Massachu	42.36364	71.09433	MIT	MIT looks to stay in vanguard of digital education: @MIT president Rafael Reif talks to @washingtor
20	massachu	Massachu	42.36364	71.09433	MIT	.@MIT is unveiling a $1.2 billion plan for Kendall Square http://t.co/xeQyTJurMb http://t.co/thcyIA(
21	harvardur	Harvard U	42.37791	71.11696	Harvard U	Mzee Jomo Kenyatta attended the London School of Economics while Barack Obama Snr went to Ha
22	princeton	Princeton	40.34479	74.65158	Princeton	Colleges with the top ROI: 1. Princeton University 2. Dartmouth College3. Williams CollegeMore: ht
23	princeton	Princeton	40.34479	74.65158	Princeton	#TopColleges 2015: 1. Pomona College2. Williams College3. Stanford UniversityMore: http://t.co/h:
24	princeton	Princeton	40.34479	74.65158	Princeton	St. Xavier OL Alex Deters committed to Princeton University today. http://t.co/I77tIwrlbP @stxspor
25	americanu	American	38.93706	77.0909	American	American University. FC Barcelona's first training session #tourFCB http://t.co/pHi0KtOgZM
26	americanu	American	38.93706	77.0909	American	'American 'Freshman': 12 Words That the University of New Hampshire Has Deemed 'Problematic' I
27	americanu	American	38.93706	77.0909	American	Second training session at the American University in Washington DC http://t.co/gVk0pNgsUF #Tou

Figure 7: An example of tweets retrieved from Twitter.com.

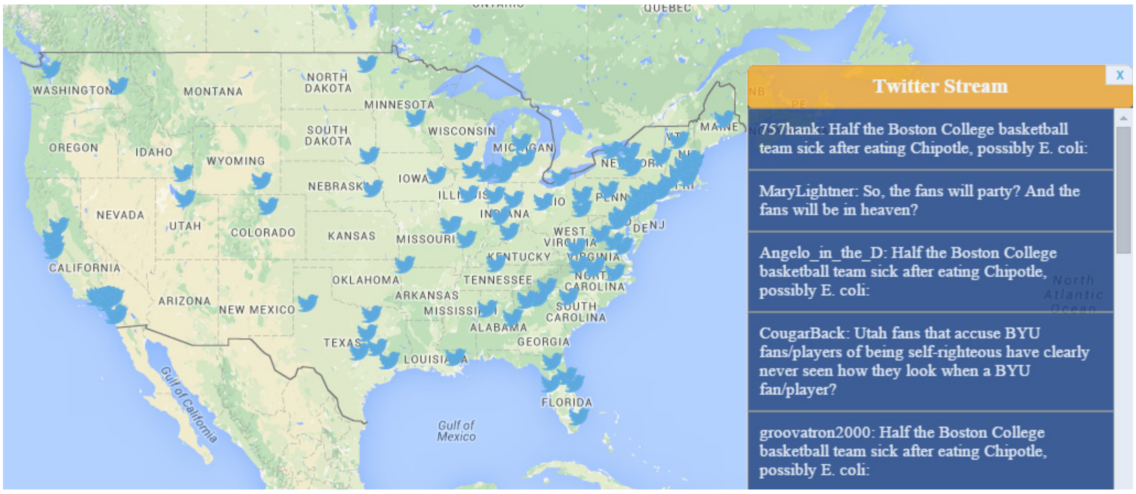

Figure 8: An interactive map view of sentiment trends of public opinions using streaming tweets.

To test out the concept of retrieving public opinions from a variety of data sources, tweets thus are used in this study. In this study, we focus on a list of targeted colleges in the US. Tweets from Twitter.com are retrieved using predefined queries (Figure 7) or streamed using a list of keywords in real time (Figure 8). Clean texts are extracted from received raw tweets and then further analyzed using our developed sentiment analyzer.

3.3 Big Data Computing Platforms

Data and information from the Internet are generally unstructured and mostly stored as images and texts. Our endeavor in enhancing service quality in this study substantially relies on the successful design, development, and deployment of big data computing platforms. Our deployed platforms use a scalable Lambda architecture to deal with big data volume and velocity simultaneously, supporting a hybrid computation model as both batch and real-time data processing can be combined transparently. The distribution layer consists of an Apache Kafka messaging broker. The batch layer includes HDFS, MapReduce, Hive, Pig, and Spark batch. The Apache Spark streaming layer includes Spark core and resilient distributed datasets, HBase, Cassandra, and MongoDB to perform lightning-fast cluster computing transformations and actions.

As shown in Figure 3, ratings, comments, and sentiment scores are processed in either batches or streaming, depending on how public opinions are retrieved from their data sources. Ratings, comments, and sentiment scores are aggregated, consolidated, and archived; they become readily available for use, i.e., visualizations or further aggregations and computations.

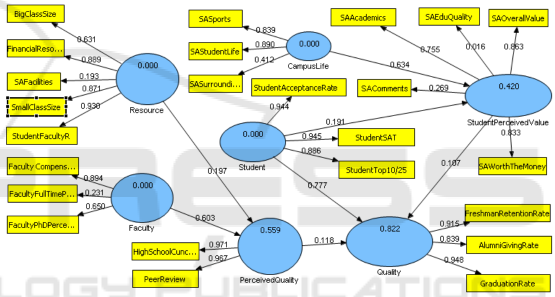

Figure 9: Enhancing the HESSEM by including sentiment scores of public opinions.

3.4 Ranking Modeler

Although demonstrating how educational service quality on the US higher education gets modeled in a quantitative and real-time manner is not the purpose of this paper, briefly showing how the assessment of service quality or performance gets enhanced by incorporating public opinions should be worthwhile. Figure 9 provides an overview of enhanced HESSEM models for top 100 colleges in the US, which has taken into consideration the above-mentioned sentiment scores computed from public opinions (Ravi, 2015; Huang & Qiu, 2015). A full list of new rankings can be found in Ravi (2015).

3.5 Visualizations of Aggregated Public Opinions and Sentiment Trends

As discussed in last section, the performance of educational services of a given college perceived by

Sentiment Analysis (last 24 hours)					
University	Positive Tweets Avg. SentiScore	Negative Tweets Avg. SentiScore	Positive Tweets Total SentiScore	Negative Tweets Total SentiScore	Net SentiScore
Massachusetts Institute Of Technology	0.44	-0.36	1,331.48	-507.14	824.34
Penn State University	0.47	-0.29	494.52	-164.64	329.87
University Of Miami	0.48	-0.12	298.73	-16.04	282.69
New York University	0.45	-0.24	349.48	-147.70	201.79
Duke University	0.68	-0.18	205.69	-5.97	199.72
Cornell University	0.31	-0.29	197.12	-7.54	189.58
The University Of Georgia	0.61	-0.45	205.11	-20.49	184.62
Johns Hopkins University	0.77	-0.32	187.21	-3.80	183.41
Columbia University	0.52	-0.32	184.70	-20.73	163.98
Brown University	0.53	-0.41	170.95	-65.21	105.75
Ball State University	0.48	-0.33	139.07	-47.46	91.62
The Ohio State University	0.50	-0.34	89.48	-16.43	73.05
University Of Florida	0.45	-0.30	83.29	-22.25	61.03
University Of Pennsylvania	0.52	-0.30	76.29	-15.34	60.95
University Of Maryland	0.19	-0.26	71.42	-10.79	60.63

Figure 10: A statistic report of sentiment trends of public opinions based on tweets.

the public changes with public opinions. If the proposed approach and system gets fully deployed with the ability of assessing the quality of college's services on a daily basis, aggregating and visualizing public opinions can then play an important role in helping stakeholders promptly understand what the public values the performance and quality of their provided education services. Sentiment trends can be one of effective indicators.

Sentiment trends could timely help administrators understand what the public is thinking about the moving direction of their provided services. A sudden jump of the number of tweets on a college might serve an alert, indicating that an event is currently drawing much public attention. Figure 8 shows an interactive map view of sentiment trends of public opinions using streaming tweets. By clicking a college tweet icon on the map, one can clearly see its sentiment trend for last 15 days or a customized interval. Figure 10 presents a statistic report of sentiment trends of public opinions based on tweets.

4 CONCLUSIONS

As discussed earlier, HESSEM allows ranking factors to be easily changed over time. But it is challenging to identify meaningful factors and then collect sufficient data for the identified factors. As public opinions play a key role in assessing customers' perception of their consumed services, this paper focused on introducing a systems approach to aggregating and visualizing public opinions. We demonstrated that capturing and understanding public ratings and comments on higher education helped enhance service quality assessment in general and develop a better and more effective rating system for education in the future.

By capturing and deciphering market trends in real time, the presented systems approach truly possesses promising potential of facilitating decision-making of addressing the needs of customers in the service industry. Although there will be a variety of research areas we could further our studies, collecting more data and information from other popular websites including facebook and Google trends and improving sentiment analysis accuracy in the education service domain are surely what we will work on in the near future. Through educational data mining and learning analytics, we could promptly uncover more insights to assist stakeholders in administrating and transforming their higher education practices in an effective and satisfactory manner. From a systems perspective, the proposed big data based evaluation system could become smarter and smarter as both the assessing model and the used service quality factors can be evolved over time.

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