CS224W Project: Tracking the Flow of Political Money

Beyang Liu: beyangl, RJ Walsh: rjwalsh

December 8, 2010

1 Abstract

In this project, we study the graph of political contributions that flows from political action committees to candidates for U.S. Congress. By applying graph algorithms, including influence maximization, Hyperlink-Induced Topic Search, and PageRank, we seek to identify key nodes within this political network. We also explore an attempt at using this information to predict votes on bills that come before the House and Senate floor.

2 Background

The Federal Election Commission (FEC) was founded in 1975 in response to the Federal Election Campaign Act. The mission of the FEC is to disclose campagin finance information to the public, such that any citizen is able to lookup who and what entities have donated to any candidate during an election cycle, thus making campaing finance overall more transparent. Transparency in campaign finance has become particularly important due to the recent Supreme Court ruling in "Citizens United v. Federal Election Commission", in which the Supreme coure ruled that unions and corporations are free to donate to candidates as they see fit.

This information has also become much more useful in the modern era, as computers enable anyone, such as our project group, do download and analyze the data themselves. Some organizations have also created tools which provide insight into this data, such as Wired's "Influence Tracker", available at http://www.wired.com/threatlevel/2010/10/influence-tracker/.

3 Dataset

Our study incorporates three different sets of data: (1) a database of financial transactions within the network of political candidates and political action committees (PACs), (2) a list of key bills annotated with supporting and opposing interest groups, and (3) the membership lists of pertinent U.S. Congresses.

The political transactions dataset covers all officially reported transactions between PACs and Congressional candidates for every 2-year federal election cycle from 1990 to 2010. The data was obtained from OpenSecrets.org, a website run by the nonpartisan Center for Responsive Politics. OpenSecrets.org, in turn, produces the data from official records reported by the Federal Election Commission. OpenSecrets.org cleans up the raw data (which is available at www.fec.gov) by merging duplicate entities, discarding minor transactions, and making the format more analysis-friendly. The data consists of a list of candidates, PACs, and transactions for each election cycle. Each candidate record includes the candidate's name and party. Each committee record includes the parent organization name, party affiliation (if applicable), and a code describing the PAC's main industry of interest. There are two types of transaction records: PAC-to-candidate and PAC-to-PAC. Both types of record include the IDs of the donor and recipient, the amount of money exchanged, and the type of transaction (which can be one of many types of contribution, loan, disbursement, etc. listed by the FEC – see fec.gov/finance/disclosure/ftpdet.shtml for more details). We do not consider contributions from private individuals.

The data on key bills and interest groups was obtained from the site MAPLight.org. The membership lists of the U.S. Congress from 1991 to 2010 was obtained from *The Washington Post* at the URL projects.washingtonpost.com/congress/.

4 Network Model Overview

We represent the transaction data as a directed graph in which the nodes correspond to PACs and candidates and the edges correspond to aggregate cash flows between nodes. The weight of an edge (u, v) is the total amount of money that u contributes to or spends on behalf of v over the time span of the data (this includes both directon contributions and indirect expenditures). This weight is negative if u spends money *against* v. Note that it is entirely possible to have both an edge (u, v) and an edge (v, u). One instance in which this occurs is when a candidate borrows money from a committee and then repays it later.

5 Dataset Characteristics

5.1 Basic Statistics

We first characterize our dataset by reporting some statistical properties. Below, we list a table of basic statistics for the data over the the 2008 election cycle and the full 20 year range from 1990 to 2010. We purposely do not present data for 2010 because this data may still be incomplete and in addition, the January 2010 SCOTUS ruling in *Citizens United vs. Federal Election Commission* may have impacted campaign spending reporting in unusual ways.

Election Cycle Timespan	**2008**	**1990-2010**
Number of candidates	3,968	20,596
Number of PACs	10,908	34,034
Number of nodes	14,876	54,630
Number of edges	140,452	184,373
Amount of money from PACs to candidates	886,479,002	4,804,512,724
Amount of money from PACs to PACs	1,755,363,099	6,589,644,490
Number of SCCs	10,967	51,202
Number of nodes in largest SCC	3,210	3,698
Number of nodes in 2nd largest SCC	5	8
Number of edges in largest SCC	112,577	148,512
Number of WCCs	6,791	46,813
Number of nodes in largest WCC	7,337	7,774
Number of nodes in 2nd largest WCC	6	11
Number of edges in largest WCC	139,865	183,973
Number of edges from PAC to candidate	107,836	141,718
Number of edges from PAC to PAC	26,084	35,219
Number of edges from candidate to PAC	6,532	7,436
Number of edges from candidate to candidate	0	0

Below, we list the 20 nodes in the graph that received the most net money, as well as the 20 nodes that gave the most money in the 2008 election cycle.

Nodes Gave Most Cash (2008)		Nodes Received Most Cash (2008)	
Obama Victory Fund	-281,075,896.0	Barack Obama (D)	221,589,863.0
McCain-Palin Victory 2008	-146,985,815.0	John McCain (R)	84,634,726.0
McCain Victory 2008	-122,005,482.0	Republican National Cmte	72,600,608.0
Mitt Romney (R)	-46,067,488.0	Romney for President	46,484,761.0
Democratic Senatorial Campaign Cmte	-45,285,773.0	Democratic Party of Ohio	29,893,003.0
Cmte for Change	-33,922,708.0	National Republican Congressional Cmte	29,031,190.0
McCain Victory California	-28,702,003.0	Obama for America	26,810,518.0
McCain Victory Cmte	-22,245,660.0	Democratic Party of Florida	26,537,173.0
Friends of Hillary	-20,202,900.0	Hillary Clinton (D)	25,246,358.0
John McCain 2008	-20,125,791.0	McCain-Palin Compliance Fund	25,069,379.0
Service Employees International Union	-19,372,728.0	Republican Party of Florida	25,017,287.0
Democratic White House Victory Fund	-19,345,751.0	Democratic Party of Pennsylvania	24,435,603.0
National Rifle Assn	-19,174,891.0	Democratic Party of Virginia	20,918,920.0
Service Employees International Union	-15,972,889.0	Republican Party of Ohio	20,050,620.0
American Fedn of St/Cnty/Munic Employees	-12,284,814.0	Democratic Party of Michigan	18,951,901.0
Friends of Chris Dodd	-9,479,760.0	Democratic Party of Colorado	18,489,917.0
National Republican Trust PAC	-9,384,714.0	Democratic Party of North Carolina	17,932,218.0
John Kerry for President	-8,429,619.0	Gordon H Smith (R)	17,732,788.0
American Fedn of St/Cnty/Munic Employees	-8,252,587.0	Hillary Clinton for President	17,644,117.0
Dollars for Democrats	-8,086,442.0	Republican Party of Pennsylvania	15,974,456.0

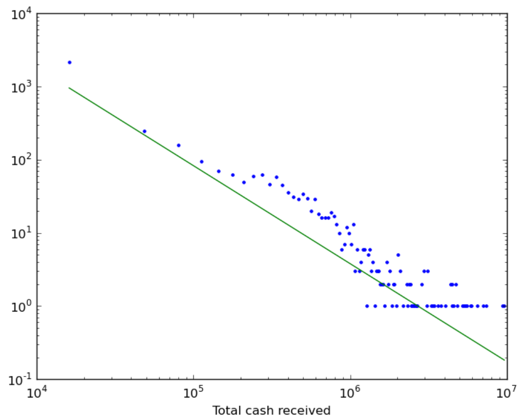
The above table includes both candidates and committees. To emphasize the correlation between fundraising and election outcome, we list the top and bottom 20 candidates (with respect to net cash received) below.

Candidates Received Most Cash (2008)		Candidates Lost Most Cash (2008)	
Mitt Romney (R)	-46,067,488.0	Barack Obama (D)	221,589,863.0
John Edwards (D)	-7,974,088.0	John McCain (R)	84,634,726.0
Bruce Lunsford (D)	-7,695,581.0	Hillary Clinton (D)	25,246,358.0
Mike Erickson (R)	-2,013,672.0	Gordon H Smith (R)	17,732,788.0
Tom Tancredo (R)	-1,923,011.0	Saxby Chambliss (R)	15,681,594.0
Harry Teague (D)	-1,913,752.0	Norm Coleman (R)	15,017,296.0
Daniel P Meuser (R)	-1,796,704.0	John E Sununu (R)	14,481,324.0
James D Oberweis (R)	-1,777,061.0	Elizabeth Dole (R)	13,981,217.0
Chris D Gorman (R)	-1,760,999.0	John Kerry (D)	13,130,651.0
Alan Grayson (D)	-1,713,085.0	Roger Wicker (R)	10,959,331.0
Don Wiviott (D)	-1,582,706.0	Mitch McConnell (R)	10,724,920.0
James Kenneth Harlan (D)	-1,205,205.0	Al Franken (D)	10,556,588.0
Matt Shaner (R)	-1,199,697.0	Jeanne Shaheen (D)	9,299,392.0
Vic Vickers (R)	-1,143,218.0	Kay R Hagan (D)	8,836,362.0
Francisco Canseco (R)	-909,805.0	Bob Schaffer (R)	8,525,503.0
Derek A Walker (R)	-897,251.0	Mark Udall (D)	7,794,870.0
E J Pipkin (R)	-856,875.0	Jeff Merkley (D)	7,351,977.0
Gregory Edward Fischer (D)	-785,380.0	Mary L Landrieu (D)	6,847,450.0
Michael Peter Skelly (D)	-778,290.0	James Francis Martin (D)	6,231,470.0
David W Cuddy (R)	-722,941.0	Ronnie Musgrove (D)	5,706,568.0

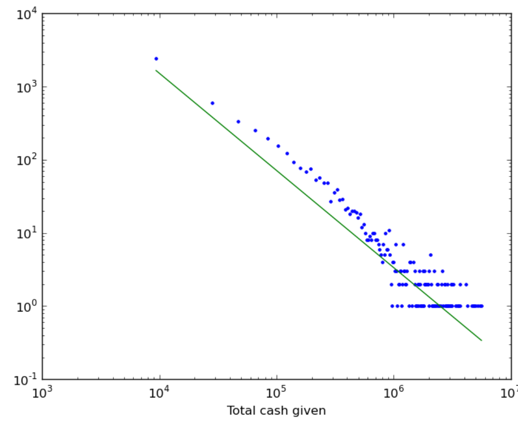
We also present histograms of net amounts received and disbursed over the dataset. In these histograms, we throw out outliers (party committees that give and receive large amounts of cash, and the large number of minor candidates that raise zero dollars in cash). By ignoring these outliers, we can see that the distribution closely follows a power distribution.

5.2 Contributions Over Time

We also display the amount of contributions over time over different election cycles. The volume (i.e. total cash amount) of transactions has increased significantly over the past 2 decades. In particular, the



(a) Histogram of Total Cash Received Per Entity
$\alpha = 1.34, \sigma = 5.634 \cdot 10^{-03}, x_{\mathrm{min}} = 1000$



(b) Histogram of Total Cash Given Per Entity
$\alpha = 1.38, \sigma = 4.520714 \cdot 10^{-03}, x_{\mathrm{min}} = 1000$

spike in contributions just before the election has become more pronounced.

5.3 Degree Distribution

The in-degree and undirected-degree distribution of the network exhibits a power-law distribution. However, the out-degree distribution is closer to an exponential distribution. This suggests the existence of a few active committees that contribute to many different candidates while the vast majority of committees contribute to much fewer entities. Closer examination reveals that the few committees that give to many nodes are national party comittees, that contribute funds to a variety of local committees as well as candidates.

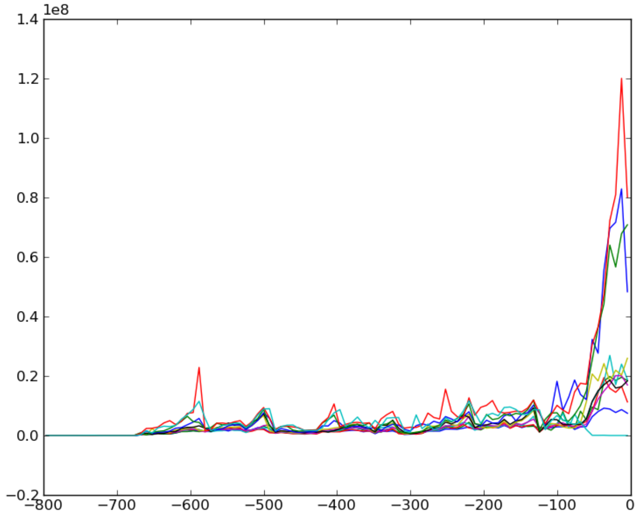
5.4 Clustering Coefficient

The average clustering coefficient of the 2010 contribution graph is 0.016221. Note that this is an order of magnitude smaller than the type of clustering coefficient that we would expect to see in a typical online social network (see lecture slides 3). We attribute this observation to the fact that the graph is mostly bipartite. Many edges flow from one set of nodes (PACs) to a disjoint set of nodes (candidates) with relatively few edges within these sets. Candidates do not make direct contributions to or expenditures on behalf of other candidates, and though a large amount of money does flow between committees, there are relatively few edges that transmit these cash flows. Furthermore, we hypothesize that the flow of money among committees is hierarchical (i.e. that national party committees give money to local committees and vice versa), and this hierarchical structure does not beget triangle formation within the graph. Intuitively, if A gives money to B and A gives money to C, we are not inclined to believe that B and C exchange money directly. Since there are relatively few triadic closures, the clustering coefficient is extremely low.

5.5 Graph Diameter

To compute the diameter, we first convert the directed graph into an undirected graph (each directed edge becomes an undirected edge). The diameter of the largest connected component of the undirected graph is 10. The average shortest path in this connected component is

Figure 1: Volume of Political Contributions ($) vs. Days Before Election (each line represents a different election cycle)



6 Influence Model

"Influence," in our scenario, is propagated through cash flow. In the following section, we define 2 notions of influence sets and present results of influence maximization algorithms using these two influence set types.

6.1 Influence Sets

6.1.1 Type 1

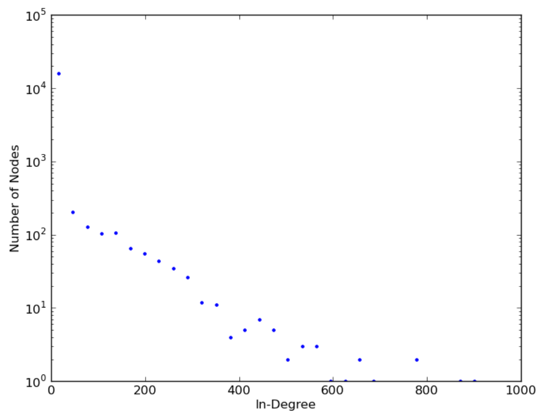
We define the influence set of a node to be the set of all its outgoing neighbors in the directed contribution graph (i.e. the set of nodes to which the node directly contributes money).

6.1.2 Type 2

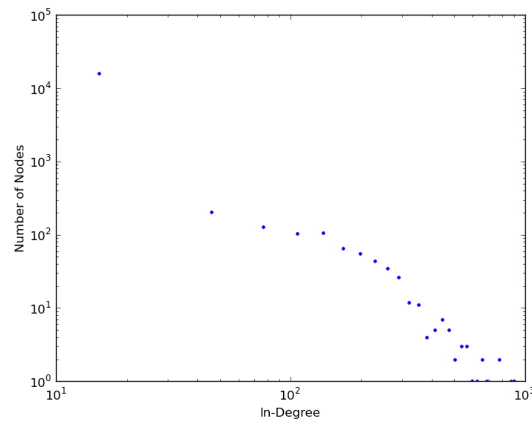
We define the influence set of a node to be the set of nodes that are two outgoing hops away in the directed contribution graph. This is a weaker notion of influence, and is motivated by the intuition that some entities (e.g. party committees) act as intermediaries that funnel cash from donors to actual candidates. Contributing to such an intermediary entity still buys you some amount of influence over the candidates that ultimately receive the money.

6.2 Influence Maximization

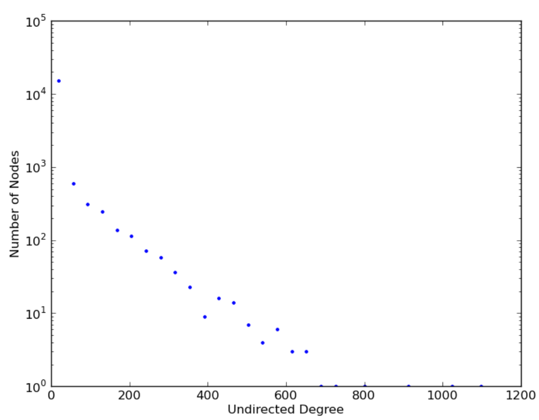
We apply the standard greedy influence maximization algorithm to each type of influence set (as defined above).



(a) Distribution of In-Degree

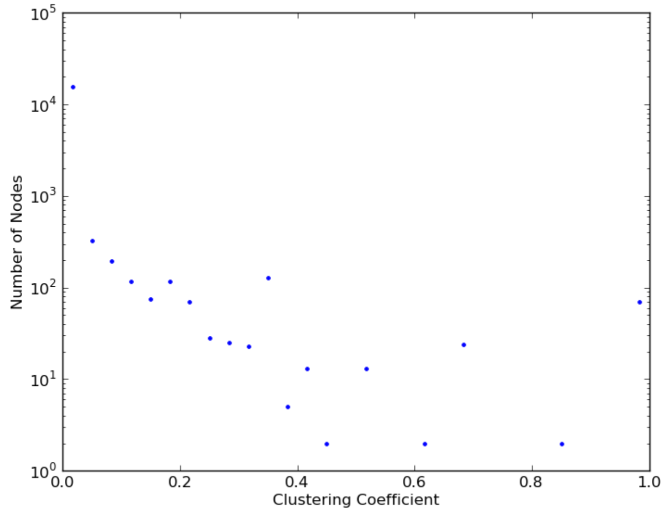


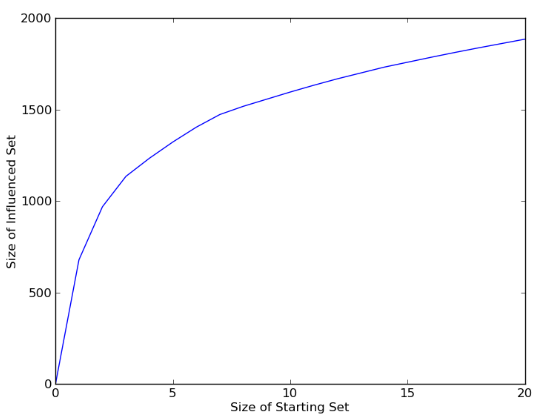
(b) Distribution of Out-Degree



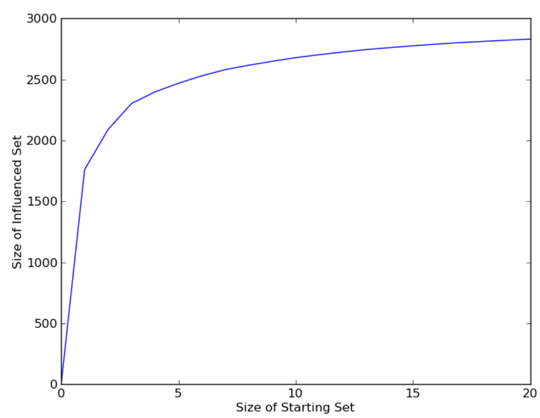
(c) Distribution of Overal Degree

Figure 2: Clustering Coefficient Histogram





(a) Type 1 Influence Greedy Maximization



(b) Type 2 Influence Greedy Maximization

6.3 Connectivity

The largest weakly connected component of the network consists of 7337 nodes. The second largest WCC consists of only 10 nodes. Empirical observation suggests that most of the smaller WCCs correspond to political fringe groups or secluded networks centered around a single minor candidate. We list the nodes of the 2nd, 3rd, and 5th, largest WCCs below:

2nd WCC:	Libertarian Party of Virginia Libertarian Party of Florida Libertarian Party of Nevada Libertarian National Cmte Alexander Andrew Snitker (L) Libertarian Party of Nevada Libertarian Party of Illinois Cmte to Elect Jeremy Swartz for Senate Libertarian Party of Ohio Strohm for Congress
3rd WCC:	Prindle for Congress Jim Prindle (L) Collin County Conservative Movement
5th WCC:	Joseph L. Kennedy (I) Eric Sundwall (L) Liberty Congressional PAC Libertarian Assn of Massachusetts

7 Ranking Candidates and Committees

We apply two standard node ranking algorithms to our data – HITS and PageRank to determine the most "important" candidates and committees. For computational reasons, we restrict these algorithms to run on the subgraph of the largest weakly connected component. Since the smaller connected components contain very minor entities (e.g. minor candidates not elected to office and the committees that support them), we do not lose much by discarding them. Furthermore, this reduces the size of the graph adjacency matrices from approximately 15,000 x 15,000 to 7,000 x 7,000.

7.1 HITS Algorithm

We apply the Hyperlink-Induced Topic Search (HITS) algorithm toward the task of identifying key nodes in the graph. The HITS algorithm assigns every node 2 scores – a hub score and an authority score. Intuitively, authorities are nodes that are "important," i.e. they receive a large number of in-links from other nodes in the graph. Hubs are "knowledgeable," in that they point to important nodes. The two scores are mutually recursive, in that a node is assigned a higher hub score if it points to nodes with high authorities and a node is assigned a higher authority if it is pointed to by nodes with high hub scores. Let a and h be the authority and hub score vectors for all nodes in the graph. The equations that define this relationship are:

$$a_j := \sum_{i \to j} h_i \tag{1}$$

$$h_i := \sum_{i \to j} a_j \tag{2}$$

$$a_j := \frac{a_j}{|a|} \tag{3}$$

$$h_i := \frac{h_i}{|h|} \tag{4}$$

Let M be the adjacency matrix of the graph. These equations can then be rewritten as the matrix equations:

$$h := Ma \tag{5}$$
$$a := M^T h \tag{6}$$
$$h := \frac{h}{|h|} \tag{7}$$
$$a := \frac{a}{|a|} \tag{8}$$

We apply these equations iteratively until we reach a fixed point for both the authority and hub vectors. This fixed point will correspond to the principal eigenvectors of $M^T M$ and MM^T. Concretely, we initialize the hub and authority vectors to be uniform vectors on the unit sphere (note that the starting point does not affect the output of the algorithm, provided that we avoid degenerate starting cases like the zero vector or any other eigenvectors of the matrix). Then, we iteratively multiply these vectors by the matrices $M^T M$ and MM^T until we reach convergence. We make the this computation feasible by restricting our graph to the nodes in the largest weakly connected component. There are approximately 7,000 of these. Matrix multiplication of 7,000 x 7,000 matrices is quick and our algorithm converges in just five steps.

In the context of financial transactions, the notion of hubs and authorities has an intuitive interpretation. Authorities correspond to nodes that receive money from sources that give a substantial amount of money to other nodes as well. In practice, these correspond to candidates who receive funds from a variety of major donors (see the Appendix for top authorities as determined by the HITS algorithm). Conversely, hubs will be nodes that contribute to many authorities. In practice, these tend to be well-endowed corporate committees that contribute to influential candidates. Note that the "top 20" list produced for hubs and authorities by the HITS algorithm is much different and in many ways better than the naive list produced by simply looking at the top 20 nodes that gave and received the most money. In particular, the naive list was dominated by major party committees and did not give us much insight into who were the major interest groups supplying the money or who were the major candidates who received money from these interest groups. In the authorities list generated by HITS, we still see a few major party committees (e.g. the National Republican Senatorial Committee), but also a large number of well-established congressmen, in particular future House majority leader John Boehner, outgoing House Majority leader Steny Hoyer, Senate majority leader Harry Reid, and Blanche Lincoln/Lambert (who up until she was voted out of office in the 2010 election was a key figure and fundraiser in the Democratic Party). On the hub side, we see a list of major corporate donors, rather than a list of major party committees or candidate "leadership" PACs.

We also present results for a weighted version of the HITS algorithm, in which edge links are weighted by the size of the cash flow between 2 nodes. However, these results were skewed by large transactions made between Linda McMahon and her leadership PAC, which ended up receiving almost 100% of the ranking weight.

7.2 PageRank

We also applied four variants of the PageRank algorithm to our graph. We applied both standard PageRank and a weighted version of the algorithm that weights a link by the amount of the cash flowing across it. Let M be the stochastic adjacency matrix used in standard PageRank. Recall that the columns of M sum to 1 and that each nonzero entry in a column j represents a transition probability from node j to the node i, where i is the row of the entry. All nonzero entries within a column are equal, i.e. the transition distribution is uniformly distributed across all out-links. Let M' be the stocahstic adjacency matrix for weighted PageRank. The columns of M' still sum to 1, but distribution over out-links is now skewed proportionately to the weight of the out-links, i.e. the amount of money flowing from j to a given i.

We also run both standard PageRank and weighted PageRank on the reversed graph, the intuition being that "importance" in a political graph flows both ways. I.e., both candidates that receive a lot of money and committees that give a lot of money are important.

We believe we achieved the most success with the reversed graph PageRank algorithm (see Appendix for "top 20" lists). These lists have significant overlap with the HITS hub list (in particular, sharing groups such as the National Association of Realtors, The American Bankers Association, and Southwestern Bell). In general, however, the results seemed less interesting, as they included a significant number of relatively minor figures as well as uninteresting party committees.

8 Influence Propagation Algorithm

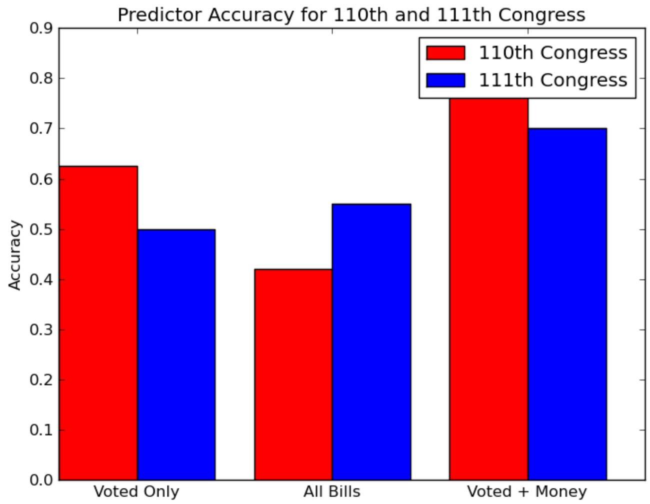
Our final task was to apply an influence propagation algorithm to the data set, in order to build a predictive model for bills. Given a graph G, constructed from the FEC data equivalent to the sections above, a bill B on which candidates are to vote, a set S of organizations which support the bill, and a set O of organizations which support the bill, we output a pair (y, n) of predicted yes votes and no votes on the bill.

The algorithm we used works as follows. For all nodes $n \in G$, initialize the probability that n will vote for B to $p_n = 0.5$. For all nodes $s \in S$, initialize $p_s = 1$ and for all nodes $o \in O$ initialize $p_o = 0$, where p_x is the probability that a particular node x would vote for a bill. We then specify an update rule $p_x = \sum_{n \in pred(x)} p_n * w_n / sizeof(pred(x))$ where $pred(x)$ represents the set of x's predecessors in the graph, w_n specifies the weight of the edge from n to x, that is, the amount of money donated to the node x from n. We then iterate until convergence, which for our data set usually occurred in approximately 20 iterations.

8.1 Predictor Results

Our results with the predictor illustrated various shortcomins with our dataset. Because the graph was built using FEC OpenSecrets.org data, but the bill positions were obtained through the MapLight.org API, there was a mismatch between the names in our dataset and what we actually were able to use. As a result, many bills were missing supporting and opposing organization information, thus skewing the predictor. The best results on raw data were approximately 55 percent accuracy. To filter this, we observed several fixes we could make in the data. First, we counted bills which were not voted on as failed bills, which increased our accuracy to approximatley 70 percent. Finally, we counted failed votes where we matched the donation amount as a successful prediction, increasing our accuracy to about 80 percent. This indicates that this predictor could be a reliable tool for prediction the outcome of bills.

Figure 3: Accuracy of Bill vote prediction for 110th and 111th congress



9 Appendix: Top Ranked Entities by HITS and PageRank

Basic HITS			
Top Authorities		Top Hubs	
Lisa Murkowski (R)	0.0774563951144	Deloitte Touche Tohmatsu	0.0837828244006
John Boehner (R)	0.0785941723807	National Assn of Home Builders	0.0839014293538
Eric Cantor (R)	0.0804619513159	International Assn of Fire Fighters	0.0863170387233
Johnny Isakson (R)	0.0804951420181	National Air Traffic Controllers Assn	0.0867875236577
John Thune (R)	0.0806567567668	American Dental Assn	0.0924243887451
Earl Pomeroy (D)	0.0821088913922	American Family Life Assurance	0.0928894244163
Patty Murray (D)	0.0837255706413	Bell Atlantic	0.0934873016949
Dave Camp (R)	0.0838066785022	Credit Union National Assn	0.095936525864
National Republican Senatorial Cmte	0.0845920483575	American Bankers Assn	0.10094593318
Kirsten Gillibrand (D)	0.0874891402319	Boeing Co	0.101488183556
National Republican Congressional Cmte	0.0893010472089	American Hospital Assn	0.102197204697
Richard Burr (R)	0.0910992777953	Lockheed Martin	0.102515427066
James E Clyburn (D)	0.0914779785939	National Beer Wholesalers Assn	0.103423313762
Chuck Grassley (R)	0.0930006442626	National Assn of Pharmacists	0.103653381404
Charles E Schumer (D)	0.0941763912337	Comcast Corp	0.104834469498
Democratic Congressional Campaign Cmte	0.0945845291898	General Electric	0.108504511366
Steny H Hoyer (D)	0.0964773937953	United Parcel Service	0.110410887989
Democratic Senatorial Campaign Cmte	0.0967164637099	AlliedSignal Inc	0.120239754648
Harry Reid (D)	0.0985694734402	Southwestern Bell	0.120900206014
Blanche Lambert (D)	0.109226075169	National Assn of Realtors	0.120967655422

Weighted HITS			
Top Authorities		Top Hubs	
Democratic Party of Wisconsin	4.00313938821e-05	Friends of Congressman George Miller	2.41464667134e-05
Democratic Party of Minnesota	4.43396740377e-05	Senate Victory 2010	2.68735949423e-05
Democratic Party of Texas	4.5782459152e-05	Congressman Waxman Campaign Cmte	2.73705859369e-05
Bill Owens (D)	5.34338892144e-05	Becerra for Congress	2.740689387e-05
Democratic Party of Massachusetts	5.4103837353e-05	Larson for Congress	2.74449279896e-05
Democratic Party of Georgia	5.4803121941e-05	Boxer Victory Fund	3.42400119502e-05
Democratic Party of New York	5.8304996076e-05	Van Hollen for Congress	3.69034334571e-05
Scott Murphy (D)	9.95771381988e-05	California Senate 2010	4.73656936738e-05
Democratic Party of Pennsylvania	0.00011399847003	Pennsylvania Senate Victory 2010	5.26064791998e-05
Democratic Party of Nebraska	0.000134706520454	Friends of Schumer	5.30322993985e-05
Democratic Party of Ohio	0.000135327341492	Democratic Congressional Campaign Cmte	6.17341419953e-05
Democratic Party of Florida	0.000138473229666	Cmte to Re-elect James E Clyburn	6.9642288005e-05
Barack Obama (D)	0.000162112895646	Hoyer for Congress	7.16714313956e-05
Democratic Properties Corp	0.000170240954622	Nancy Pelosi for Congress	7.91311138736e-05
Democratic Party of Virginia	0.000274447875016	House Senate Victory Fund	8.08823219321e-05
Democratic Party of New Jersey	0.000316791960211	Service Employees International Union	0.000228698488047
Democratic Senatorial Campaign Cmte	0.000345337372359	Service Employees International Union	0.00044352098949
Democratic Congressional Campaign Cmte	0.000397220434221	Democratic National Cmte	0.000842886989724
Service Employees International Union	0.00172901651764	Service Employees International Union	0.00191591831724
Linda McMahon for Senate	0.999998196625	Linda McMahon (R)	0.999997655725

PageRank	
Top-Ranked	
Associated General Contractors	0.0882263673663
Laborers Union	0.0911443897914
Tom Reed (R)	0.0914555400917
American Postal Workers Union	0.0945270335907
American Dental Assn	0.0967475666897
United Food & Commercial Workers Union	0.104378002568
Bill Owens (D)	0.104756005355
Credit Union National Assn	0.105523857947
National Auto Dealers Assn	0.11067853197
National Assn of Health Underwriters	0.111454297471
Republican National Cmte	0.118315798333
National Republican Congressional Cmte	0.123740022338
Intl Brotherhood of Electrical Workers	0.130337804047
Democratic Party of Delaware	0.14903783831
National Air Traffic Controllers Assn	0.150383523252
American Federation of Govt Employees	0.151465778683
Chris Coons (D)	0.162463716816
Chris Coons for Delaware	0.166526063773
Farm Credit Council	0.168575268132
Transport Workers Union	0.172807626435

Weighted PageRank	
Top-Ranked	
Jack Conway (D)	0.0524574626386
Conway for Senate	0.0571924326256
Democratic National Cmte	0.0603690682543
Doug Hoffman for Congress	0.0694323764479
Fiegen for US Senate	0.0738011345866
Thomas L. Fiegen (D)	0.0756492377652
Democratic Congressional Campaign Cmte	0.0784969676392
Republican National Cmte	0.0805601374761
Democratic Party of Delaware	0.0862968191559
Chris Coons for Delaware	0.0880519275489
Democratic Senatorial Campaign Cmte	0.0903498624987
Chris Coons (D)	0.0906947881188
Senate-House Dinner 2009	0.11618289059
Tim Burns (R)	0.130804332074
National Republican Senatorial Cmte	0.139552769452
Tim Burns for Congress	0.14153743848
National Republican Congressional Cmte	0.143390816674
Bill Owens for Congress	0.479898987893
Democratic Party of New York	0.507665724109
Bill Owens (D)	0.541232527547

PageRank on Reversed Graph	
Top-Ranked	
American Bankers Assn	0.0752990504142
National Rifle Assn	0.0779013152344
Southwestern Bell	0.0805302531174
Investment Co Institute	0.0826356185976
Robert F Bennett (R)	0.0849351017318
Harry Reid (D)	0.0887845255514
National Assn of Realtors	0.0898344517948
AlliedSignal Inc	0.0924192736659
John Tanner (D)	0.10730887555
Democratic Congressional Campaign Cmte	0.108388638142
Intl Brotherhood of Electrical Workers	0.108619020901
Evan Bayh (D)	0.111909547983
EVAN BAYH Cmte	0.12492650999
Democratic Party of Indiana	0.140331239947
Ken Salazar (D)	0.147900573381
Friends of Chris Dodd	0.200151110008
Arlen Specter (R)	0.200796150011
Chris Dodd (D)	0.220835620468
Byron L Dorgan (D)	0.321824331952
Friends of Byron Dorgan	0.347716424506

Weighted PageRank on Reversed Graph	
Top-Ranked	
National Assn of Realtors	0.108558567747
McCain-Palin Victory 2008	0.111232141695
Democratic Senatorial Campaign Cmte	0.118964727084
Service Employees International Union	0.140385394458
North Dakota-Oregon Victory Fund	0.146502707806
Service Employees International Union	0.146775963697
Arlen Specter (R)	0.148355304057
Obama for America	0.149685271314
EVAN BAYH Cmte	0.1499807644
EchoStar Communications	0.150058810498
Connecticut Victory 2010	0.153582994057
Friends of Chris Dodd	0.157384089899
Republican National Cmte	0.159458796983
National Assn of Realtors	0.162353233351
Chris Dodd (D)	0.167811320246
Democratic Party of Indiana	0.188448219642
Obama Victory Fund	0.234884774155
Byron L Dorgan (D)	0.270642871642
Democratic National Cmte	0.286073634179
Friends of Byron Dorgan	0.371994922698

10 Citations

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