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Graph Data Modeling for Political Communication on Twitter

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DEDICATION

I lovingly dedicate this thesis to my mother, Maya. Her support and love has sustained me throughout this journey. I also dedicate this work to my father, Bijendra Singh and sister, Preeti. I will always appreciate all they have done.

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ABSTRACT

Twitter has become a political reality where political parties, presidential candidates, legislatures and journalists post tweets about the latest events sharing texts, pictures, hashtags, URLs, and mentioning other users. Gaining insight from the vast amount of political data on Twitter is only possible with proper computational tools.

We propose to store and manage Twitter data in an optimized Neo4j graph database for serving queries about political communication among state legislators of 50 U.S. states, state reporters, and presidential candidates for the 2016 presidential election. Our rationale for selecting this relatively new database technology is threefold: (1) ease of use in explicitly modeling and visualizing communication relationships among entities of interest; (2) flexibility to evolve the database overtime to quickly adapt to changes in user requirements; and (3) user-friendly intuitive query interface. We developed a Python-based Google App Engine application using Twitter API to collect tweets from the Twitter's handlers of the aforementioned political actors. We employed best practice guidelines in graph database design to develop five different database models in order to distinguish the impact of each query optimization technique. We evaluated each of the models on the same set of tweets posted during January 1, 2016 to November 11, 2016 using the same set of queries of interest to political communication scholars in terms of the average query response times. Our experimental results confirmed the benefits of the best practice design guidelines. In addition, they show that the optimized database model is able to provide significant improvement in query response times. Reducing the number of hops used in the graph queries and using database indexes on most commonly used attributes reduced the average query response time in our dataset by as much as 74.52% and by 85.27%, respectively, compared to the reference model. Nevertheless, the reduction in the average query response time comes with the cost of the increase in graph database relationship store size by 5.49% compared to the reference model.

Our contributions are as follows. (1) The optimized Neo4j graph database that will be updated weekly with new tweets; the access to this database can be made available to political communication scholars. (2) The above findings added to currently limited guidelines in graph database designs. (3) The findings about political communication prior to the Iowa caucus of the 2016 primary presidential election.

CHAPTER 1. INTRODUCTION

Due to ever expanding data on the web at a very fast rate and the rise of online journalism [1, 2], there is a need for effective and efficient ways of processing abundant data and presenting relevant and important information [3]. Twitter, a popular micro-blogging platform [4], is a vast source of data including political data that have gained tremendous interests among social science research studies [5, 6, 7]. Jungherr surveyed 115 articles about the use of Twitter in politics [7]. The survey mentions the usage of Twitter by politicians, by constituents during elections, and by campaign strategists to facilitate campaign events. Twitter has become an important tool for data journalists for political news [8-12].

To the best of our knowledge, the communications on Twitter among this group of political actors, namely, state legislators, state reporters, and presidential candidates have not been studied because of lack of proper computational tools. Some interesting questions are as follows. In a given time period, who are influential among state legislators or reporters? What hashtags or URLs are popular among this group and whether they imply or carry any agendas? Do state reporters' tweets carry the same message as those in state legislators' tweets? Is there a group of state legislators who frequently mention each other or retweet each other's tweets? Are they in the same state or across states? Is there a similar interaction among a group of state reporters?

This thesis focuses on designing an optimized database for serving the first set of queries about political communication on Twitter within the above group of political actors. We propose to use a Neo4j graph database management system to manage the database due to the following reasons. (1) At the time of this writing, Neo4j is the most widely used graph database management system (GDBMS) [13]. It has good documentation and is able to integrate with several third-party programs such as Tableau [14], a popularly used visualization tool by data journalists. (2) Neo4j supports a simple property graph model that explicitly models relationships as edges among entities (modeled as nodes) of interest; therefore, we can model communication relationships among political actors explicitly. (3) Neo4j query language is called Cypher which is declarative yet powerful to let users formulate their text queries into Cypher queries relatively easy. (4) GDBMS does not have a schema; hence, it can evolve quickly in order to adapt to rapid changes in user requirements [15, 16]. (5) Neo4j, in particular, has a user-friendly query interface that supports visualization of query results in a graphical format. Last, in terms of query response time, Neo4j was shown to offer better query performance compared to other GDBMS such as DEX [17], NativeSail [18] and HypergraphDB [19].

GDBMS is relatively new database management technology. Compared to an established database management systems such as relational database management systems (RDBMS) [20] or other No-SQL database management systems [21], GDBMS is more intuitive for modeling, querying, and visualizing complex relationship data [22, 23]. Nodes and edges are the key elements of any graph data model. There are several graph data models such as a simple property graph model [24], a Resource Description Framework graph model [25], and a hypergraph model [26]. In a simple property graph model, a single node represents one real-world entity of interest, e.g. a person, a category, a place or a thing. An edge represents an individual relationship between two nodes in the graph. Properties of entities or relationships are modeled as properties of individual nodes or individual edges, respectively. Nodes can be grouped into the same group and assigned the same label name. A similar grouping of edges is also done. GDBMS supports Create, Read, Update and Delete (CRUD) operations [27, 28] of nodes and edges. The network of nodes and connected edges is what we term the structure of the graph in this thesis. The graph structure can significantly influence query response times for the same returned results as shown in previous studies of graph databases about movies [29] and about tweets and Twitter users [30, 31]. Indexing frameworks together with rule and cost based optimizations for graph queries have been developed [32-35].

1.1 Contributions

In this thesis work, we designed a set of queries about political communication on Twitter among presidential candidates, state reporters, house representatives, senates and senators. We developed a Python-based Google App Engine application using Twitter API to collect tweets from the Twitter's handlers of the aforementioned political actors. We collected 167,671 tweets during January 1, 2016 to November 11, 2016. We designed five different graph data models and determined the most efficient data model for our set of queries written in Neo4j's query language called Cypher [36]. Our experimental results show that the key to achieve low query response time is (1) to use fewer numbers of hops between nodes in the queries and (2) to query using schema indexing on attributes that are most frequently used in the query conditions. The largest improvements were of 74.52% and 85.27% in average query response time compared to those of the reference model due to these two key features, respectively.

Our contributions are the following. (1) The optimized Neo4j graph database that will be updated weekly with new tweets; the access to this database can be made available to political communication scholars who would use the pre-defined Cypher queries to obtain the information or use Tableau to visualize the query results from our database. (2) The findings on graph query optimization to be added to the currently limited guidelines in graph database designs. (3) The findings about political communication prior to the Iowa caucus of the 2016 primary presidential election that the database queries reveal.

1.2 Organization

In Chapter 2, we discuss related work on graph databases with emphasis on techniques for improving performance of graph database queries. Chapter 3 presents the proposed graph data models. In Chapter 4, we present experimental results and findings on how to design an efficient graph data model, when we should create a new node for an entity, when to introduce new edges in our data model, and when and how to use indexing to maximize the performance of the Neo4j Cypher queries and other considerations to keep in mind while designing the Cypher queries in order for them to offer low query response time.

CHAPTER 2. RELATED WORK

In this chapter, we present related work relevant to techniques for improving performance of graph database queries. In Section 2.1, we provide background on indexing features and internal query optimization in Neo4j [37]. In Section 2.2, the graph design guidelines given by Neo4j [38] were summarized. In Section 2.3, we describe query optimization techniques by adding additional edges and/or nodes to direct the search to only relevant nodes such as the "time-tree" approach [39] that was proposed to support time-based range queries to find events occurring in a given time period.

2.1 Query Optimization and Indexing Mechanism in Neo4j

Indexing is an internal data structure of a database management system for narrowing down the search space for the data of interest. Neo4j provides two indexing mechanisms: label indexing and schema indexing [40]. Label indexing is automatically created when a label is created. However, schema indexes have to be manually created given a label name and one attribute name of the label to create an index on. For instance, a user can manually create an index on the "name" attribute of the "User" label. Unlike RDBMS, a composite search key of several attributes is not allowed. Schema indexing is automatically considered in the following cases. (1) When there exists an equality comparison of the indexed attribute and a value without any function performed on the attribute. (2) When the indexed attribute is used in the "in" clause. (3) When the use of the index is explicitly specified in the query. The schema indexing is not considered when the indexed attribute appears in the inexact matching condition or when a function is applied on the indexed attribute even in equality condition.

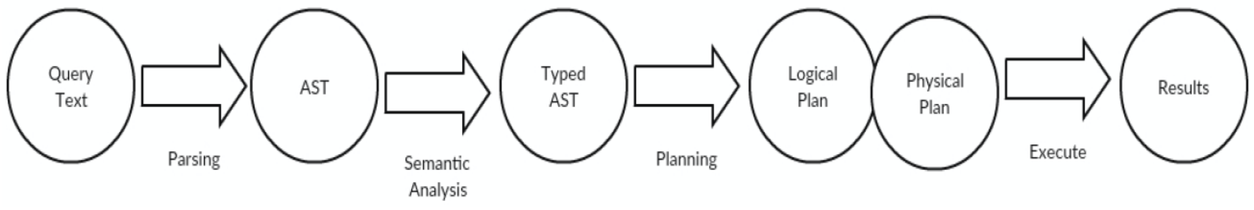


Figure 2.1 Cypher query execution process

Neo4j executes a Cypher query in a sequence of steps as shown in Figure 2.1. It first parses the input query and tokenizes it to build the corresponding abstract syntax tree (AST in Figure 2.1). It does basic syntax error checking of the query. If the query has no syntax error, Neo4j continues with semantic analysis. Neo4j’s documentation does not provide concrete details about how semantic analysis is done. We speculate that this process is similar to a typical semantic analysis process in RDBMS, which includes checking for undefined attributes, for incompatible operand types with the operation in the query, and for incorrect semantic of the query graph such as missing the join condition [41]. Next, Neo4j normalizes and optimizes the abstract syntax tree. Then, it rewrites the query such that all the labels and types are moved from the match clause in the query to the where clause and converts all equality statements (e.g., hashtag=“GOPDebate”) into an “In” statement (e.g., hashtag in [“GopDebate”]). One or more logical query plans are then created, depending on which query planner is used. A query plan/tree is a tree of operators such as NodeByLabelScan, NodeUniqueIndexSeek, CartesianProduct, ShortestPath, and Limit. Each operator takes no more than two operands (inputs). Once the final logical plan is selected, the algorithm for each logical operator in the final logical query plan is determined, which results in the physical query plan.

The early version of Neo4j only supports a rule-based planner. Although it utilizes relevant indexes to produce query plans [42], no query cost is estimated and no statistics are used in the rule-based planner. Starting from version 2.2.0, Neo4j offers a cost-based planner in addition to the rule-based planner. Utilizing the same principles in RDBMS, Neo4j cost-based planner estimates the cost of each logical query plan using statistics kept in the database such as label and index selectivity factors of the labels or indexes used in the query. Selectivity factor is the ratio of the number of output rows produced by an operator to the number of input rows coming in to the operator. The query tree with high selectivity (i.e., low selectivity factor) at the base of the query tree tends to give a faster query execution time because less results are available to subsequent operators in the tree to process. Several logical query plans are considered by Neo4j cost-based planner. The cheapest plan is then selected for execution by a greedy algorithm in Neo4j version 2.2 or a dynamic programming algorithm in Neo4j version 2.3. Because the cost-based planner offers much better performance than the rule based planner, all read-only Cypher queries use the cost-based planner by default. To force the use of the rule-based planner, either set the **dbms.Cypher.planner** option to **RULE** in the configuration file, which forces the rule-based planner on all Cypher queries submitted to this Neo4j server, or prepend **CYPHER planner = rule** before the Cypher query, which forces the use of the rule-based planner only this query.

2.2 Guidelines for Graph Data Model Design

Since GDBMS is relatively new technology, there are very few principles available for designing graph databases. Neo4j's developers provide some guidelines for graph database model design [43]. Real-world entities are typically modeled as nodes and nodes with similar properties are grouped into a label. Simple properties (single-value properties) should be kept as node properties. A composite property consisting of multiple components, for instance, an address consisting of the first line, the second line, city, state, and zip code, should be broken down into multiple nodes, one for each component of the property. These nodes are linked via labeled edges with the main node.

Two-way relationships among entities are modeled as edges. Quality of relationships is modeled as the property of the edge. If the relationship involves more than two entities, an intermediate node is used to link all the node entities. The data model should attempt to reduce redundant data in the database to reduce the search space. Nodes can be linked in a linear fashion to indicate the order they occur in time. Nodes can be linked in a tree fashion termed multi-level indexing structure where the root node has its children nodes representing individual years; each year node has its children nodes representing individual months; each month node has its children nodes representing individual days; the children nodes are linked together in chronological order. Each day node has its children representing individual events on that day. This idea is similar to the time-tree idea mentioned in the next section. If we only keep the date of the events as the property in the event node and use it in the query to find events in a particular time period, Neo4j needs to search through all the event nodes to find the event nodes in the required time period. We can use the multi-level indexing structure to find the beginning node representing the start date and the end node representing the end date in the given time interval and only search through the nodes linked in between these two nodes. One may ask why not using schema indexing on the event date property instead of creating the additional multi-level indexing structure, which further increases the size of the database. The reason is that Neo4j will not use schema indexing if a function is applied on an attribute value in which the index exists. A date consists of day, month, and year. If we want to look at a particular date, a function has to be applied to extract the date, which prohibits Neo4j from using the indexing on this property.

2.3 Query Optimization via Graph Structure Change

We describe the application of the time-tree approach using our dataset. To model each tweet and its various properties such as time when it was posted and the tweet text, we can use a node with the label “Tweet” to store properties of each tweet as node properties. We refer to the nodes having this label as Tweet nodes. One naïve approach for retrieving tweets posted within a given time range is to compare it with the corresponding property value of Tweet nodes, but it can be very time consuming since Neo4j has to check this property value against those of all the Tweet nodes in the database, depending on the number of tweet nodes in the database. Furthermore, showing tweets posted in a particular order by time requires further sorting of the results, which increases the query processing overhead. Therefore, multi-level tree data structures were introduced to support queries for data in a given time range [44]. Tweet nodes are attached to the leaves of the time tree. To show tweets posted within a specified time period is to traverse through relevant branches in the time tree structure. In Figure 2.2, the time tree has a root node labelled as a “Century” node, followed by nodes representing individual years on the first level, nodes representing individual months on the second level, nodes representing individual days on the third level, and so on [45]. The individual leaf nodes of the time tree has edges to tweet nodes posted at that time as illustrated in Figure 2.2.

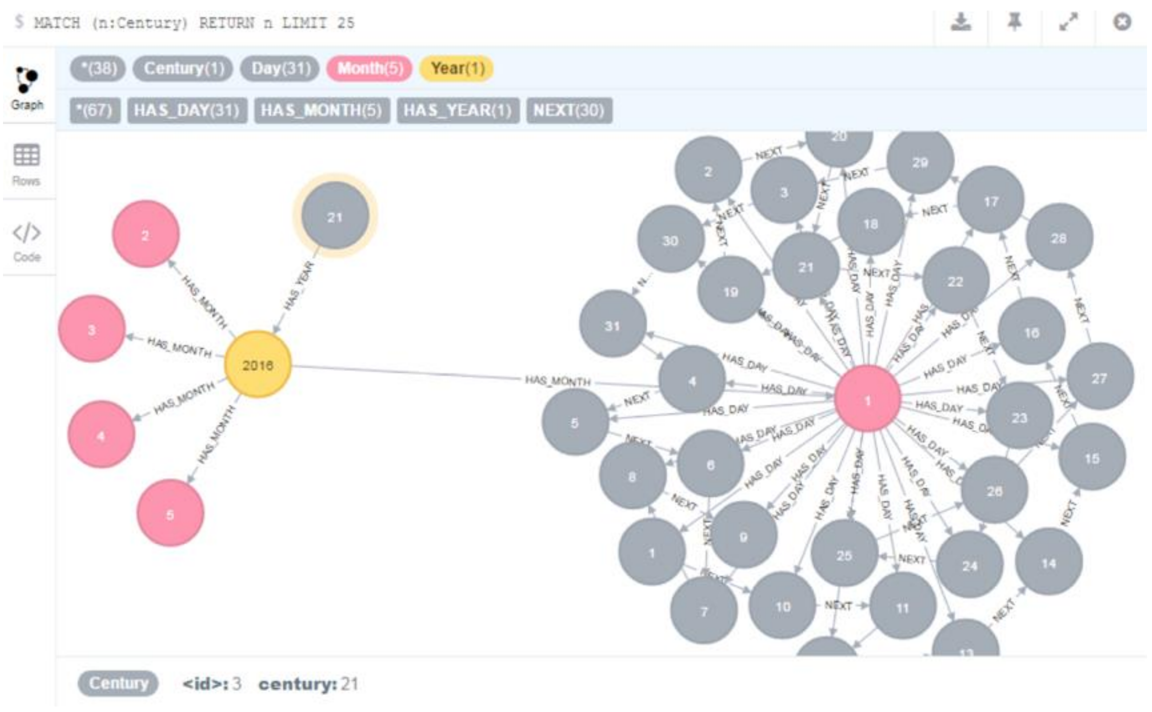

$ MATCH (n:Century) RETURN n LIMIT 25
*(38) Century(1) Day(31) Month(5) Year(1)
*(67) HAS_DAY(31) HAS_MONTH(5) HAS_YEAR(1) NEXT(30)
Graph
Rows
Code
2016
21
HAS_YEAR
HAS_MONTH
NEXT
HAS_DAY
Century <id>: 3 century: 21

Figure 2.2 Time tree example

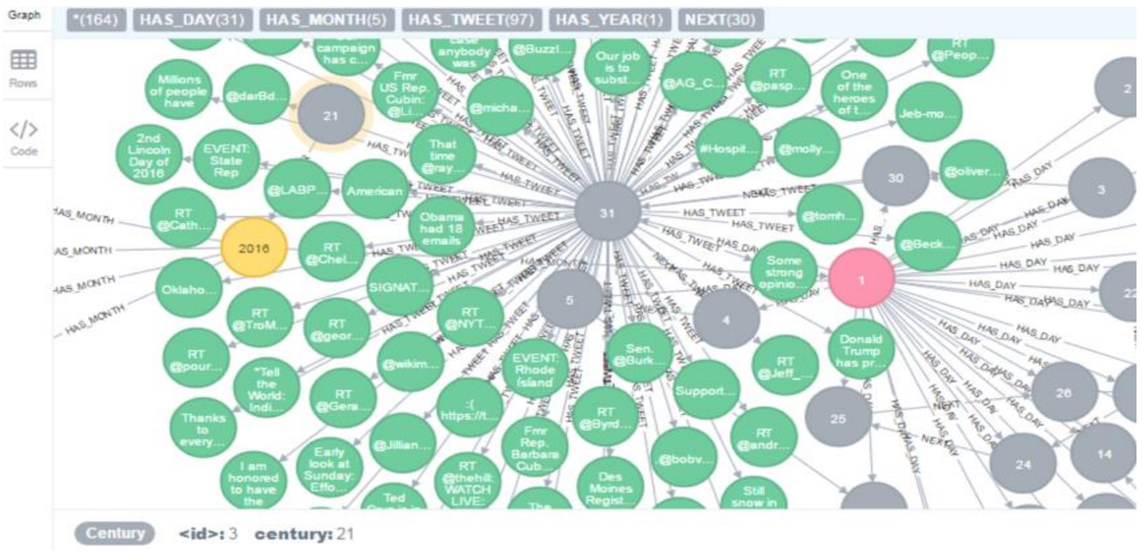
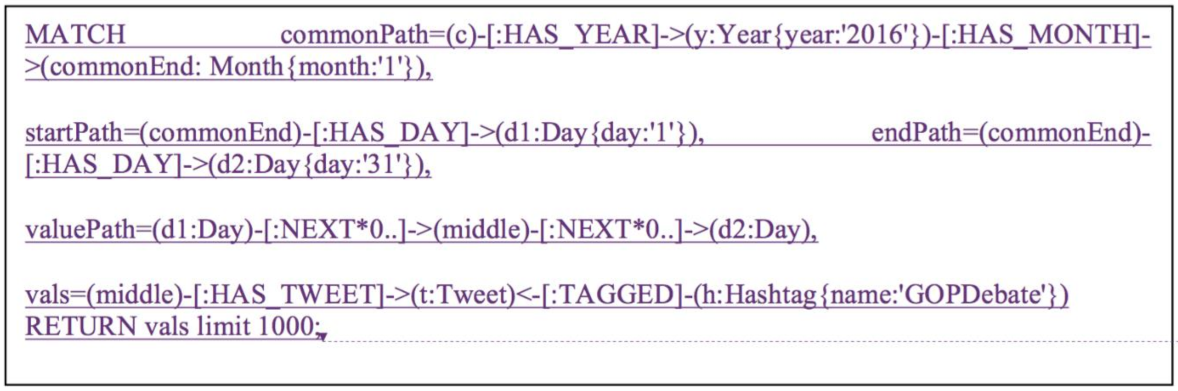

Graph
Rows
Code
*(164) HAS_DAY(31) HAS_MONTH(5) HAS_TWEET(97) HAS_YEAR(1) NEXT(30)
2016
21
31
HAS_TWEET
HAS_DAY
HAS_MONTH
Century <id>: 3 century: 21

Figure 2.3 “Tweet” nodes attached to “Day” nodes linked via “:NEXT” edges

In order to get tweets posted in a given time period using the time tree, we rewrite the query to find the starting path node and ending path node and collect the tweets attached to the day nodes which are ordered and connected through the next relationship edge in Neo4j. See the rewritten query in Figure 2.4 for tweets with the hashtag “GOPDebate” in it during January 2016.



```
MATCH                commonPath=(c)-[:HAS_YEAR]->(y:Year{year:'2016'})-[:HAS_MONTH]-
>(commonEnd: Month{month:'1'}),

startPath=(commonEnd)-[:HAS_DAY]->(d1:Day{day:'1'}),               endPath=(commonEnd)-
[:HAS_DAY]->(d2:Day{day:'31'}),

valuePath=(d1:Day)-[:NEXT*0..]->(middle)-[:NEXT*0..]->(d2:Day),

vals=(middle)-[:HAS_TWEET]->(t:Tweet)<-[:TAGGED]-(h:Hashtag{name:'GOPDebate'})
RETURN vals limit 1000;
```

Figure 2.4 Cypher query utilizing the time tree

There are two approaches for creating the time tree. The first approach is to create the tree with nodes and labels representing the predefined number of years (e.g., Year nodes), months (e.g., Month nodes), and days (e.g., Day nodes), respectively. Then, attach each Tweet node to the Day node the tweet was posted. But the problem with this approach is that we should know in advance about the time range of the tweets to add to the database. The second approach is to create the time tree nodes dynamically while adding the tweets to the database [41]. The time tree can further be expanded to include the time information about the tweets posted.

Cattuto et al. introduced a graph data model for representing and efficiently querying the time-varying social network data in Neo4j [31]. They collected data from participants wearing badges equipped with active Radio Frequency Identification devices during the 20th ACM Hypertext 2009 conference from June 29th to July 1st 2009. Their model allows rich queries involving combinations of a social network topology. Their proposed data model included a similar time-tree graph structure to support time-based range queries. The model was implemented in Neo4j and was shown to perform well.

Goonetilleke et al. stored micro-blogging queries in most widely used graph databases: Neo4j and Sparksee [30]. The data model is simple, consisting of user nodes, tweet nodes, and hashtag nodes with posts, mentions, follows, and retweets relationships among user nodes and tags between tweet nodes and hashtag nodes. No time-tree like structure was used to support range search queries in a given time period. The authors implemented their graph in Neo4j with nearly 50 million nodes and 326 million edges. They used Twitter as the data source having 284 million follows relationships among 24 million users. Their simple queries included select queries, adjacency queries to retrieve the immediate neighborhood of a node. For advanced queries, they used the count, order by, and limit clauses in Neo4j. Other queries included co-occurrence queries, recommendation and influence queries. In their work, they did not evaluate the performance of the graph database management systems.

2.3 Other GDBMS Query Optimization, Indexing, and Benchmarking

Dai et al. investigated the performance of rule-based query optimization by sharing the state and computation between multiple queries [32]. They have introduced new abstractions, physical operators, and rules. The experiment results were measured on both real world datasets and synthetic benchmark. However, their framework is limited to a specific set of queries. They have not tested their framework against a cost-based optimizer which is the default planner for the latest version of Neo4j as it performs much better than rule-based planners. Trißl proposed a cost-based optimization framework for graph queries where graph nodes and edges are stored in RDBMS [35]. In this work, two implementations of path operators were introduced. The performance of the proposed method was evaluated on synthetic data only. More work is needed for the framework to handle path length and path queries.

Zhao and Han proposed a new pattern-based graph indexing framework using a decomposed shortest path algorithm for efficiently searching graph structures in large networks [33]. They implemented their framework for searching protein structures in a biological graph database. They evaluated the performance of their framework on both synthetic and real biological datasets. However, they still need to develop their framework for large graph networks that grow over time and also need to address the issue of noise and failure in the network before their indexing technique can be adopted. Williams et al. proposed a novel method of indexing the graph databases for subgraph isomorphism queries and similarity queries [46]. They tested the performance of their method on protein motif datasets and on synthetic datasets as well. However, their technique is limited to small graphs (less than ~ 20 nodes).

Benchmarking of GDBMS was also intensively studied as summarized in Tang's thesis [47]. Ciglan et al. discussed various challenges of developing fair benchmarking methodologies of graph traversal operations [18]. They implemented their benchmarking suite for 5 graph databases: Neo4j, DEX, OrientDB, NativeSail and SGDB. They performed experiments with the datasets having nodes varying from 1,000 to 100,000 vertices. The larger datasets had vertices varying from 200, 400, 800 thousands and 1 million vertices. They developed their design to test the ability of GDBMS in different memory constrained environments performing breath first traversal and community detection. For the benchmarking dataset, they used LFR-Benchmark generator which was primarily designed for testing algorithms for community detection in a graph. They concluded that operations involving local traversals in a large network are more suitable for the tested systems than operations involving traversals of the whole graph structure. Dominguez-Sal et al. evaluated the performance of four graph databases: Neo4j, Jena, Hypergraph DB and DEX. Using their HPC Graph Analysis Benchmark, they tested the performance on different graph sizes. They showed that Neo4j and DEX are the most efficient ones.

For the cloud environments, Dayarathna and Suzumura developed XGDBench benchmarking framework [48]. They used Multiplicative Attribute Graph (MAG) model for realistic modeling of attributes of the graph databases and used the R-MAT algorithm to build the graphs for different sizes and edge densities. They evaluated the applicability of the MAG model and conducted performance evaluation. For small graphs, all GDBMS performed reasonably, but only Neo4j and DEX could load the largest datasets. DEX scales better traversing 15K traversing edges per second but Neo4j had a better throughput for some operations. DEX had best performance for most operations, and in operations in which Neo4j was the fastest, DEX performance was comparable to that of Neo4j.

CHAPTER 3
PROPOSED GRAPH DATA MODELLING FOR POLITICAL COMMUNICATION ON TWITTER

In this chapter, we present our proposed approach. We start with questions about political communication in Section 3.1. In Section 3.2, we present the process for collecting tweets from Twitter and the challenges we faced. In Section 3.3, we discuss our design of five different graph data models along with the rationale. We provide Cypher queries for each data model in the Appendix A. Appendix B provides description on how to run the data collection program.

3.1 Questions of Interest to Political Communication

Communication scholars are interested in studying communication on Twitter to produce some meaningful stories such as important political communication on Twitter between US state reporters and political leaders and the impact on political policy making. Under a consultation with a communication scholar, we design 26 queries of her interest as listed in Table 3.1. Hashtags are assumed to carry out common interests. Therefore, hashtags used in tweets, users' mentions in tweets, and retweets among different parties are of particular interests. Each user has an associated category among presidential candidate, house representative, reporter, senator, senate, and house. Each user also has an associated political party to which she belongs. A screen name of a user is used to represent a user's name as all the users must have their screen name but may leave their name empty.

Table 3.1 Queries of Interest to Communication Scholars

Q1	Find top *k* most retweeted tweets by users in GOP and Democrat parties in a given month; show the retweet count, tweet text, user's name, and user's party in descending order of the retweet count. **Example parameter values:** *k* is 100 and the month is Jan. 2016 **Rationale:** This query finds *k* most influential tweets in a given month and the user who posted them.
Q2	In a given month, find top *k* users who used a given hashtag in a tweet with the most number of retweets; show user's name, user's party, tweet text, and retweet count in descending order of the retweet count. **Example parameter values:** *k* is 100; hashtag is GOPDebate and the month is Jan. 2016. **Rationale:** This query finds top *k* influential users who used a given hashtag that may represent a certain agenda.
Q3	Find top *k* hashtags that appeared in the most number of states; show the number of states it appeared in, the list of the distinct states it appeared, and the hashtag in descending order of the number of distinct states the hashtag appeared. **Example parameter values:** *k* is 100 **Rationale:** This query finds top *k* hashtags that are most widely spread across states, which could indicate a certain agenda that is widely discussed.
Q4	Find distinct states along with the month and the date of a tweet posted by state legislature (senate, senators, house, and house representatives) or state reporters using a given hashtag in a given year. **Example parameter values**: hashtag is GOPDebate; the year is 2016. **Rationale:** This query aims to find the spread across states of a given hashtag among state legislatures and reporters that could represents a topic of interest along with the timeline of the discussion.

Table 3.1 (continued)

Q5	Find tweets that have a given hashtag posted by users of a given state for a given month. Show tweet text and retweet count in descending order of the retweet count. **Example parameter values**: hashtag is GOPDebate; the state is New Jersey; the month is Jan. 2016. **Rationale:** This query finds most influential users in a given state for a particular topic of interest (hashtag).
Q6	Find *k* users who used a given set of hashtags in their tweets. Show the user's name and the US state to which the user belongs in the alphabetical order of the names. **Example parameter values**: hashtags are GOPDebate, DemDebate, GOP; *k* is 100. **Rationale**: This query finds *k* users who share similar interests (based on hashtags).
Q7	Find users who used a given hashtag in a given state in a given month; show the count of tweets posted with that hashtag along with the user's name and category in descending order of the tweet counts. **Example parameter values**: hashtag is GOPDebate and the state is New Jersey; month is Jan. 2016. **Rationale**: This query finds users who used a given hashtag most often in a given state. These users could influence an agenda within the state.
Q8	Find *k* tweets posted by a given user for a given hashtag in a given state for a given month. Show the tweet text and the user's name. **Example parameter values**: *k* is 1000; the user's name is SusanKLivo; the hashtag is GOPDebate; the state is New Jersey; the month is Jan. 2016. **Rationale:** This query is to be used after Q7 to find out more about the content of the tweets with the hashtag of interest.

Table 3.1 (continued)

Q9	Find top *k* most followed users; show the user's name, the user's party, and the number of followers in descending order of the number of followers. **Example parameter values**: category values are GOP or democrat. **Rationale**: This query finds the most influential user measured by the number of followers; this query can be extended to find the influential user of a certain category or a certain party.
Q10	Find the list of distinct hashtags that appeared in one of the states in a given list in a given month; show the list of the hashtags and the state in which they appeared. **Example parameter values**: state list includes Ohio, Alaska, Alabama; the month is Jan. 2016. **Rationale:** This query is to find common interest among the user in the states of interest.
Q11	Find tweets with hashtags posted by republican (GOP) or democrat members of a given state in a given month; show the tweet text, the hashtag, the user's name of the user who posted the tweet, and the user's party. **Example parameter values**: state is Ohio; the month is Jan. 2016 **Rationale:** This query allows exploration of the context in which the hashtags were used.
Q12	Show hashtags, tweets, user, state nodes for a given state for a given month with the maximum limit of *k* results **Example parameter values**: state is Ohio; the month is Jan. 2016; k is 1000. **Rationale:** This query gives detailed activities in a given state.
Q13	Show at most *k* nodes representing tweets that has a given hashtag used in a given month. **Example parameter values**: hashtag is GOPDebate; the month is Jan. 2016; k is 100.

Table 3.1 (continued)

Q14	Find at most *k* users who used a given hashtag in their tweet in a given month; show user’s name, user’s party, and the name of the state the user belong in increasing order of the tweet posted date. **Example parameter values**: hashtag is GOPDebate; the month is Jan. 2016; k is 1000. **Rationale:** This query finds users who used the given hashtag in the given period of time.
Q15	Show user’s name and user’s state along with the list of URLs used in tweets posted by these user for a given month in ascending order of the dates the tweets were posted. **Example parameter values**: user’s party is GOP for Mar. 2016 **Rationale:** This query finds the URLs shared by user of a given party.
Q16	Find top *k* tweets of users who belong to one of the parties in the given list of parties and in a given month. Show user’s name, user’s party, tweet text, retweet count, and the url used in the tweet in descending order of the retweet count **Example parameter values:** user’s party is GOP or democrat for the month of Jan. 2016; k=100. **Rationale:** This query finds the most influential tweets along with the user who posted them and the urls used by the user.
Q17	Find *k* users of a given party in a given month. Show user’s name, user’s party, and the list of URLs used by the user in their tweets. **Parameter values:** user’s party is GOP for the month of Jan. 2016; k=100. **Rationale:** This query helps us to find the URLs shared by members of the same political party.
Q18	Find *k* users who were mentioned in tweets of users of a given party; show tweet text, user’s name, user’s state, and name of the user mentioned in the tweet in ascending order of the days of the month. **Parameter values:** user’s party is GOP for the month of Jan. 2016; k=1000; **Rationale**: This query finds interactions among users on Twitter.

Table 3.1 (continued)

Q19	Find *k* users of a given party and users who they mentioned in their tweets in a given month. **Parameter values:** user's party is GOP; the month is Jan. 2016; k=1000 **Rationale:** This query finds interactions among users on Twitter.
Q20	Find *k* hashtags used by users of a given state in a given month; Show hashtag nodes, day nodes, month node, and year node. **Parameter values:** state is New Jersey for the month of Jan. 2016; k=1000. **Rationale:** This query visualizes these hashtags and connections.
Q21	Find top *k* hashtags among users of a given party in a given month; show the hashtags and count of the number of time the hashtag appeared in descending order of the count. **Example parameter values:** user's party is GOP; the month is Jan. 2016; k=1000. **Rationale:** This query finds *k* most popular hashtags.
Q22	Find top *k* hashtags among all the users; show the number of tweets (count) that each hashtag has been used and the list of distinct user's states of these tweets, and the count of the distinct states, in descending order of the tweet count. **Example parameter values:** Month is Jan. 2016; k=1000 Rationale: This query finds the spread of popular hashtags among state.
Q23	Find top *k* hashtags posted by users in a given list of parties in a given list of months in a range of days. Show the hashtag and the count of the tweets the hashtag appeared in the descending order of the count **Example parameter values:** party list contains GOP and democrat; the month is Jan. 2016 and Feb. 2016 and the day range is 1-8. **Rationale:** This query finds popular hashtags during certain days (e.g., before Iowa caucus).

Table 3.1 (continued)

Q24	Find top *k* hashtags posted by users in a given list of parties in a given month; show the hashtag, the count of tweets the hashtag appeared in. **Example parameter values:** user's party list contains GOP and democrat; the month is Jan. 2016; k=1000. **Rationale:** This query finds the most popular hashtags posted by users in a given list of parties.
Q25	Find *k* users mentioned in tweets by users in a given party list in a given month; show tweet text, user's name and the name of the user mentioned in ascending order of the month and the day of the tweet. **Example parameter values:** user's party list consists of GOP and democrat; the list of month is Jan. 2016 and Feb. 2016; k=10,000. **Rationale:** This query helps us to find the users mentioned.

3.2 Data collection and storage techniques used

For our data collection we focused on Twitter accounts of US state reporters, Presidential Candidates, House Representatives, Senate and Senators. Overall, we collected tweets posted by Twitter accounts.

In order to collect tweets from Twitter, we developed an application using Python 2.7.10 communicating with Neo4j 2.3.3 which is the most commonly deployed graph database worldwide. Py2neo 2.0.9 and Tweepy 2.2 python libraries were used in your application. Py2neo is a library to interact with Neo4j whereas Tweepy is a library for interacting with the Twitter Search API, which is a part of Twitter's REST API. For collecting user timeline tweets we used GET statuses/user_timeline which returns a collection of the most recent Tweets posted by the user indicated by the screen_name or user_id parameters. Our program does not fetch duplicated tweets. For this we used cursoring technique [49] to paginate large result sets of user timeline tweets. With each Twitter search API request, we retrieved 200 tweets in one single page and for the next request we used the tweet id of the oldest fetched tweet in the previous page as a cursor to fetch the next set of tweets in reverse chronological order.

For storing tweets, we used Google AppEngine 1.9.35 [50]. For each tweet fetched we stored tweet text, urls, hashtags used, user mentioned/replied in the tweet, tweet posted date, retweet status and count, user followers, following, screen name and the state user belongs to and tweet posted information. We observed that most of the tweets do not contain location information of the user. Due to this limitation, we had to manually update the state information of the user. Due to rate limit on Twitter search API which limits the number of requests that can be made in 15 minutes to 180 calls [51], we used 4 different user credentials. When we hit the rate limit, we can continue making requests using a different user credential. Our program is designed to be run automatically after a specified period of time (e.g., every 3 hours) to fetch tweets and save them in the Appengine data store in the key-value pair format with unique Tweet ID as key and its various fields as properties with string data type.

3.3 Graph Data Modeling

Based on the information that we get from the user tweets and queries, we investigate four data models to find the one that gives the minimum average query response time for the queries described in Section 3.1. Table 3.1 summarizes the intuition behind the design and describe each model in its own section.

Table 3.2 Summary of the design choice to study query performance

Data Model	**Design Intuition**
Data Model 1	We followed the basic guidelines for graph database design [43]. That is to use nodes to model entities like tweets, users, and states as well as nodes for representing multiple values in a tweet such as hashtags and urls. We model relationships between nodes using edges. This data model is used as our reference data model for our performance comparison.
Data Model 2	We pulled out the atomic attributes from tweet nodes and user nodes to study the effect of increasing number of hops in our queries and the use of index on sub_category property since it is the most frequently used property in our queries.

Table 3.2 (continued)

Data Model 3	The aim is to study the impact of reducing the number of hops in the query by introducing new edges between hashtag nodes and user nodes as well as hashtag nodes and state nodes into the reference data model.
Data Model 4	This model is the hybrid model of model 2 and model 3, which has new node for the SubCategory with the index on it; we observed that forcing queries to scan by index reduces much query response time compared to the scan by label. Furthermore, this model has new edges between hashtag, state and user nodes to reduce the number of the hops in our Cypher queries for performance improvement.

3.3.1 Data Model 1

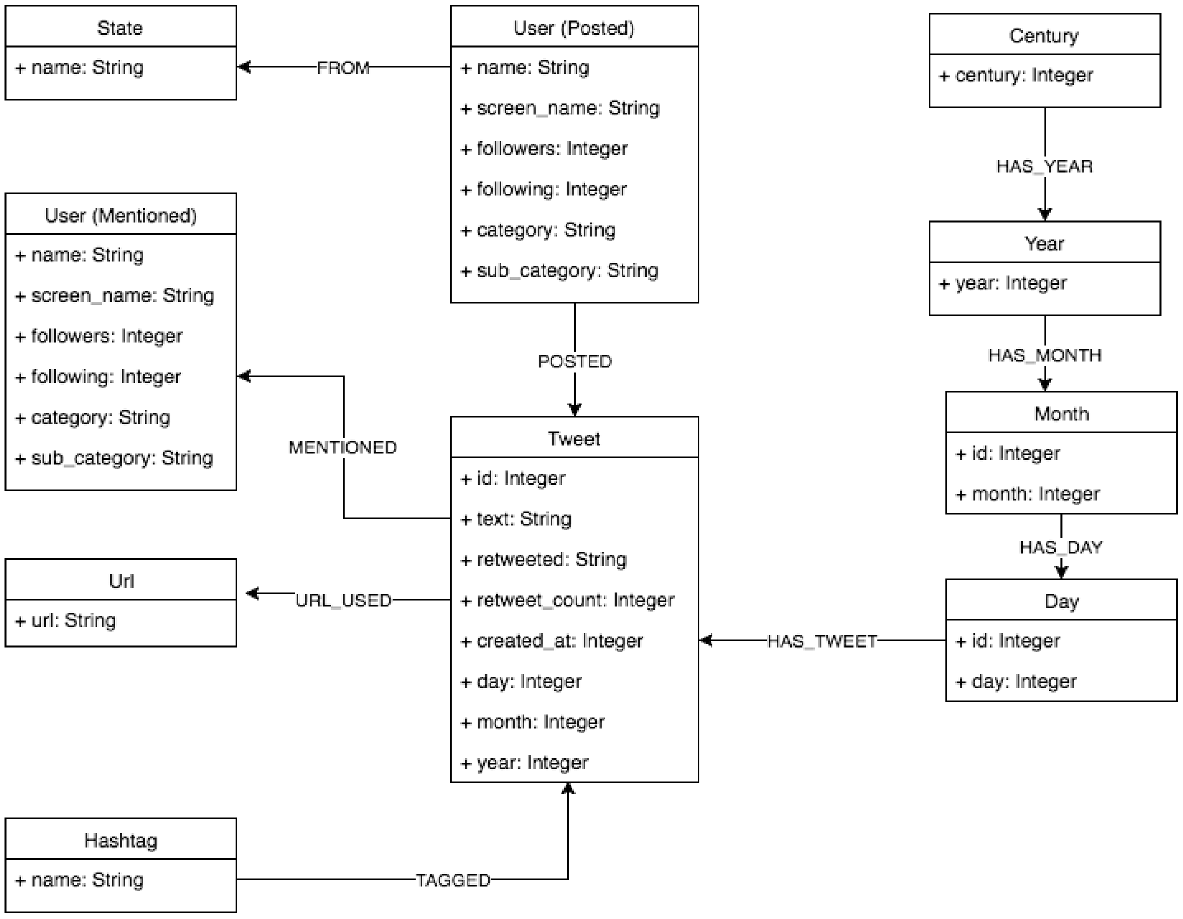


Figure 3.1 Data Model 1

This is the simplest model among the five models with the time tree on the right to speed up queries based on time. Figure 3.1 shows the schema. We follow the basic graph data model guidelines, making nodes for entities and edges to represent relationship between nodes. For properties like hashtags and urls where multiple of them can occur in a tweet, we separate them as nodes instead of properties. In the end, we have 5 types of node labels: Tweet, User, Url, Hashtag and State. Tweet nodes have properties: tweet id which is used to uniquely identify the tweet, retweet_count (number of retweets of this tweet), retweeted (whether this tweet has been retweeted by the user), tweet text, created_at (timestamp value of the tweet posted), day (integer values from 1 to 31), month (integer values from 1 to 12) and year (2016). Day, month and year values are extracted from the created_at field of the tweet. Tweet nodes have index on id property. User nodes have properties: user screen_name (user screen name on Twitter profile), followers (indicating the number of followers) and following (indicating the number of people this user follows), sub_category (GOP, democrat, na), category (house_representative, senator, presidential_candidate, senate, reporter) and name (user full name on Twitter profile). User nodes have indexing on screen_name property. State and Hashtag nodes have the name property used to indicate the state of the user and hashtag used by the user with indexing on these two properties. Url has the url property (expanded URLs used by the User in their Tweets) with indexing on it as shown in Figure 3.1. The sub_category indicates whether the user belongs to a party, 'GOP', 'democrat' or 'na'. The category property value is either senate (for Senate official handlers), presidential_candidate (for presidential candidates), reporter (for reporters), senator and house_representative, for senators and house representatives

These nodes are connected with directed edges labeled as shown in Figure 3.1. We have timeline attached to tweet nodes in data model 1. We use timeline here to show results of Cypher queries that involve time range [39]. We have generated time tree dynamically for our study as we do not have the information about the range of years, months and days to support the tweets in the data model.

3.3.2 Data Model 2

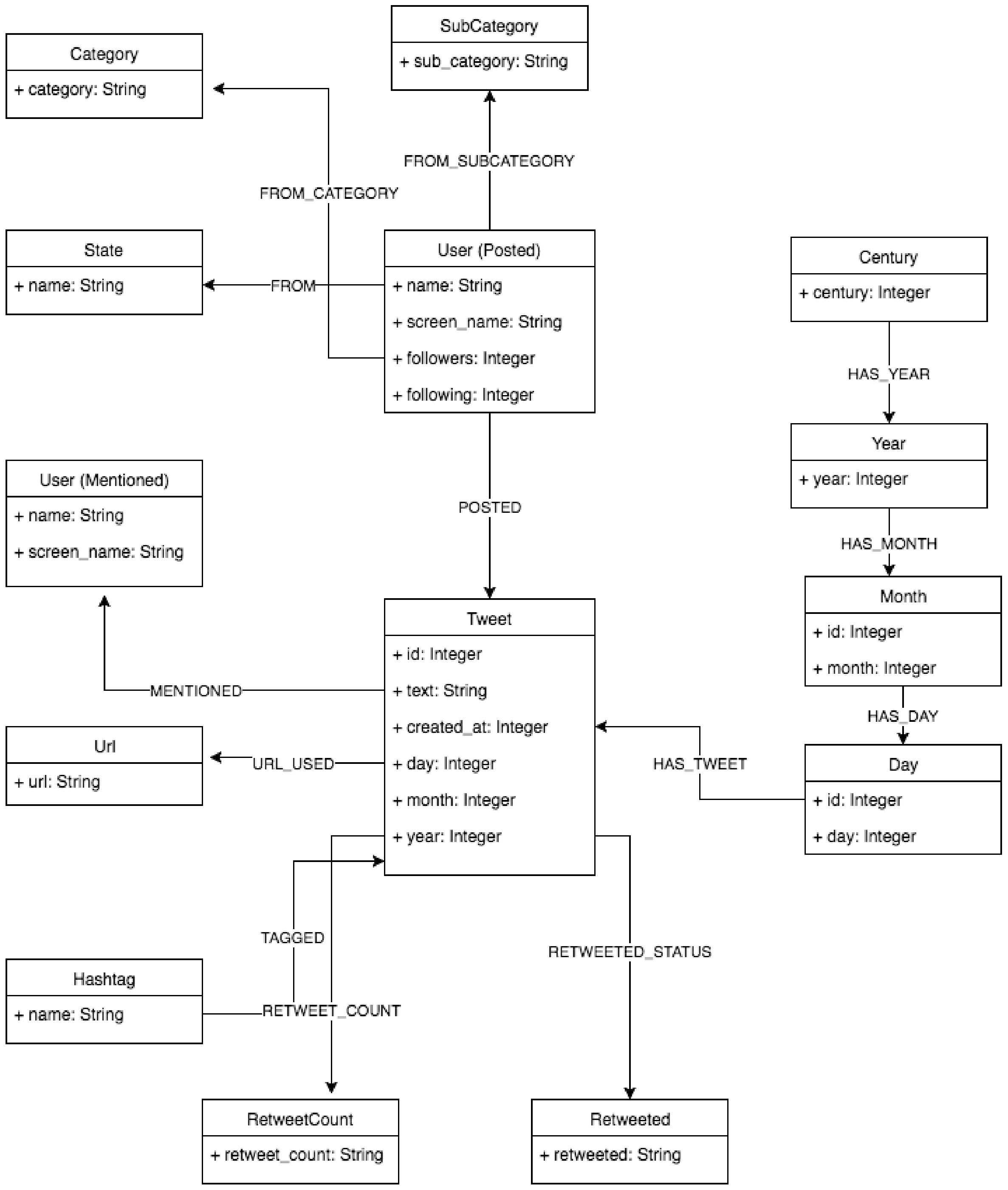


Figure 3.2 Data Model 2

Figure 3.2 shows the schema of this model. In order to study how performance of the read-only Cypher query changes, we create new nodes for retweet_count and retweeted properties of Tweet nodes with indexing on them to observe the effect of increasing the number of hops in Cypher queries. Similarly, we create new nodes for the user category and sub_category properties of the User node with indexing on them. We create an index on SubCategory nodes to observe the performance when we force queries to use scan by index instead of scan by label. Apart from this we have indexes on name property of Hashtag, State, id property of Tweet, url property of Url and screen_name property of User node.

3.3.3 Data Model 3

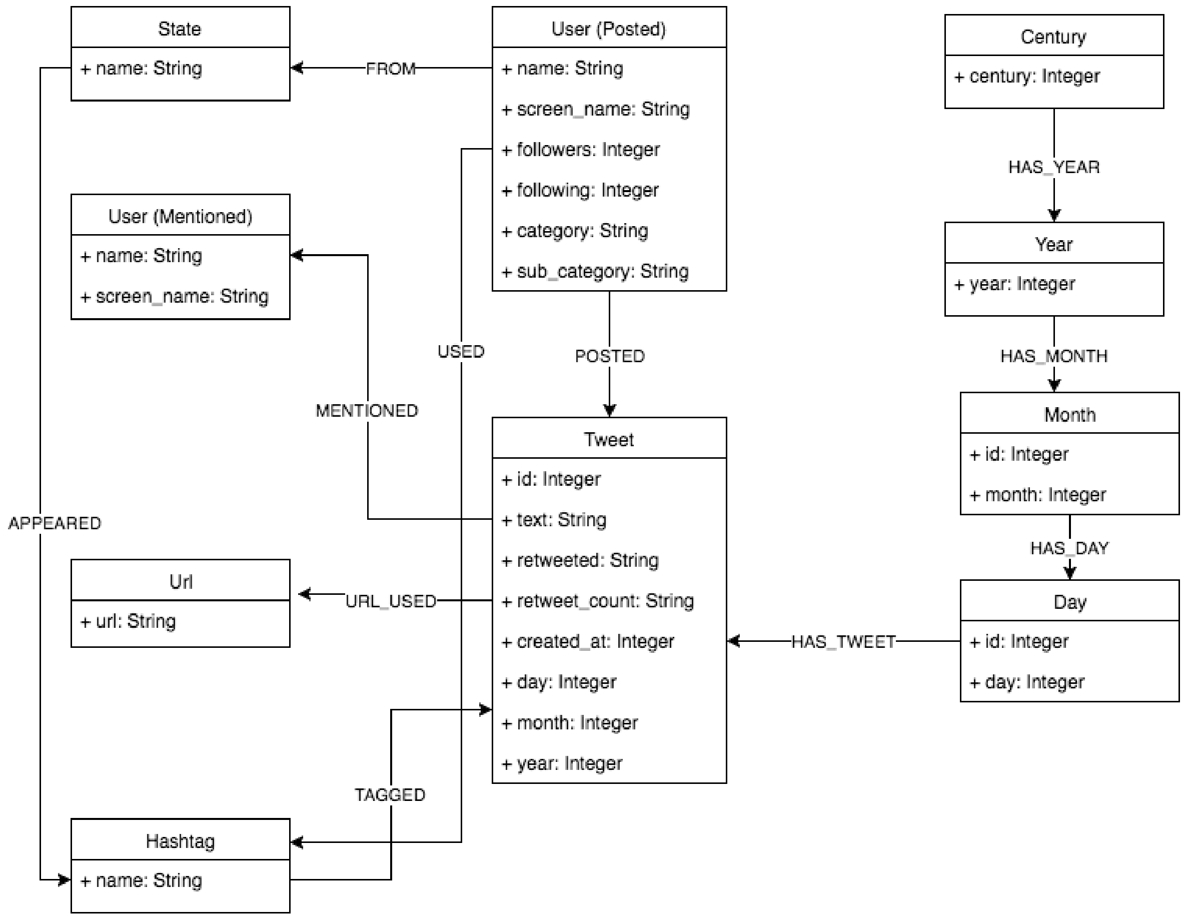


Figure 3.3 Data Model 3

For our data model 3, we have modified data model 1 and introduced new edges between hashtag and state and user nodes as shown in Figure 3.3 to compare the performance of the data models when number of hops are reduced in our Cypher queries. In data model 3, we have indexes on screen_name, id, url and name property of the User, Tweet, Url, Hashtag and State nodes respectively.

3.3.4 Data Model 4

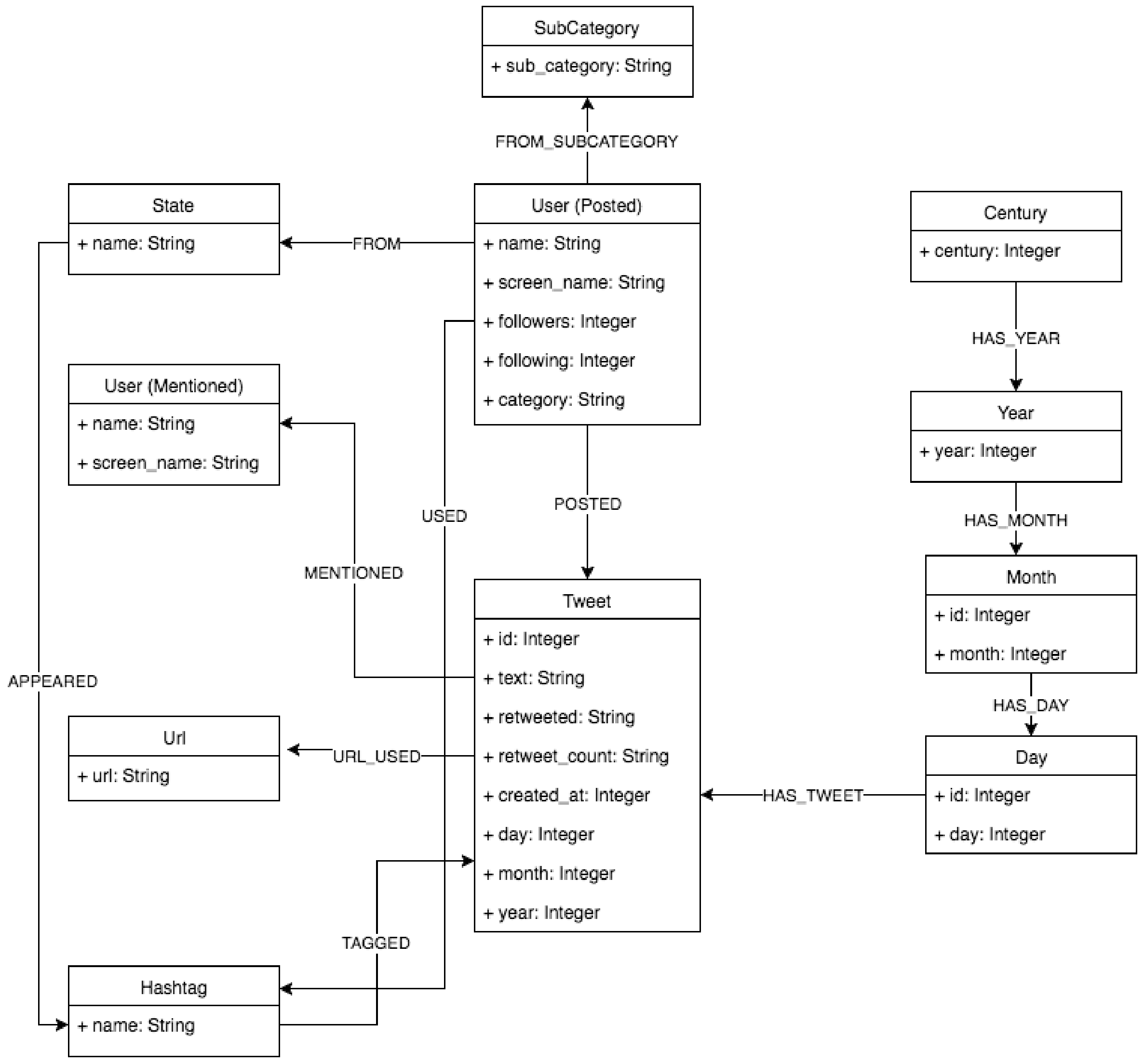


Figure 3.4 Data Model 4

This model is the most efficient data model among the four models for most queries. We designed this data model after analysis of the performance of the first three data models. It has new SubCategory nodes with the index on the sub_category property and new edges between state, user and hashtag nodes as shown in Figure 3.4.

CHAPTER 4
EXPERIMENTAL RESULT AND PERFORMANCE EVALUATION

This chapter describes our data collection methods, performance metrics, evaluation results of the data models per our metrics, and query results and findings about political communication.

4.1 Data Collection and Database Creation

We developed two programs in Python 2.7 [52]. We used Neo4j 2.3.3 Community Edition for Windows [53]. Our first program running in Google App Engine environment collected tweets using Tweepy 2.3.0 and saved the data into Comma Separated Values (CSV) format. The second Python program used Py2neo 2.0.9 [54] library to insert the data from the CSV file into Neo4j to create the database for each data model. This way we can ensure that all the data models have the same set of data. Figure 4.1 illustrates this process. We ran our data collection program for 2 days to collect tweets posted since January 1, 2016 till November 11, 2016. The total number of tweets are 167,671 and they are divided into the following categories shown in Table 4.1.

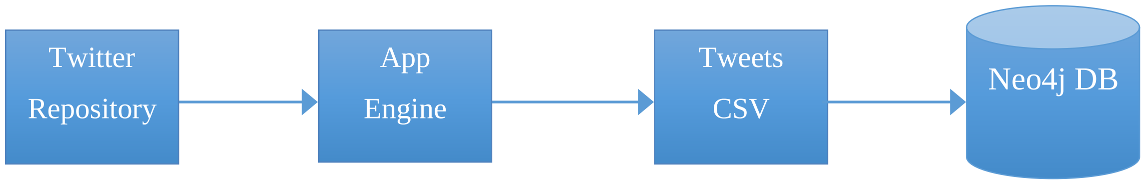


Figure 4.1 Process for importing tweets and related data

Table 4.1. Collected data

Category of Users	Number of Twitter handlers	Number of tweets collected
Presidential candidates	10	14,721
Senates	72	50,412
Reporters	45	38,925
Individual senators	88	15,084
House representatives	198	48,529

Because the graph data models are different, the Cypher queries are also different. We developed five sets of Cypher queries, one for each data model. Table 4.2 presents the details about each data model. The number of nodes and edges are not necessarily the same because we added auxiliary edges and nodes as part of our optimization methods. The database sizes of the databases with the same number of nodes and edges could also be different due to whether there were additional schema indexes added to the databases or not.

Table 4.2 Sizes of Data Models

Model	**Model 1 (Reference Model)**	**Model 2**		**Model 3**		**Model 4**	
Category	MBytes	MBytes	% Change	MBytes	% Change	MBytes	% Change
Array Store	8	8	0.00	8	0.00	8	0.00
Logical Log	102.48	179.04	74.71	116.91	14.08	109.71	7.06
Node Store	4.13	4.21	1.94	4.13	0.00	4.13	0.00
Property Store	24.66	18.32	-25.71	24.66	0.00	24.66	0.00
Relationship Store	29.88	40.79	36.51	31.51	5.46	31.52	**5.49**
String Store Size	34.89	34.89	0.00	34.89	0.00	34.89	0.00
Total Store Size	712.88	794.19	11.41	728.87	2.24	719.78	0.97
Number of nodes	288298	294224	2.06	288298	0.00	288305	0.00
Number of edges	661520	997688	50.82	709884	7.31	972136	**46.95**

4.2 Performance Metric and Measurements

The performance metric is the average query execution time for each query that is calculated as follows. Each query was run 40 times consecutively on each data model and the average time for each query was calculated using the last 30 recordings; the first 10 query response times were not used in the calculation since the execution times were significantly differences due to cache warm up. In other words, the average performance measured should be the best case scenario for Neo4j as it may cache the query results. After we finished one data model, we moved on to measure performance of the next data model until all the data models were measured. All the queries were executed on the same workstation, an Intel 3.50 GHz CPU with 32 GB RAM running Windows 7 Enterprise 64 bit operating system. We used the default server and cache configuration of Neo4j 2.3.3 Community Edition for Windows in our experiments.

4.3 Experimental Results

We present the comparison of the query response time for all the 25 queries on all the four data models. Data model 1 is used as the reference model. We summarize the important findings in Section 4.3.1.

Table 4.3.1 Average time taken by queries in seconds

	Model 1 (Reference Model)	**Model 2**		**Model 3**		**Model 4**	
Query ID	(seconds)	(seconds)	(% Change)	(seconds)	(% Change)	(seconds)	(% Change)
1	0.49497	0.43460	-12.196	0.49607	0.222	0.38997	-21.214
2	0.01527	0.01493	-2.183	0.02053	34.498	0.02013	31.878
3	0.58060	0.59287	2.113	0.14610	-74.836	0.14793	-74.521
4	0.01540	0.00970	-37.013	0.02183	41.775	0.02000	29.870
5	0.00570	0.00533	-6.433	0.00880	54.386	0.00727	27.485
6	0.01460	0.01050	-28.082	0.00437	-70.091	0.00590	-59.589
7	0.00770	0.00437	-43.290	0.00753	-2.164	0.00803	4.329
8	0.00880	0.00810	-7.955	0.00647	-26.515	0.00933	6.061
9	0.08937	0.01190	-86.684	0.08407	-5.931	0.01317	-85.267
10	0.05160	0.04520	-12.403	0.04223	-18.152	0.04853	-5.943
11	0.02900	0.03253	12.184	0.02567	-11.494	0.03137	8.161
12	0.34230	0.32780	-4.236	0.31480	-8.034	0.32937	-3.778
13	2.01973	2.24280	11.044	1.88413	-6.714	2.24417	11.112
14	0.01887	0.01417	-24.912	0.01347	-28.622	0.01637	-13.251
15	0.13313	0.13983	5.033	0.12470	-6.335	0.12190	-8.438
16	0.43363	0.43657	0.676	0.42887	-1.099	0.33210	-23.415
17	0.18100	0.13850	-23.481	0.16570	-8.453	0.14483	-19.982
18	0.18670	0.24623	31.887	0.17530	-6.106	0.18427	-1.303
19	0.17320	0.14023	-19.034	0.16870	-2.598	0.15037	-13.183
20	0.06410	0.06793	5.980	0.06760	5.460	0.07260	13.261
21	0.18810	0.16913	-10.083	0.18913	0.549	0.15163	-19.387
22	0.32360	0.32250	-0.340	0.31247	-3.440	0.30583	-5.490
23	0.41587	0.35467	-14.716	0.42150	1.355	0.33737	-18.876
24	0.41110	0.33777	-17.838	0.39800	-3.187	0.31420	-23.571
25	0.42770	0.44143	3.211	0.42583	-0.436	0.40570	-5.144

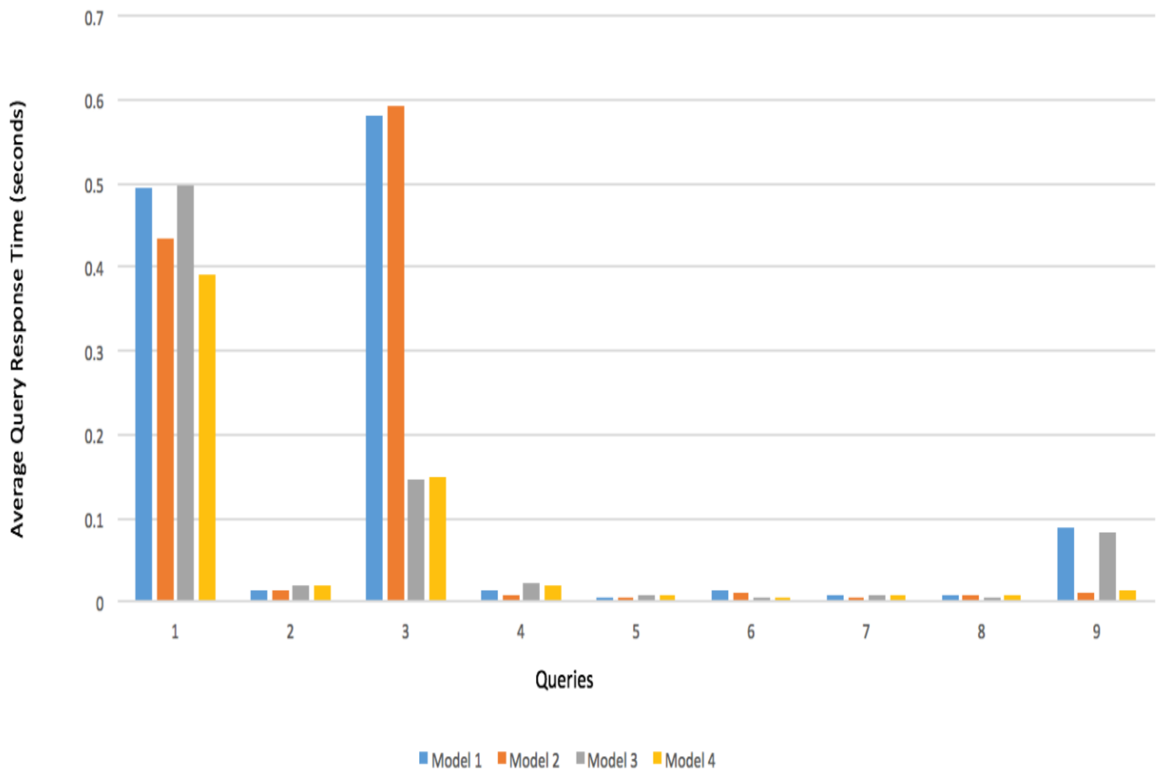


Figure 4.2.1 Comparison of average query response times of Q1-Q9

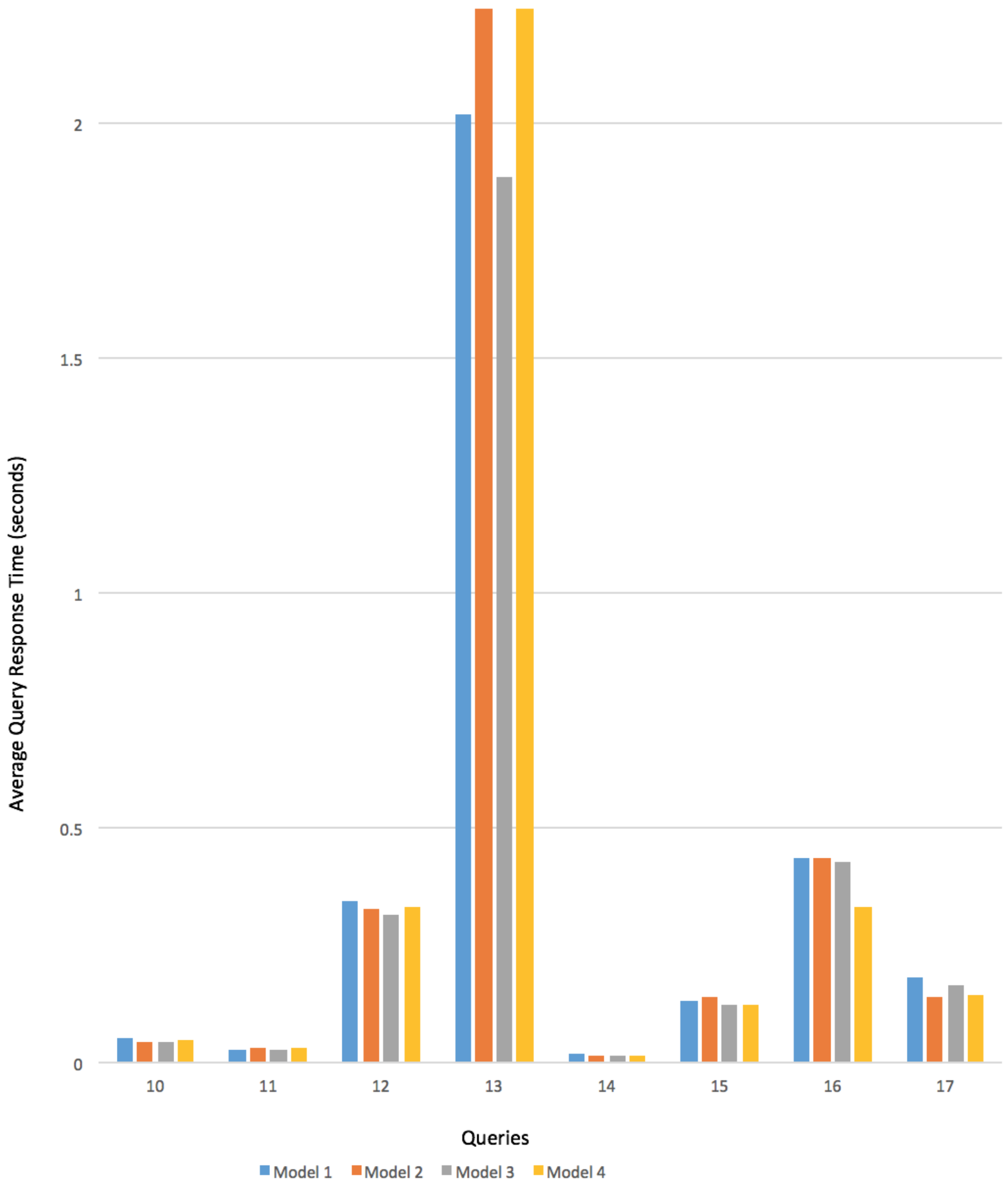


Figure 4.2.2 Comparison of average query response times of Q10-Q17

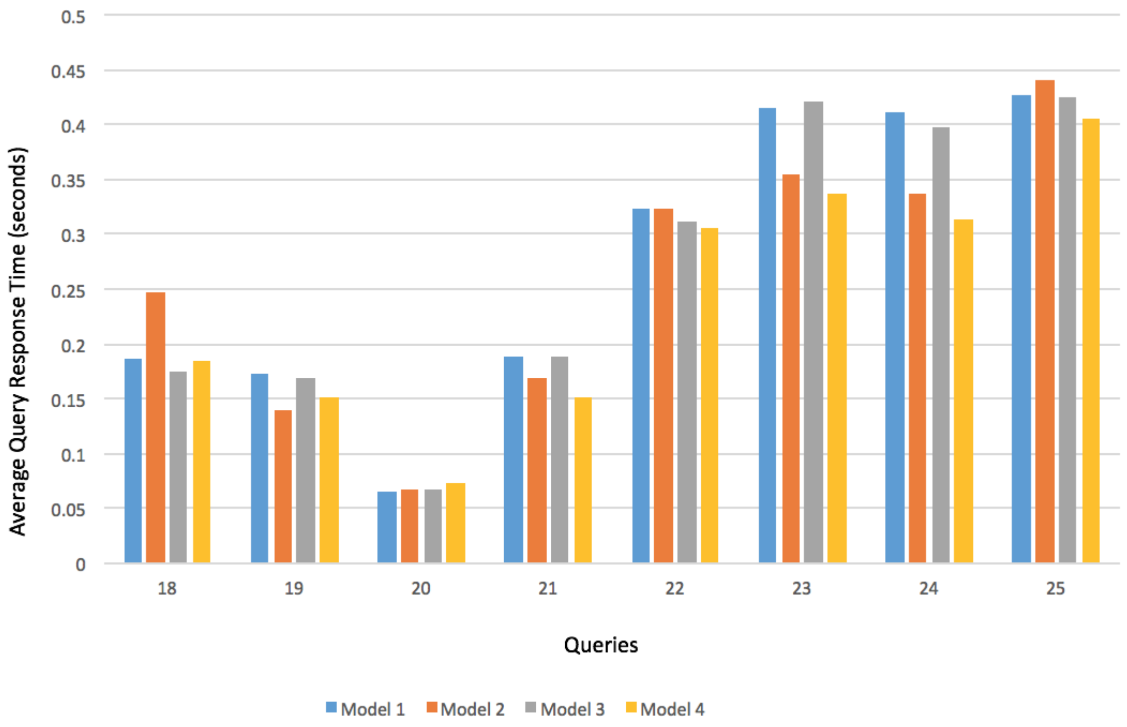


Figure 4.2.3 Comparison of average query response times of Q18-Q25

4.4. Important Findings

There is 21.21% improvement for the Q1 in model 4 from model 1 as query scan by index on the user sub-category property used in model 4 is much faster than query scan by label in model 1. For Q2, model 2 gives the best performance due to the use of RetweetCount as nodes is better than the use of the property retweet_count of Tweet nodes.

For Q3 there is 74.52% improvement in model 4 from model 1 as we have introduced new edges between the hashtags and the state nodes so the number of hops gets reduced to 1 hop in model 4 compared to 3 hops in model 1.

For Q6 there is 59.59% improvement in model 4 compared to model 1 even though in both the models we have scan by index. This is because we have introduced new edges between user and hashtags used by the user, which resulted in 2 hops instead of 3 hops in model 1. For Q13, Cypher query is same for model 2, model 3 and model 4 but still model 3 has least query execution time, it is likely due to the fact that model 3 has least number of edges.

For Q9, Q19, Q21, Q23, Q24 and Q25, there is significant improvement of 85.27%, 13.18%, 19.39%, 18.88%, 23.57% and 5.14%, respectively because of introduction of new nodes for user sub category and scan by index on those nodes.

Model 4 requires 0.00243%, 46.95%, and 5.49% more in terms of the number of nodes, the number of edges, and the relationship store size in MBytes, respectively compared to the reference model.

Other findings: Queries designed with directed edges where ASCII arrows are used to describe the direction and using colon (:) prefix with named relationships enclosed by square brackets take less time to execute than queries with no directed edges and colon prefix used in the queries.

To summarize, while designing graph data models we created nodes for entities and label them and created edges between the nodes to define the relationships between the nodes. For non-atomic attributes of nodes, we created separate nodes e.g. hashtag nodes for hashtags used in the tweet. We found that it is good to pull out an atomic attribute and create a separate node in two scenarios. (1) When that attribute is used in the query condition (i.e., WHERE clause) in frequently used queries (e.g., sub-category of user nodes) or (2) When the attribute is frequently associated (used in WHERE clause or RETURN clause) with more than one type of nodes. For example, we created state nodes instead of using the location property in user nodes and introduced new edges to the state nodes (e.g., the edges between state and hashtag nodes) to reduce the number of hops in the queries needing this information.

4.5 Limitations of the Experiment

In our experiment, we have not considered the use of multiple match statements for queries having large number of hops, effect of adding indexing to the time tree like Lucene external index as well, comparison of time tree queries versus queries using the timestamp property attribute.

4.6 Findings about Political Communication

We are interested to learn more about political communications among reporters, senators, house representatives, and reporters during January, 2016, one week before the Iowa Caucus for the 2016 presidential election primary.

Under consultation with a communication scholar, queries Q3, Q11, Q15, and Q18 yielded interesting findings. Q3 provides information about how a hashtag or news is diffused among different states. Q11 provides information about the similar messages being used by the parties. Q15 provides insight about the links being used among state reporters and Q18 helps to do a network analysis of the political actors.

CHAPTER 5 CONCLUSION AND FUTURE WORK

Twitter has emerged as a new medium for political communication and social media analysis. We collected 167,671 tweets from 10 presidential candidates, 72 senates, 45 reporters, 88 individual senators, 198 house representatives of 50 states and designed 25 queries and 4 different data models for studying political communication and social media analysis efficiently by evaluating the performance of the data models. From the findings of our experiment we have come up with the best data model having the least query execution time for the most of the queries designed. From the experiment results we observed that there is 85.27% and 74.52% improvement in query execution time due to introduction of scan by index and introduction of new edges.

Our future work includes (a) studying the effect of multiple match statements for queries having a large number of hops and (b) effect of adding indexing to the time tree like Lucene external index.

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APPENDIX A. CYPHER QUERIES

Cypher Queries for model 1

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1: MATCH (u:User)-[:POSTED]->(t:Tweet) where t.retweet_count>0 and u.sub_category in ['GOP', 'democrat'] and t.year=2016
and t.month=1 and t.day>=1 and t.day<=31 return t.retweet_count AS retweet_count,t.text as tweet,u.screen_name as
user_screenname,u.sub_category as user_party order by t.retweet_count desc limit 100;
2: MATCH (u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where h.name = 'GOPDebate' and u.sub_category in
['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return distinct(u.screen_name) as
user_screenname, u.sub_category as user_party, t.retweet_count as retweet_count, t.text as tweet order by retweet_count desc
limit 100;
3: MATCH (h:Hashtag)-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) return (count(distinct(c.name))) AS
longest_path,collect(distinct(c.name)) as states, h.name AS hashtag order by longest_path desc limit 100;
4: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(n:Hashtag) match (t:Tweet)<-[:HAS_TWEET]-
(d:Day)<-[:HAS_DAY]-(m:Month)<-[:HAS_MONTH]-(y:Year{year: 2016}) where n.name='GOPDebate' RETURN
distinct(c.name) as states,m.month as month,d.day as day",
5: Match (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where t.year=2016 and t.month=1 and
t.day>=1 and t.day<=31 and c.name = 'New Jersey' and h.name = 'GOPDebate' return t.text AS tweet,t.retweet_count AS
retweet_count order by t.retweet_count desc;
6: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where h.name in ['GOPDebate',
'DemDebate', 'GOP'] return distinct(u.screen_name) AS user_screenname, c.name AS location order by user_screenname limit
100;
7: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) WHERE h.name = 'GOPDebate'
and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return count(t) AS count,u.screen_name as
user_screenname, u.sub_category as user_party order by count desc;
8: MATCH (c:State)<-[:FROM]-(u:User {name: 'SusanKLivio'})-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) WHERE
h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.text as
tweet,u.screen_name as user_screenname Limit 1000;
9: MATCH (u:User) where u.sub_category in ['GOP', 'democrat'] return u.screen_name as user_screenname, u.sub_category as
user_party, u.followers as followers_count order by followers_count desc limit 1000;
10: Match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-
[:FROM]->(c:State) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31
and c.name in ['Ohio', 'Alaska', 'Alabama'] return collect(distinct(h.name)) as hashtag_list,c.name as state limit 1000;
11: Match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-
[:FROM]->(c:State) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where u.sub_category in ['GOP', 'democrat'] and y.year=2016
and m.month=1 and d.day>=1 and d.day<=31 and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 and c.name='Ohio'
return distinct(t.text) as tweet, t.year as year, t.month as month, t.day as day, h.name as hashtag, u.screen_name as user,
u.sub_category as user_party order by year, month, day desc limit 1000;
12: Match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-
[:FROM]->(c:State) match (h:Hashtag)-[:TAGGED]->(t:Tweet) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31
and c.name='Ohio' return h,t,u,c,d,m,y limit 1000;
13: MATCH commonPath=(c)-[:HAS_YEAR]->(y:Year{year:2016})-[:HAS_MONTH]-
>(commonEnd:Month{month:1}),startPath=(commonEnd)-[:HAS_DAY]->(d1:Day{day:1}), endPath=(commonEnd)-
[:HAS_DAY]->(d2:Day{day:31}), valuePath=(d1:Day)-[:NEXT*0..]->(middle)-[:NEXT*0..]->(d2:Day),vals=(middle)-
[:HAS_TWEET]->(t:Tweet)<-[:TAGGED]-(h:Hashtag{name:'GOPDebate'}) RETURN vals limit 100;
14: Match (h:Hashtag{name: 'GOPDebate'})-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) where
u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day,
u.screen_name as user_screenname,u.sub_category as user_party,c.name as state order by t.created_at asc limit 1000;
```

15: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(url:Url) where u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, u.screen_name as user_screenname,c.name as reporter_of_state, collect(url.url) as urls order by t.day limit 100;

16: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) where u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.retweet_count AS retweet_count,t.text as tweet,u.screen_name as user_screenname,u.sub_category as user_party, ul.url as url order by t.retweet_count desc limit 100;

17: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) where u.sub_category='GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as user_screenname,u.sub_category as user_party, collect(distinct(ul.url)) as url limit 100;

18: MATCH (c:State)<-[:FROM]-(u)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, t.text as tweet,u.screen_name as user_screenname, c.name as from, collect(m.screen_name) as mentioned_user order by day asc limit 1000;

19: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as user_screenname, collect(m.screen_name) as mentioned_user limit 1000;

20: Match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet) match (h:Hashtag)-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name='New Jersey' return h,d,m,y limit 1000;

21: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) WHERE u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN tag.name as hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

22: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) WHERE t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN COUNT(r) as number_of_tweets_appeared, tag.name as hashtag, collect(distinct(c.name)) as state ORDER BY number_of_tweets_appeared DESC LIMIT 1000;

23: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) WHERE u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month in [1,2] and t.day>=1 and t.day<=8 RETURN tag.name as tags, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

24: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) WHERE u.sub_category in ['GOP', 'democrat'] and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 RETURN tag.name as hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

25: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where m.sub_category in ['GOP', 'democrat'] and u.sub_category = 'GOP' and t.year=2016 and t.month in [1, 2] and t.day>=1 and t.day<=31 return t.month as month, t.day as day, t.text as tweet,u.screen_name as user_screenname, m.screen_name as mentioned_user order by month,day asc limit 10000;

Cypher Queries for Model 2

1: MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:RETWEET_COUNT]->(retweet_count:RetweetCount) using index cat:SubCategory(sub_category) where retweet_count.retweet_count>0 and cat.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return retweet_count.retweet_count AS retweet_count,t.text as tweet,u.screen_name as user_screenname,cat.sub_category as user_party order by retweet_count.retweet_count desc limit 100;

2: MATCH (sc:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:RETWEET_COUNT]->(rc:RetweetCount) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where h.name = 'GOPDebate' and sc.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return distinct(u.screen_name) as user_screenname, sc.sub_category as user_party, rc.retweet_count as retweet_count, t.text as tweet order by retweet_count desc limit 100;

3: MATCH (h:Hashtag)-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) return (count(distinct(c.name))) AS Longest_Path,collect(distinct(c.name)) as States, h.name AS Hashtag order by Longest_Path desc limit 100;

4: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(n:Hashtag) match (t:Tweet)<-[:HAS_TWEET]-(d:Day)<-[:HAS_DAY]-(m:Month)<-[:HAS_MONTH]-(y:Year{year: 2016}) where n.name='GOPDebate' RETURN distinct(c.name) as states,m.month as month,d.day as day",

5: match (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:RETWEET_COUNT]->(rc:RetweetCount) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 and c.name = 'New Jersey' and h.name = 'GOPDebate' return t.text AS Tweet,rc.retweet_count AS retweet_count order by retweet_count desc;

6: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where h.name in ['GOPDebate', 'DemDebate', 'GOP'] return distinct(u.screen_name) AS user_screenname, c.name AS location order by user_screenname limit 100;

7: match (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) using index h:Hashtag(name) WHERE h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return count(t) AS count,u.screen_name as user_screenname, cat.sub_category as user_party order by count desc;

8: MATCH (c:State)<-[:FROM]-(u:User {name: 'SusanKLivio'})-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) WHERE h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.text as tweet,u.screen_name as user_screenname Limit 1000;

9: MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) where cat.sub_category in ['GOP', 'democrat'] return u.screen_name as user_screenname, cat.sub_category as user_party, u.followers as followers_count order by followers_count desc limit 1000;

10: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name in ['Ohio', 'Alaska', 'Alabama'] return collect(distinct(h.name)) as hashtag_list,c.name as state limit 1000;

11: MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (h:Hashtag)-[:TAGGED]->(t:Tweet) where cat.sub_category in ['GOP', 'democrat'] and y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 and c.name='Ohio' return distinct(t.text) as tweet, t.year as year, t.month as month, t.day as day, h.name as hashtag, u.screen_name as user_screenname, cat.sub_category as user_party order by year, month, day desc limit 1000;

12: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (h:Hashtag)-[:TAGGED]->(t:Tweet) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name='Ohio' return h,t,u,c,d,m,y limit 1000;

13: MATCH commonPath=(c)-[:HAS_YEAR]->(y:Year{year:2016})-[:HAS_MONTH]->(commonEnd:Month{month:1}),startPath=(commonEnd)-[:HAS_DAY]->(d1:Day{day:1}), endPath=(commonEnd)-[:HAS_DAY]->(d2:Day{day:31}),valuePath=(d1:Day)-[:NEXT*0..]->(middle)-[:NEXT*0..]->(d2:Day),vals=(middle)-

[:HAS_TWEET]->(t:Tweet)<-[:TAGGED]-(h:Hashtag{name:'GOPDebate'}) RETURN vals limit 100;

14: MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) match (h:Hashtag{name: 'GOPDebate'})-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) using index h:Hashtag(name) where cat.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, u.screen_name as user_screenname,cat.sub_category as user_party,c.name as State order by t.created_at asc limit 1000;

15: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(url:Url) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) where cat.sub_category='GOP' and t.year=2016 and t.month=3 and t.day>=1 and t.day<=31 return t.day as day, u.screen_name as user_screenname,c.name as reporter_of_state, collect(url.url) as urls order by t.day limit 100;

16: match (t:Tweet)-[:RETWEET_COUNT]->(retweet_count:RetweetCount) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) using index cat:SubCategory(sub_category) where ul.url <> '' and cat.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return retweet_count.retweet_count AS retweet_count,t.text as tweet,u.screen_name as user_screenname,cat.sub_category as user_party, ul.url as url order by retweet_count.retweet_count desc limit 100;

17: MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) where cat.sub_category='GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as user_screenname,cat.sub_category as user_party, collect(distinct(ul.url)) as url limit 100;

18: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) where m.screen_name <> '' and cat.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, t.text as tweet,u.screen_name as user_screenname, c.name as from, collect(m.screen_name) as mentioned_user order by day asc limit 1000;

19: MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where cat.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as user_screenname, collect(m.screen_name) as mentioned_user limit 1000;

20: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet) match (h:Hashtag)-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name='New Jersey' return h,d,m,y limit 1000;

21: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) WHERE cat.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN tag.name as Hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

22: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) WHERE t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN COUNT(r) as number_of_tweets_appeared, tag.name as hashtag, collect(distinct(c.name)) as state ORDER BY number_of_tweets_appeared DESC LIMIT 1000;

23: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) WHERE cat.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month in [1,2] and t.day>=1 and t.day<=8 RETURN tag.name as tags, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

24: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) WHERE cat.sub_category in ['GOP', 'democrat'] and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 RETURN tag.name as Hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

25: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) MATCH (mcat:SubCategory)<-[:FROM_SUBCATEGORY]-(m:User) MATCH (cat:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index cat:SubCategory(sub_category) where mcat.sub_category in ['GOP', 'democrat'] and cat.sub_category = 'GOP' and t.year=2016 and t.month in [1, 2] and t.day>=1 and t.day<=31 return t.month as month, t.day as day, t.text as Tweet,u.screen_name as user_screenname, m.screen_name as mentioned_user order by month,day asc limit 10000;

Cypher Queries for Model 3

1: MATCH (u:User)-[:POSTED]->(t:Tweet) where t.retweet_count>0 and u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.retweet_count AS retweet_count,t.text as tweet,u.screen_name as user_screenname,u.sub_category as user_party order by t.retweet_count desc limit 100;

2: MATCH (u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where h.name = 'GOPDebate' and u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return distinct(u.screen_name) as user_screenname, u.sub_category as user_party, t.retweet_count as retweet_count, t.text as tweet order by retweet_count desc limit 100;

3: MATCH (c:State)-[:APPEARED]->(h:Hashtag) return (count(distinct(c.name))) AS Longest_Path,collect(distinct(c.name)) as States, h.name AS Hashtag order by Longest_Path desc limit 100;

4: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(n:Hashtag) match (t:Tweet)<-[:HAS_TWEET]-(d:Day)<-[:HAS_DAY]-(m:Month)<-[:HAS_MONTH]-(y:Year{year: 2016}) where n.name='GOPDebate' RETURN distinct(c.name) as states,m.month as month,d.day as day",

5: match (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 and c.name = 'New Jersey' and h.name = 'GOPDebate' return t.text AS tweet,t.retweet_count AS retweet_count order by t.retweet_count desc;

6: MATCH (c:State)<-[:FROM]-(u:User)-[:USED]->(h:Hashtag) where h.name in ['GOPDebate', 'DemDebate', 'GOP'] return distinct(u.screen_name) AS user_screenname, c.name AS location order by user_screenname limit 100;

7: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) WHERE h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return count(t) AS count,u.screen_name as user_screenname, u.sub_category as type order by count desc;

8: MATCH (c:State)<-[:FROM]-(u:User {name: 'SusanKLivio'})-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) WHERE h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.text as tweet,u.screen_name as user_screenname Limit 1000;

9: MATCH (u:User) where u.sub_category in ['GOP', 'democrat'] return u.screen_name as user_screenname, u.sub_category as user_party, u.followers as followers_count order by followers_count desc limit 1000;

10: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name in ['Ohio', 'Alaska', 'Alabama'] return collect(distinct(h.name)) as hashtag_list,c.name as state limit 1000;

11: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where u.sub_category in ['GOP', 'democrat'] and y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 and c.name='Ohio' return distinct(t.text) as tweet, t.year as year, t.month as month, t.day as day, h.name as hashtag, u.screen_name as user_screenname, u.sub_category as type order by year, month, day desc limit 1000;

12: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (h:Hashtag)-[:TAGGED]->(t:Tweet) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name='Ohio' return h,t,u,c,d,m,y limit 1000;

13: MATCH commonPath=(c)-[:HAS_YEAR]->(y:Year{year:2016})-[:HAS_MONTH]->(commonEnd:Month{month:1}),startPath=(commonEnd)-[:HAS_DAY]->(d1:Day{day:1}), endPath=(commonEnd)-[:HAS_DAY]->(d2:Day{day:31}),valuePath=(d1:Day)-[:NEXT*0..]->(middle)-[:NEXT*0..]->(d2:Day),vals=(middle)-[:HAS_TWEET]->(t:Tweet)<-[:TAGGED]-(h:Hashtag{name:'GOPDebate'}) RETURN vals limit 100;

14: match (h:Hashtag{name: 'GOPDebate'})-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) where t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, u.screen_name as user_screenname,u.sub_category as user_party,c.name as State order by t.created_at asc limit 1000;

15: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(url:Url) where u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, u.screen_name as user_screenname,c.name as

reporter_of_state, collect(url.url) as urls order by t.day limit 100;

16: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) where u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.retweet_count AS retweet_count,t.text as tweet,u.screen_name as user_screenname,u.sub_category as user_party, ul.url as url order by t.retweet_count desc limit 100;

17: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) where u.sub_category='GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as user_screenname,u.sub_category as user_party, collect(distinct(ul.url)) as url limit 100;

18: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, t.text as tweet,u.screen_name as user_screenname, c.name as from, collect(m.screen_name) as mentioned_user order by day asc limit 1000;

19: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as user_screenname, collect(m.screen_name) as mentioned_user limit 1000;

20: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet) match (h:Hashtag)-[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name='New Jersey' return h,d,m,y limit 1000;

21: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) WHERE u.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN tag.name as Hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

22: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) WHERE t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN COUNT(r) as number_of_tweets_appeared, tag.name as hashtag, collect(distinct(c.name)) as state ORDER BY number_of_tweets_appeared DESC LIMIT 1000;

23: MATCH (u:User)-[:POSTED]->(t:Tweet)<-[r:TAGGED]-(tag:Hashtag) WHERE u.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month in [1,2] and t.day>=1 and t.day<=8 RETURN tag.name as Hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

24: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) WHERE u.sub_category in ['GOP', 'democrat'] and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 RETURN tag.name as Hashtag, COUNT(r) as appeared ORDER BY appeared DESC LIMIT 1000;

25: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) where m.sub_category in ['GOP', 'democrat'] and u.sub_category = 'GOP' and t.year=2016 and t.month in [1, 2] and t.day>=1 and t.day<=31 return t.month as month, t.day as day, t.text as Tweet,u.screen_name as user_screenname, m.screen_name as mentioned_user order by month,day asc limit 10000;

Cypher Queries for Model 4

1: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet) using index sub:SubCategory(sub_category) where t.retweet_count>0 and sub.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.retweet_count AS retweet_count,t.text as tweet,u.screen_name as user_screenname,sub.sub_category as user_party order by t.retweet_count desc limit 100;

2: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where h.name = 'GOPDebate' and sub.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return distinct(u.screen_name) as user_screenname, sub.sub_category as user_party, t.retweet_count as retweet_count, t.text as tweet order by retweet_count desc limit 100;

3: MATCH (c:State)-[:APPEARED]->(h:Hashtag) return (count(distinct(c.name))) AS longest_path,collect(distinct(c.name)) as states, h.name AS hashtag order by longest_path desc limit 100;

4: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(n:Hashtag) match (t:Tweet)<-[:HAS_TWEET]-(d:Day)<-[:HAS_DAY]-(m:Month)<-[:HAS_MONTH]-(y:Year{year: 2016}) where n.name='GOPDebate' RETURN distinct(c.name) as states,m.month as month,d.day as day;

5: match (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) where t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 and c.name = 'New Jersey' and h.name = 'GOPDebate' return t.text AS tweet,t.retweet_count AS retweet_count order by retweet_count desc;

6: MATCH (c:State)<-[:FROM]-(u:User)-[:USED]->(h:Hashtag) where h.name in ['GOPDebate', 'DemDebate', 'GOP'] return distinct(u.screen_name) as user_screenname, c.name AS location order by user_screenname limit 100;

7: match (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) using index h:Hashtag(name) WHERE h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return count(t) AS tweet_count,u.screen_name as user_screenname, sub.sub_category as user_party order by tweet_count desc;

8: MATCH (c:State)<-[:FROM]-(u:User {name: 'SusanKLivio'})-[:POSTED]->(t:Tweet)<-[:TAGGED]-(h:Hashtag) WHERE h.name = 'GOPDebate' and c.name='New Jersey' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.text as tweet,u.screen_name as user_screenname Limit 1000;

9: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index sub:SubCategory(sub_category) where sub.sub_category in ['GOP', 'democrat'] return u.screen_name as user_screenname, sub.sub_category as user_party, u.followers as followers_count order by followers_count desc limit 1000;

10: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (t:Tweet)<-[:TAGGED]-(h:Hashtag) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name in ['Ohio', 'Alaska', 'Alabama'] return collect(distinct(h.name)) as hashtag_list,c.name as state limit 100;

11: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (h:Hashtag)-[:TAGGED]->(t:Tweet) where sub.sub_category in ['GOP', 'democrat'] and y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 and c.name='Ohio' return distinct(t.text) as tweet, t.year as year, t.month as month, t.day as day, h.name as hashtag, u.screen_name as user_screenname, sub.sub_category as user_party order by year, month, day desc limit 1000;

12: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) match (h:Hashtag)-[:TAGGED]->(t:Tweet) where y.year=2016 and m.month=1 and d.day>=1 and d.day<=31 and c.name='Ohio' return h,t,u,c,d,m,y limit 1000;

13: MATCH commonPath=(c)-[:HAS_YEAR]->(y:Year{year:2016})-[:HAS_MONTH]->(commonEnd:Month{month:1}),startPath=(commonEnd)-[:HAS_DAY]->(d1:Day{day:1}), endPath=(commonEnd)-[:HAS_DAY]->(d2:Day{day:31}),valuePath=(d1:Day)-[:NEXT*0..]->(middle)-[:NEXT*0..]->(d2:Day),vals=(middle)-[:HAS_TWEET]->(t:Tweet)<-[:TAGGED]-(h:Hashtag{name:'GOPDebate'}) RETURN vals limit 100;

14: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) match (h:Hashtag{name: 'GOPDebate'})-[:TAGGED]-

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>(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) using index h:Hashtag(name) where sub.sub_category in ['GOP',
'democrat'] and t.year=2016 and t.month=1 and t.day>=1 and t.day<=30 return t.day as day, u.screen_name as
user_screenname,sub.sub_category as user_party,c.name as state order by t.created_at asc limit 1000;
15: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(url:Url) MATCH (sub:SubCategory)<-
[:FROM_SUBCATEGORY]-(u:User) using index sub:SubCategory(sub_category) where sub.sub_category='GOP' and
t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, u.screen_name as user_screenname,c.name as
reporter_of_state, collect(url.url) as urls order by t.day limit 100;
 16: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) using
index sub:SubCategory(sub_category) where sub.sub_category in ['GOP', 'democrat'] and t.year=2016 and t.month=1 and
t.day>=1 and t.day<=31 return t.retweet_count AS retweet_count,t.text as tweet,u.screen_name as
user_screenname,sub.sub_category as user_party, ul.url as url order by t.retweet_count desc limit 100;
 17: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:URL_USED]->(ul:Url) where
sub.sub_category='GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as
user_screenname,sub.sub_category as user_party, collect(distinct(ul.url)) as url limit 100;
18: MATCH (c:State)<-[:FROM]-(u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) MATCH (sub:SubCategory)<-
[:FROM_SUBCATEGORY]-(u:User) using index sub:SubCategory(sub_category) where  sub.sub_category = 'GOP' and
t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return t.day as day, t.text as tweet,u.screen_name as user_screenname,
c.name as from, collect(m.screen_name) as mentioned_user order by day asc limit 1000;
19: MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User)
where  sub.sub_category = 'GOP' and t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 return u.screen_name as
user_screenname, collect(m.screen_name) as mentioned_user  limit 1000;
20: match (y:Year)-[:HAS_MONTH]->(m:Month)-[:HAS_DAY]->(d:Day)-[:HAS_TWEET]->(t:Tweet) match (h:Hashtag)-
[:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) where y.year=2016 and m.month=1 and d.day>=1 and
d.day<=31 and c.name='New Jersey' return h,d,m,y limit 1000;
21: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) MATCH (sub:SubCategory)<-
[:FROM_SUBCATEGORY]-(u:User) using index sub:SubCategory(sub_category) WHERE sub.sub_category = 'GOP' and
t.year=2016 and t.month=1 and t.day>=1 and t.day<=31 RETURN tag.name as Hashtag, COUNT(r) as
number_of_tweets_appeared ORDER BY number_of_tweets_appeared DESC LIMIT 1000;
22: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User)-[:FROM]->(c:State) WHERE t.year=2016 and
t.month=1 and t.day>=1 and t.day<=31 RETURN COUNT(r) as number_of_tweets_appeared, tag.name as hashtag,
collect(distinct(c.name)) as state ORDER BY number_of_tweets_appeared DESC LIMIT 1000;
23: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) MATCH (sub:SubCategory)<-
[:FROM_SUBCATEGORY]-(u:User) using index sub:SubCategory(sub_category) WHERE sub.sub_category in ['GOP',
'democrat'] and t.year=2016 and t.month in [1,2] and t.day>=1 and t.day<=8 RETURN tag.name as hashtag, COUNT(r) as
number_of_tweets_appeared ORDER BY number_of_tweets_appeared DESC LIMIT 1000;
24: MATCH (tag:Hashtag)-[r:TAGGED]->(t:Tweet)<-[:POSTED]-(u:User) MATCH (sub:SubCategory)<-
[:FROM_SUBCATEGORY]-(u:User) using index sub:SubCategory(sub_category) WHERE sub.sub_category in ['GOP',
'democrat'] and t.day>=1 and t.day<=31 and t.month=1 and t.year=2016 RETURN tag.name as hashtag, COUNT(r) as
number_of_tweets_appeared ORDER BY number_of_tweets_appeared DESC LIMIT 1000;
25: MATCH (u:User)-[:POSTED]->(t:Tweet)-[:MENTIONED]->(m:User) MATCH (msub:SubCategory)<-
[:FROM_SUBCATEGORY]-(m:User) MATCH (sub:SubCategory)<-[:FROM_SUBCATEGORY]-(u:User) using index
sub:SubCategory(sub_category) where msub.sub_category in ['GOP', 'democrat'] and sub.sub_category = 'GOP' and t.year=2016
and t.month in [1, 2] and t.day>=1 and t.day<=31 return t.month as month, t.day as day, t.text as tweet,u.screen_name as
user_screenname, m.screen_name as mentioned_user order by month,day asc limit 10000;
```

APPENDIX B. THE STEPS TO RUN THE PROGRAM ARE AS FOLLOWS

1. To run the program to fetch tweets:
   1.1. Open terminal and make google_appengine (C:\Program Files (x86)\Google\google_appengine) as the working directory and run the following command at the command prompt.
   python dev_appserver.py <path to project>
   For instance, python dev_appserver.py C:\Users\pku\Downloads\twitter-django-cy\twitter-django
   1.2. Open browser and enter the url: localhost:8080/fetchtweets to start the cron job to fetch tweets.
   1.3. To get the csv file with the tweets collected, enter url: localhost:8080/getcsv in another web browser page.
      1.3.1. Enter the file name of the csv file on the pop up dialog box for the file and save it.
2. To open the admin dashboard, enter the url: localhost:8000 in another web browser page.
3. To create a Neo4j graph database:
   3.1. Copy the csv file and create_model_x_db_from_csv.py into the parent directory of Neo4j installation parent directory.
   3.2. Run Neo4j instance by running the bin/Neo4j file.
   3.3. Open create_model_x_db_from_csv.py and enter the name of the csv file under the main() function
   3.4. Open terminal and make Neo4j installation directory as the working directory and run command: python create_model_x_db_from_csv
4. To record the query execution time of 25 Cypher queries:
   4.1. Open terminal and make Neo4j installation directory as the working directory and run command: python tweets_model_x_read_queries. After successful completion of the program a csv file will be generated with the running time of all the 25 queries.