ANALYZING VOTING RESULTS USING INFLUENCE MATRIX

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Abstract - *This project aims at modelling and inferring the influence among people from ballot information (or additional typically from actions that square measure selected by selecting one amongst totally different options). The ballot information square measure modelled as outcomes of a separate random method, that we tend to consult with because the vote model, whose evolution is ruled by the DeGroot opinion dynamics with stubborn nodes.*

Based on the projected model, we tend to formulate the maximum-a-posterior expert for the opinions and influence matrix (or the transition matrix) and derive a tractable approximation that leads to a convex improvement downside. the project, the identifiability of the network dynamics parameters and therefore the vote prediction procedure supported the influence matrix, square measure mentioned exhaustive. The outcome prediction will be shown on a bar graph, using that graph results are predicted. Curiously, despite the comparatively little information record offered, the influence matrix inferred from the important information is with the common intuition regarding the influence structure.

Key Words: Influence Matrix, Maximum-a-Posterior, Opinion Dynamics, Vote Model, Vote Prediction, Influence Structure.

1. INTRODUCTION

This work proposes a discuss-then-vote model to capture the underlying dynamics that govern the voting outcomes under social pressure and provides a novel interpretation of the voting data based on opinion dynamics. Specifically, we model the voting outcomes as realizations of a categorical distribution parameterized by the steady state opinions in DeGroot opinion dynamics. Opinion dynamics model the change of the belief of an agent under social pressure. This belief is the probability of taking an action, like a vote. Many computational problems have explicit matrices as their input (e.g., adjacency matrices of graphs, experimental observations etc.) while others refer to some matrix implicitly (e.g., document-term matrices, hyperlink structure, object-feature representations, network traffic etc.). We refer to algorithms which use the spectrum, i.e., eigenvalues and vectors, singular values and vectors, of the input data or matrices derived from the input as Spectral Algorithms. Such algorithms are the focus of this book. In the first part, we describe applications of spectral methods in algorithms for problems from combinatorial optimization, learning, clustering, etc. In the second part of the book, we study efficient randomized algorithms for computing basic spectral quantities such as low-rank approximations. The Singular price Decomposition (SVD) from algebra and its shut relative, Principal Component Analysis (PCA), are central tools in the design of spectral algorithms. If the rows of a matrix are viewed as points in a high dimensional space, with the columns being the coordinates, then SVD/PCA are typically used to reduce the dimensionality of those points, and solve the target problem in the lower-dimensional space. The machine blessings of such a projection ar apparent; additionally, these tools are often able to highlight hidden structure in the data. Chapter 1 provides an introduction to SVD via an application to a generalization of the least-squares fit problem. The next three chapters are motivated by one of the most popular applications of spectral methods, namely clustering. Tackles a classical problem from Statistics, learning a mixture of Gaussians from unlabeled samples; SVD leads to the current best guarantees. Studies spectral bunch for distinct random inputs, victimization classical results from random matrices, whereas Analyzes spectral bunch for discretionary inputs to get approximation guarantees. We turn to optimization and see the application of tensors to solving maximum constraint satisfaction problems with a bounded number of literals in each constraint. This powerful application of low-rank tensor approximation substantially extends and generalizes a large body of work.

1.1 Objective

To set the stage for our proposed estimation problem, we study the maximum a posteriori (MAP) estimator of the opinions as well as the influence matrix. A spectral algorithm based on the influence matrix technique is described for solving numerically the flow of incompressible viscous fluids. The algorithmic development is for both Newtonian and non-Newtonian flows. To investigate the performance of the method several test problems are solved.

2. EXISTING SYSTEM

Among the relevant types of data available, a popular set is that of voting results. Since the group actions are usually decided by majority votes, their impact is directly interpretable. The balloting knowledge area unit sculptural as outcomes of a separate random method, that we tend to consult with because the discuss-then-vote model, whose evolution is ruled by the DeGroot opinion dynamics with stubborn nodes. Direct prediction is the disadvantage of the existing system. In this the prediction will come after the completion of the vote.

3. PROPOSED SYSTEM

To set the stage for our proposed estimation problem, we study the maximum a posteriori (MAP) estimator of the opinions as well as the influence matrix. These methods do not give any scientific interpretation of the voting process, which we see as a fundamental benefit of the proposed model-based approach. The following are the advantages of this method are dynamic Prediction and fast process.

4. SYSTEM ARCHITECTURE

In the below figure Illustrations of the inference procedure for the influence matrix. We cluster the topics from the metadata or from any topic modeling or semantic modeling methods (e.g., for Doodle or web dataset); we could select stubborn agents via side information from the meta data; the opinion estimation follows a likelihood estimation process and the inference estimation is conducted by solving.

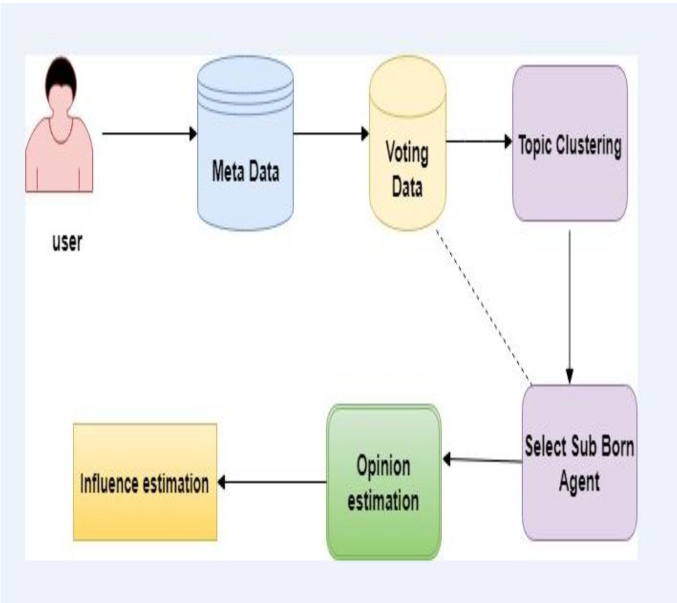

Fig-1: System Architecture

5. METHODOLOGIE

5.1. Influence Matrix Technique

A spectral algorithm based on the influence matrix technique is described for solving numerically the flow of incompressible viscous fluids. The algorithmic development is for both Newtonian and non-Newtonian flows. To investigate the performance of the method several test problems are solved.

6. IMPLEMENTATION

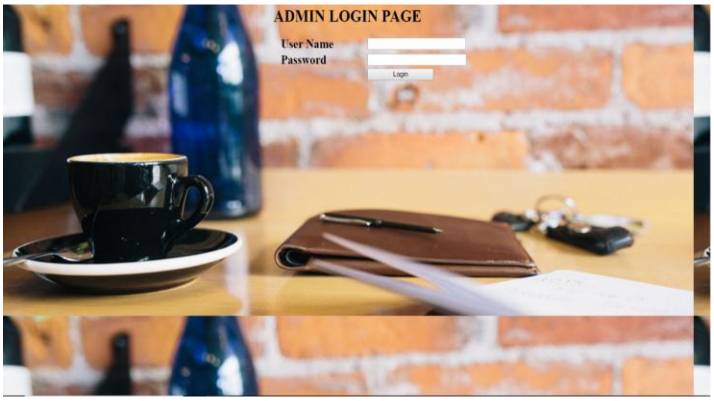

Fig-2.1: Admin Login Page

Description- After clicking on Admin it will direct to this page. Here the admin can login into his/her account. The admin has to give the correct username & the password to get login.

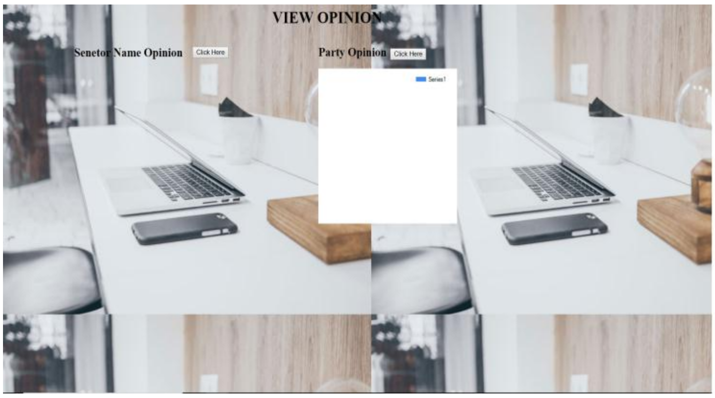

Fig-2.2: View Opinion Page 1

Description- This is view opinion page. Here the admin can view the opinion dynamically. Left side admin can view the senator votes & right side admin can view party votes.

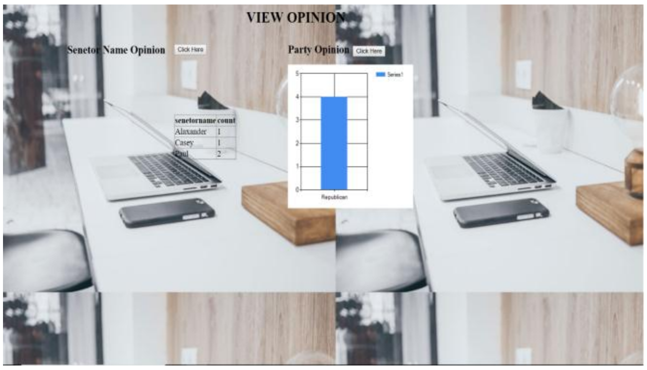

Fig-2.3: View Opinion Page 2

Description- This how the opinions are shown to the admin. For the senator the counts are shown & for the party the bar graph is shown.

Fig-2.4: Upload Dataset Page

Description- Admin can upload datasets here. Admin has to select the senator name then the which state he/she is from and the bill the person worked on then the admin will upload the datasets.

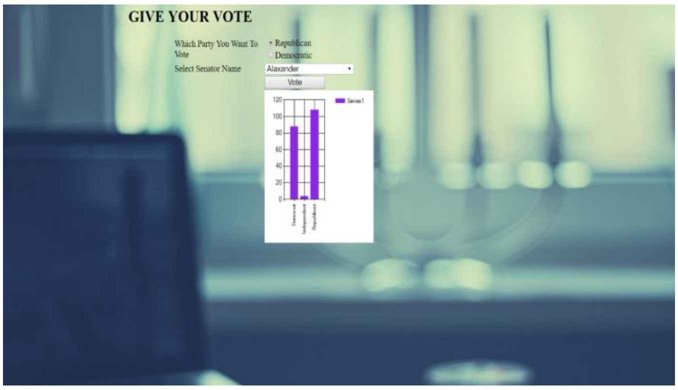

Fig-2.5: After giving Vote

Description- After user giving the vote. The opinion graph is shown to the user.

7. CONCLUSION & FUTURE ENHANCEMENT

7.1 Conclusion

To conclude, in this project we have proposed a new strategy to extract the opinion dynamics model through collecting votes from a population. We developed a discuss-then-vote model as a generative model for the observed votes, in which the votes are casted after a discussion period of opinion exchanges. To infer the model parameters, we utilized an opinion dynamics model with the existence of stubborn agents, which allows us to formulate the inference problem under the Bayesian framework. Based on the inferred model, we also derived a vote prediction procedure to predict on the vote outcomes by evaluating upper and lower bounds on the likelihoods.

7.2 Future Enhancement

The slight advantage of the random forest algorithm indicates that there is some margin for improvement; we believe that a weakness of our approach may lie in treating as independent parameters the stubborn senators' beliefs on different topics. This is an important modeling aspect that we plan to explore in future work.

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