A Proposed Government Decision Support System Based on Citizen Interactions over Social Networks

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ABSTRACT

This research proposes a Government Support Framework That analyze governmental policies (Introduced or Under discussions) and produce citizens' satisfaction rates (Real-time and Predicted) towards the policy and its Aspects by using Natural Language Processing (NLP) Techniques and Knowledge Management Processes for Citizens' e participation. Citizen to Government (C2G) interactions are analyzed to give insights to decision makers. The framework proposes the application of NLP, opinion mining and Data Mining algorithms to extract knowledge and produce predictions using Bayes Statistical Theorem over Keyword co-occurrences and sentiment analysis results to be presented through a simple dashboard Interface for unexperienced users. The produced system is a government support system that will finally lead to the inclusion of citizen satisfaction as a variable when making citizen related decisions for obtaining higher citizen satisfaction, citizen empowerment and inclusion.

Keywords— Government Decision Support; Decision Analytics; Bayesian Policy Acceptance Prediction; Citizen Satisfaction; Policy Aspects; Opinion Mining; Sentiment Analysis ;Semantic Relatedness;

I. INTRODUCTION

Citizens to Government Interactions had significant changes over the last decade since the emergence of web 2.0 and social media. Noticeable governmental efforts are ongoing for utilizing the social media for better Citizens to Government Interaction in order to ease the conversion from e government to we government. There is an increasing need for following up social trends into governmental departments' policies for the purposes of self-enhancing and raising people's satisfaction [19]. Manually monitoring web contents is ineffective. Hence, a new intelligent system for the automation of people's opinions discovery, classification and aggregation is very critical for Government officials. While everything around us is going faster and smarter, the need for this tool is essential to achieve the target of Better allocation for both, government employees efforts spent to follow up and report citizen interactions and government officials efforts spent on reading those reports. This target will be reached through the proposed government support system resulted at the end of this research. This system will offer instant and visualized analysis of citizen reactions, allowing not only faster and easier decision making process, but also more accurate decisions as it ease the insertion of citizen satisfaction variable to the decision equation. Citizen satisfaction variable is an important part of the decision making process, but it is hardly used, even if governmental official used surveys, it is often quantitative not qualitative as the latter while more accurate than the former, need more human efforts for analyzing and reporting. This proposed governmental support system will offer qualitative analysis of C2G interactions using NLP tools. In 2009 an e-Participation classification method, that classify the data set to certain domains using, Associative Networks, Spreading Activation and Unsupervised Learning was introduced [33]. This Method lacks text analysis, offering citizen satisfaction variable to decision maker, and the visualization of the analysis results. Citizen satisfaction, interactions and opinions toward governmental decisions, and efficiency are among the most important and critical governmental decision making equation variables. Therefore, a Citizen satisfaction, interactions and opinions quantitative and qualitative analysis tool, is needed as a governmental support system. Primitive or Manual quantitative and qualitative analysis methods done by human efforts, are not effective according to implementation time or results. Employee's efforts consumed days to analyze C2G web based reactions to be reported to governmental official in charge of the governmental institution in question. The proposed system will offer faster execution by adding the citizen satisfaction variable to decision equation in real time which enables real time decision making.

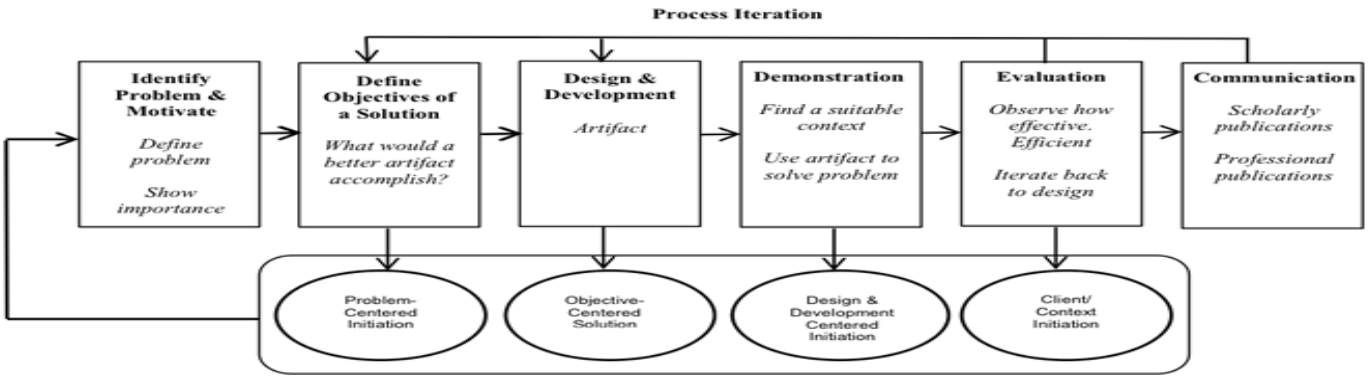


Fig. 1. Design Science Research Methodology Process Model [18].

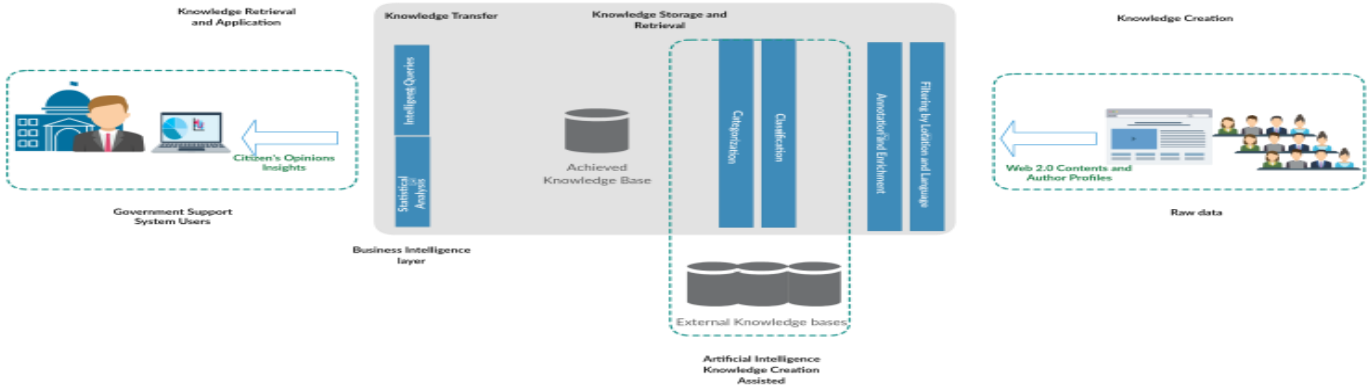


Fig. 2. Proposed C2G and e participation Interactions Analysis Solution Framework

II. LITERATURE REVIEW

Literature review covers the following research aspects:

A. *Decision Support Systems (DSS) and Government Support Systems (GSS)*

Decision Support Systems are a variety of tools that assist humans for making decisions in different domains "Almost anything could qualify as a decision support system - from a sophisticated interactive decision-modelling system, through a programmable hand-held calculator to a cup of coffee."[30].

Sprague and Carlson in early 80s provided a narrow definition of DSS as "a class of information system that draws on transaction processing systems and interacts with the other parts of the overall information system to support the decision-making activities of managers and other knowledge workers in organization."[31].

A broader and Abstracted definition by Sharda, Ramesh, Steve H Barr, and James C McDonnell, would fit better for describing this wide spectrum Systems only sharing the ability to assist human in decision making "1. 'Decision' emphasizes the primary focus on decision-making in a problem situation rather than the subordinate activities of simple in- formation retrieval, processing or reporting. 2. 'Support' clarifies the computer's role in aiding rather than replacing the decision-maker. 3. 'System' highlights the integrated nature of the overall approach, suggesting the wider context of user, machine and decision environment." [30].

In 2008 Power, Daniel J had published a useful Decision Sup- port Systems History overview, summarizing the previous four decades work on the DSS area. Power, Daniel J had presented in their research seven types of DSS prepared by Steven Alter in his MIT PhD back in 1980, these types are as follows:

1. **File drawer systems** that provide access to data items.

2. **Data analysis systems** that support the manipulation of data by computerized tools tailored to a specific task and setting or by more general tools and operators.

3. **Analysis information systems** that provide access to a series of decision oriented databases and small models.

4. **Accounting and financial models** that calculate the consequences of possible actions.

5. **Representational models** that estimate the consequences of actions on the basis of simulation models.

6. **Optimization models** that provide guidelines for action by generating an optimal solution consistent with a series of constraints.

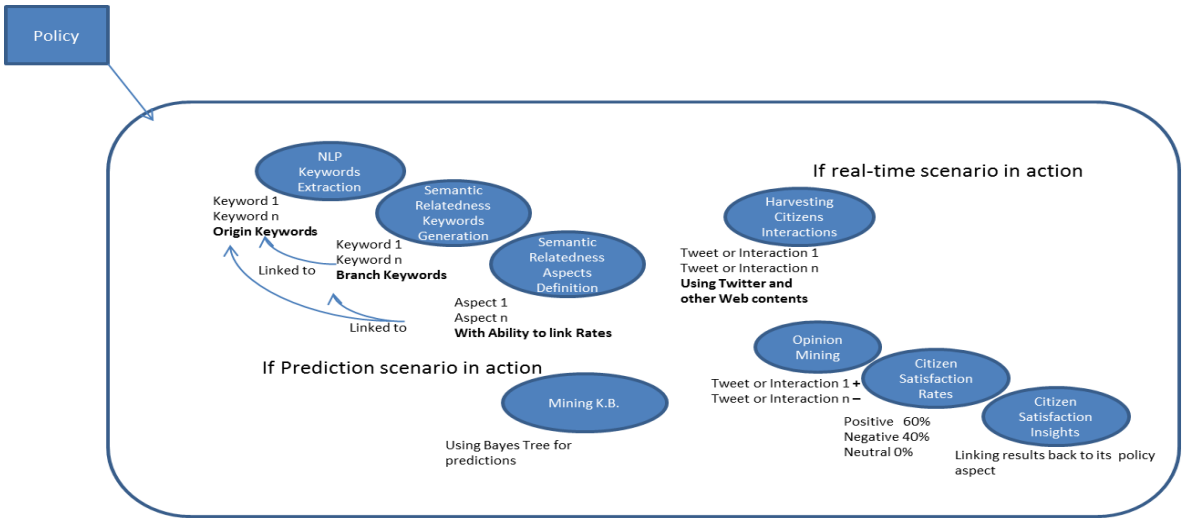


Fig. 3. Citizens' Satisfaction Analysis Model

7. Suggestion models that perform the logical processing leading to a specific suggested decision for a fairly structured or well-understood task. [26]."

According to this categorization of Decision Support Systems, the proposed citizen satisfaction will fit under Data Analysis Systems.

B. Knowledge Management Process

This research will apply Knowledge Management Process Phases: Knowledge Creation, Knowledge Storage and Retrieval, Knowledge Transfer and Knowledge Application as reviewed and introduced in [1] to produce knowledge from Citizen to government interactions, in a disciplined manner.

C. e-Participation and Citizen to Government Interactions Analysis

This research is concerned with the analysis of e participation and Citizen to Government interactions, e participation is defined as: "The participation of individuals and legal entities and groups thereof in the decision making process in the branches of government using information and communication technology (ICT) equipment. In the context of the federal government's e government activities, we interpret this along two lines, i.e.

• as an offer to participate, in a form upgraded by the use of ICT, in plans and decisions by the federal ministries and their downstream public agencies and by the German parliament,

• As an extension of applicable rules and requirements for other levels of government within the federal government's (framework) legislative powers.

In international debate, a distinction is made between the term 'e Participation' and the term 'e Democracy' in that the latter also covers elections as the most binding form of citizen participation [7]. Therefore, this study does not deal with e voting."[2], and also defined as:" 'e Participation describes efforts to broaden and deepen political participation by enabling citizens to connect with one another and with their elected representatives and governments by using Information and Communication Technologies (ICT).' [6]."[32]. By Citizen to Government we describe the relation conducted or the interactions

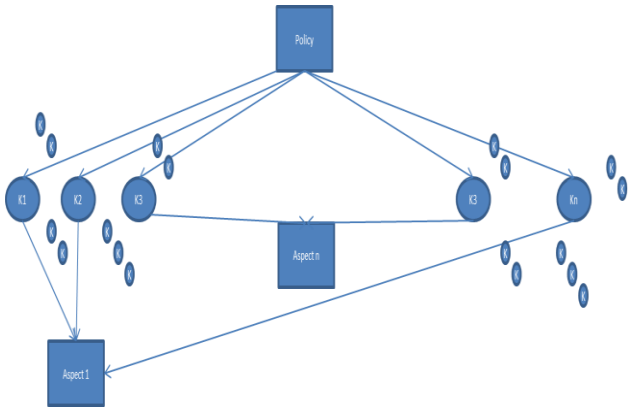


Fig. 4. Policy Aspect Detection Model

between citizens and government through Social Media (SM) as reviewed in [4]. These concepts are of importance for governmental decision effective- ness as proved by the quantity of research efforts spent to maximize their benefits to government performance (among others) [29, 14, 11, 10, 20, 5], and the huge and continues efforts spent for shaping e Participation research domain done by insight center researchers (among others)[17, 25, 22, 23, 24, 21, 9, 16].

Previous research for analyzing e Participation and Citizen to Government interactions [33], introduced a classification method for classifying e Participation and Citizen to Government interactions to certain domains

using, Associative Networks, Spreading Activation and Unsupervised Learning but lacking the analysis of the text, offering citizen satisfaction variable to decision maker, and the visualization of the analysis results.

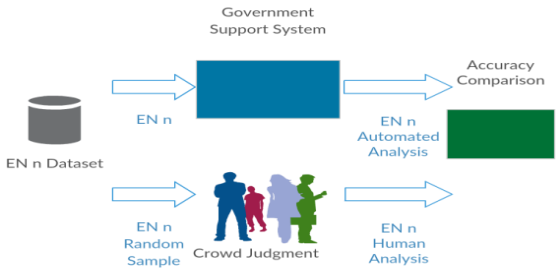
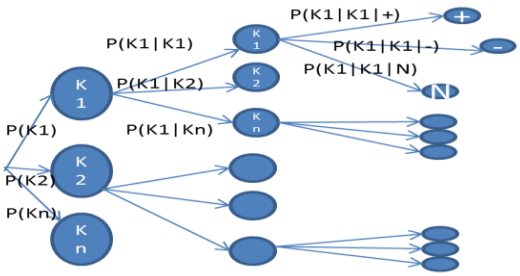


Fig 9. System Evaluation Phases

1- Building Knowledge Base to enable the usage of (Bayesian probabilities) for prediction usages when real-time in action

Analysis KW	Total Occurrences in all Data sets	Total Occurrences in all Data sets Alone	Total Co-occurrences in all Data sets With K1	Total Co-Occurrences in all Data sets With K2	Total Co-Occurrences in all Data sets With K(n)
K1	12K + 14K – 16K NEUTRAL ----- 42k	1K + 1K – 1K NEUTRAL ----- 3k	1.5K + 8K – .6K NEUTRAL ----- 10.1k	.5K + 2K – 1K NEUTRAL ----- 3.5k	7K + 2K – 1K NEUTRAL ----- 10k
K2	20K + 32K – 12K NEUTRAL ----- 64k	1K + 3K – 2K NEUTRAL ----- 6k	.5K + 2K – 1K NEUTRAL ----- 3.5k	2K + 7K – 2K NEUTRAL ----- 6k	11K + 20K – 1K NEUTRAL ----- 32k
K(n)	40K + 60K – 80K NEUTRAL ----- 180k	12K + 8K – .5K NEUTRAL ----- 20.5k	7K + 2K – 1K NEUTRAL ----- 10k	11K + 20K – 1K NEUTRAL ----- 32k	11K + 21K – 20K NEUTRAL ----- 52k

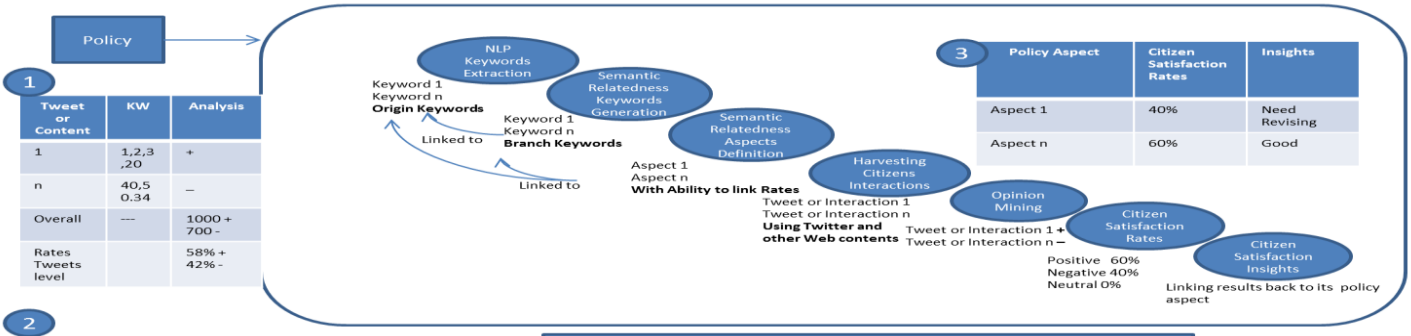
2- Bayes Probabilities Construction



3- Predictions Construction

Policy Aspect	Keyword	Bayes Probability of Positivity Intersect Ka and Kz	Bayes Probability of Negativity Intersect Ka and Kz	Bayes Probability of Neutrality Intersect Ka and Kz	Predicted Citizen Satisfaction Rates	Predicted Insights
Aspect 1	1,34	P(K1∩K34∩+) 3.2%	P(K1∩K34∩-) 6.7%	P(K1∩K34∩NEUTRAL) .1%	6.7% Negative	Need Revising
Aspect n	50,20,12	P(K50∩K20∩k12∩+) 8.0%	P(K50∩K20∩k12∩-) 2.0%	P(K50∩K20∩k12∩NEUTRAL) .2%	8.0% Positive	Good
Overall Policy Prediction	---	P (Positivity)	P (Negativity)	P (Neutrality)	Greater value	Insight

Fig. 5. Prediction Model



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Keyword	Aspect	Total Occurrence in Dataset (n)	+	-
1	1	5500	3000	2000
n	1	A+B	A	B
Overall	---	Total Occurrence of all keywords	3000	2000
Rates Keywords level			60%	40%

Building Knowledge Base to enable the usage of (Bayesian probabilities) for prediction usages

Analysis KW	Total Occurrences in all Data sets	Total Occurrences in all Data sets Alone	Total Co-occurrences in all Data sets With K1	Total Co-Occurrences in all Data sets With K2	Total Co-Occurrences in all Data sets With K(n)
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Fig. 6. Real-time Stages

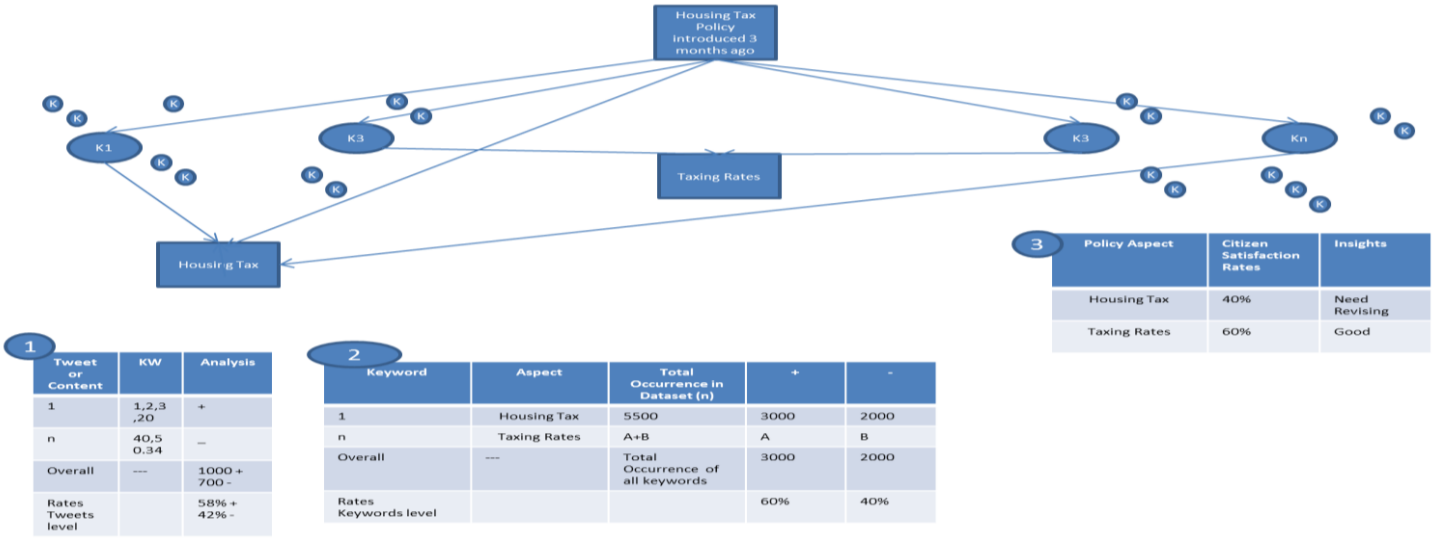


Fig. 7. Real-time usage scenario

D. Artificial Intelligence Tools

Different Artificial Intelligence tools will be applied in different parts of this research. Natural Language Processing techniques are introduced and developed in many literatures for text analysis. For the purpose of this research NLP tools will be utilized:

1) Named Entity Recognition tools e.g. Stanford Named Entity Recognizer [8] and Alchemy Entity Extractor reviewed in [28].

2) Sentiment Analysis or opinion mining tools e.g. Sentiwordnet citeesuli2006sentiwordnet and WEKA assisted [34] or a combined approach [27].

3) Knowledge Bases and ontologies to assist in text analysis e.g. Dbpedia [3].

4) Semantic Similarity tools to be used in citizen to government interactions classification and categorization into governmental departments and topics e.g. Extracting distributional related words using Co-occurrences (DISCO) introduced in [12, 13].

E. Text analysis accuracy measuring methodology

NLP research work is evaluated by comparing analysis results to human analysis of the same data set by crowd sourcing, and define their accuracy based on the distance between matching judgments with humans and mismatching judgment with human. This method has a disciplined approach, starting with measuring the accuracy of the human judgment itself before running the test. This accuracy percentage will be used in all proceeding accuracy tests made by the tested human [15].

Based on the discussed literature, the proposed Government Support System will fill the following discovered gaps:

1) Allow instant qualitative and quantitative analysis of e participation and C2G interactions using AI tools.

2) Ease and allow the insertion of citizen satisfaction variable into decision equation by presenting analysis results in a visualized dashboard.

III. METHODOLOGY

The proposed system that incorporates citizen Interactions into governmental decisions, to allow better decision making process is based upon answering the following questions:

1) What are the issues and challenges that could face building A Government Support System, including the collection and analysis process of C2G web based interactions in English language for English speaking countries?

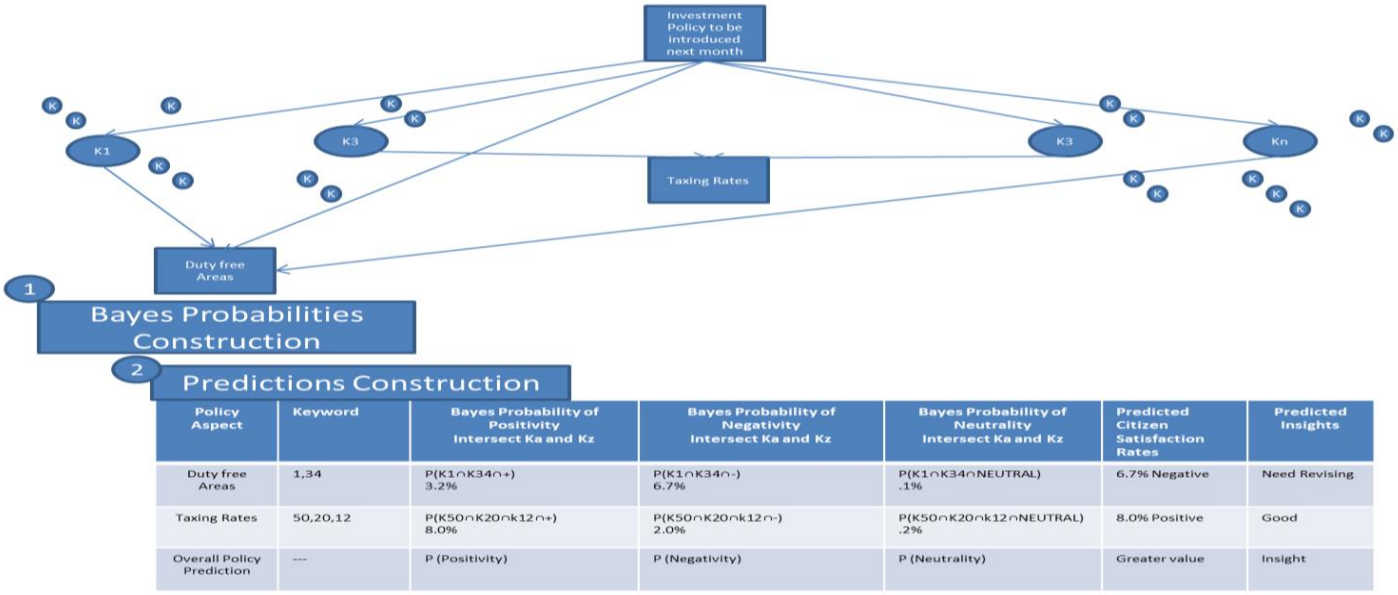
2) What is the accuracy of the resulted C2G web based interactions analysis?

These questions will be answered through applying the Design Science Research methodology. This research will introduce a solution to solve C2G web based interactions analysis "Manualization" implications which is considered to be a Problem Centric research entry point in which the proposed system is intended to solve the e-participation and C2G interaction analysis problem (Figure 1).

IV. PROPOSED SOLUTION FRAMEWORK AND COMPONENTS ABSTRACT

Our proposed Government Support System for e-participation and C2G interactions Insights and Analysis is abstracted (Figure 2), showing major components, analysis levels and processes.

A. Government Support System Users



Policy Aspect	Keyword	Bayes Probability of Positivity Intersect Ka and Kz	Bayes Probability of Negativity Intersect Ka and Kz	Bayes Probability of Neutrality Intersect Ka and Kz	Predicted Citizen Satisfaction Rates	Predicted Insights
Duty free Areas	1,34	P(K1∩K34∩+) 3.2%	P(K1∩K34∩-) 6.7%	P(K1∩K34∩NEUTRAL) .1%	6.7% Negative	Need Revising
Taxing Rates	50,20,12	P(K50∩K20∩k12∩+) 8.0%	P(K50∩K20∩k12∩-) 2.0%	P(K50∩K20∩k12∩NEUTRAL) .2%	8.0% Positive	Good
Overall Policy Prediction	---	P (Positivity)	P (Negativity)	P (Neutrality)	Greater value	Insight

Fig. 8. Prediction usage scenario

Proposed tool is meant to serve e-government officials seeking insights on citizens reaction to their decisions over the web, in order to unveil better decision making process.

B. C2G and e Participation web based interactions and Citizens Profiles data

Harvesting C2G web based interactions and Citizens Profiles data from web i.e. Social media websites, regarding relevant data access and usage rights agreements. Only interactions provided by C2G application user (decision maker) input will be harvested.

C. Language and Location Detection and Filtering

Applying language and location detection on collected data and filtering the data according to analysis specifications. Due to the added knowledge by Annotation and Enrichment phase, this part will be processed for a second time after. First run will minimize the wasted processing capacity by eliminating non targeted entries.

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Applying language and location detection on collected data and filtering the data according to analysis specifications. Due to the added knowledge by Annotation and Enrichment phase, this part will be processed for a second time after. First run will minimize the wasted processing capacity by eliminating non targeted entries.

E. Annotation and Enrichment

Annotating mentioned entities in collected interactions texts, is a very critical step, as this annotation will be used in the next levels of analysis and also will contribute significantly in the accuracy score of the solution.

F. External Knowledge Bases

After Annotating mentioned entities in collected interactions texts, the enrichment process will take place using external knowledge bases. This additional knowledge will contribute in achieving rules discovery, by defining co-occurrences between detected entities and related knowledge.

G. Classification

By classification we mean sentiment Analysis to positive and negative using available NLP tools.

H. Categorization and Topic Detection

Categorizing the collected interactions to governmental sections using available semantic relatedness tools, and filtering interactions based on analysis requirements.

I. Constructing Knowledgebase for Future Forecasting

Discovering the possible rule mining algorithms over collected data-sets, and building a knowledge base would unveil future expectation variable to decision making equation, that would help governments to achieve both new standards of performance quality, and citizens satisfaction.

J. Intelligent Queries

Offering the ability of querying over collected data and resulted knowledge.

K. Statistical Analysis to offer Citizen Opinion Insights

Applying related statistical measures on analysis processes and presenting results in a proper graphical statistics dashboard would ease the understanding of collected and processed citizen's interactions. Also, discovering the possibility to use those measures in

enriching knowledge base, through applying rule mining on it.

V. PROPOSED CITIZEN SATISFACTION ANALYSIS MODEL

A. *Analysis Model flow is proposed according to the following stages (Figure 3):*

- Policy: Is a text input fed to the proposed system that will initiate the whole processing stages. Policy is to be an old policy that is under analysis or a new policy that is under discussion to be introduced.
- Keyword Extraction and Recognition (Origin Keyword): Origin Keyword is a keyword extracted from the original policy text fed to the system. Named Entity Recognition Algorithm will be used to produce the origin keywords. Semantically Related Keyword Recognition (Branch Keyword). Branch Keywords is a keyword generated by applying semantic relatedness algorithm over origin keywords.
- Policy Aspects Detection: An Aspect of the inputted policy will be detected by applying semantic relatedness algorithm over origin keywords and branch keywords towards a set of domain aspects gathered previously.
- Harvesting Citizens' Interactions toward Policy (Real- time Scenario only): Using both origin and branch keywords the system will start harvesting online interactions, mainly from twitter as it contains most of citizens' interactions.
- Opinion Mining: At this stage an opinion mining phase will take place using sentiment analysis algorithm either over collected interactions or over Knowledge Base depending on usage scenario in action real-time or prediction.
- Knowledge Base Construction (Real-time Scenario only): Building a keywords co-occurrence matrix, annotated by opinion mining results that enable the usage of Bayes Theorem.
- Citizens' Satisfaction Rates Production: This stage calculates the satisfaction rates on policy aspects basis and overall basis.
- Citizens' Satisfaction Insights: Giving the user an indicator to each policy aspect i.e. need revising, good etc.

B. *Policy Aspects Detection Model*

In order to breakdown a policy into aspects we are proposing a semantic relatedness approach, that calculate the distance between extracted keywords from the policy text and a pre-defined aspects set corresponding to the policy domain (see Figure 4).

C. *Prediction Model (Bayes Theorem)*

When the real-time scenario in action we collect keywords and build co-occurrence matrix between them annotated by their opinion mining result.

Then when the prediction scenario in action we apply Bayes Theorem over extracted keywords, according to the previously constructed matrix to predict citizens' satisfaction rates (Figure 5).

D. *Real-time Scenario*

Our system is set to be use as a real-time citizens' satisfaction rate calculator, users may input the policy text and start the system to output them the real-time citizens' satisfaction rate towards the policy and its aspects. While this scenario in action a knowledge base is constructed to be used in the prediction scenario. Prediction scenario in action when user input policy text that is not yet introduced to citizens and ask for a predicted satisfaction rates, this is where we use the knowledge base and the Bayes Theorem to predict the rates (Figure 6).

E. *Usage Scenarios*

This system is meant to be used in tow main usage scenarios real-time and prediction and the following are two examples of those usage scenarios:

1) Real-time example

A government that have already introduced a new Housing Tax policy three months ago, and looking for citizen's satisfaction rates and insights in order to improve satisfaction (Figure 7).

The system will first extract origin keywords and branch keywords then detect policy aspects and start harvesting interactions then apply opinion mining and calculate satisfaction rates towards policy and its detected policy aspects, finally it will give insights based on the rates to advice decision maker about policy aspects that needs revision or policy aspects that are good.

2) Prediction *example*

In this case A new policy is under analysis before introducing it to citizens, and the decision maker seeks a satisfaction rate prediction and insights before introducing it to the public. By using the system in prediction mode, system will extract origin and branch keywords then detect policy aspects from the domain aspect set using NER and Semantic relatedness algorithms. But it won't harvest citizens' interactions this time as the policy isn't introduced yet. Instead system will use the previously constructed knowledge base and apply Bayes Theorem equations to predict satisfaction rates and produce insights (Figure 8).

VI. CONCLUSION AND FUTURE WORK

This research is proposing a framework for developing a government support system that will harvest citizens interactions towards government and do analysis of those interactions using Artificial Intelligence tools to produce smart analysis reports and predict patterns based on applying rule mining on collected data. Those produced reports and patterns will allow the ease of inserting citizen's

satisfaction to the decision making equation, those reports are in real time and automated.

A. System Development

According to this proposed framework a system development plan will be produced, this framework conceptualizes the system inputs, outputs. Processing throughout its modules and components.

B. System Evaluation

Analysis Accuracy Testing phase will be taken by measuring the human understanding to the same data set (sampling methods), and compare it with the automated results of the proposed solution to collected English C2G data-set (denoted as: EN0) (Figure 9).

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