ESTIMATING POLITICAL LEANINGS FROM MASS MEDIA VIA GRAPH-SIGNAL RESTORATION WITH NEGATIVE EDGES

Benjamin Renoust [*] [$], *Gene Cheung* [*], *Shin'Ichi Satoh* [*]

[*] National Institute of Informatics, Tokyo, Japan
[$] JFLI, CNRS UMI 3527, Tokyo, Japan

ABSTRACT

Politicians in the same political party often share the same views on social issues and legislative agendas. By mining patterns in TV news co-appearances and Twitter followers, in this paper we estimate political leanings (left / right) of unknown individuals, and detect outlier politicians who have views different from their colleagues in the same party, from a graph signal processing (GSP) perspective. Specifically, we first construct a similarity graph with politicians as nodes, where a positive edge connects two politicians with sizable shared Twitter followers, and a negative edge connects two politicians appearing in the same TV news segment (and thus likely take opposite stands on the same issue). Given a graph with both positive and negative edges, we propose a new graph-signal smoothness prior based on a constructed generalized graph Laplacian matrix that is guaranteed to be positive semi-definite. We formulate a graph-signal restoration problem that can be solved in closed form. Experimental results show that political leanings of unknown individuals can be reliably estimated and outlier politicians can be detected.

Index Terms— News video analysis, graph signal processing, signal restoration

1. INTRODUCTION

It is commonly observed that politicians of the same political party often share the same views on social issues and legislative agendas. Politicians are public figures, and their positions are frequently demonstrated in different media forms, such as television, radio, social media like Twitter, etc. Thus one can expect observable patterns in mass media, that when collected and analyzed, would betray political leanings (left or right) of public individuals. Estimating political leanings in this manner offers a data-driven conjecture of political affiliations for undeclared individuals. It also serves as a detection mechanism for outlier politicians with diverging views from those in their own parties. We study the problem of political leaning estimation from patterns in mass media in this paper.

Leveraging on recent advances in *graph signal processing* (GSP) [1], we formulate the political leaning estimation problem as a graph-signal restoration problem. We first construct a graph with politicians or public figures as nodes; a signal sample at a node would indicate right / conservative (positive number close to 1) or left / liberal (negative number close to -1) political leaning[1]. We then construct two types of edges connecting nodes on the graph. First, using Twitter data crawled from the Internet, we connect two nodes with a *positive* edge—signifying *similarity*—if the corresponding two politicians share a sizable group of followers. Larger fraction of shared followers would translate to a larger positive edge weight.

Second, using a large archive of NHK evening news[2] in Japan of more than 10 years [2], we first detect co-appearance of exactly two public figures in a news segment via face detection / recognition using the method from [3]. To maintain the appearance of fairness, it is observed [4] that NHK typically presents two different sides of a social or political issue, which means that the co-appeared individuals very likely take opposing stands. We thus construct a *negative* edge—signifying *dissimilarity*—to connect the respective nodes.

Because our constructed graph contains both positive and negative edges, the *combinatorial graph Laplacian* matrix $\mathbf{L}$ [1] can be indefinite, and conventional graph-signal smoothness priors based on $\mathbf{L}$ [5, 6, 7, 8] previously used in image restoration can be numerically unstable. Instead, we first define a new graph-signal smoothness prior based on a computed *generalized graph Laplacian* matrix $\mathbf{L}_g$ [9] that is guaranteed to be positive semi-definite. We then formulate a *maximum a posteriori* (MAP) graph-signal restoration problem that can be computed efficiently in closed form. Experimental results show that political leanings of unknown individuals in both Japan and the US can be reliably estimated, and outlier politicians can be detected. *To the best of our knowledge, we are the first to study the political leaning estimation problem in a data-driven manner via a graph-signal restoration formulation.* Further, among signal restoration works in the GSP literature [5, 6, 7, 8], *we are the first to incorporate negative edges into a similarity graph, and perturb the graph Laplacian matrix* $\mathbf{L}$ *to ensure numerical stability in the smoothness prior.*

The outline of the paper is as follows. We first overview related works in Section 2. We then define necessary GSP concepts and smoothness priors in Section 3. We discuss how the "optimal" perturbation matrix can be chosen to ensure positive semi-definiteness for graph Laplacian $\mathbf{L}$ in Section 4. We describe how we construct a similarity graph using available Twitter and TV co-appearance data in Section 5. We define and efficiently solve our graph-signal restoration problem in Section 6. Finally, results and conclusion are presented in Section 7 and 8, respectively.

[1] Our goal is more than simply classifying politicians into two classes (liberals and conservatives). The value of the an estimated sample should reveal where along the entire political spectrum a politician belongs.

[2] NHK is Japan's national public broadcast organization.

2. RELATED WORK

There exist a variety of approaches exploiting social media to predict political leanings: by propagation of followers on Twitter [10], from analysis of tweets content [11], as a linear-inverse problem from tweets and retweet behavior [12] (recently improved adding retweeters' publication content [13]), or even from text classification of Facebook posts [14]. In contrast, we leverage on signal restoration techniques in GSP to estimate political leanings of public figures having constructed a similarity graph.

Smoothness priors derived from the graph Laplacian $\mathbf{L}$ have been used to restore graph-signals in many applications, including image denoising [5, 6], dequantization of JPEG images [15, 7], image interpolation [16, 17] and bit-depth enhancement [8]. In all these cases, the underlying graph is undirected with positive edge weights. In contrast, we generalize to the case where weights of undirected edges can be negative, which signify dissimilarity in signal samples. To be discussed in Section 3 and 4, this more general case requires careful design of the graph spectrum for the restoration problem to be numerically stable.

An orthogonal GSP approach rooted in algebraic signal processing theories [18, 19] uses the adjacency matrix $\mathbf{A}$ as the principle variational operator. Edges can be directed and edge weights can be negative. A smoothness notion called *graph total variation* is then defined, which can be used in a similar MAP formulation. However, because the Jordan eigenvalues of $\mathbf{A}$ [20] can be negative (and possibly imaginary), one cannot naturally interpret the eigenvalues as frequencies, which are typically understood to be real, non-negative numbers. Our proposed generalized graph Laplacian $\mathbf{L}_g$ achieves this frequency interpretation while handling negative edge weights.

3. GRAPH SPECTRUM & SMOOTHNESS

3.1. Graph Definition

We first introduce definitions in GSP needed for our problem formulation. A graph $\mathcal{G}(\mathcal{V}, \mathcal{E}, \mathbf{W})$ contains a set $\mathcal{V}$ of N nodes and a set $\mathcal{E}$ of M edges. Each existing edge $(i,j) \in \mathcal{E}$ is undirected and contains an edge weight $w_{i,j}$. In this paper, we assume that $w_{i,j}$ can be positive or negative; a negative $w_{i,j}$ would mean that samples in node i and j are *dissimilar*—the samples are expected to have very different values.

A graph-signal $\mathbf{x}$ on $\mathcal{G}$ is a discrete signal of dimension N—one sample x_i for each node i in $\mathcal{V}$. In this paper, a large positive (negative) value x_i would mean a politician i has strong conservative (liberal) political leaning.

3.2. Graph Spectrum

Given an edge weight matrix $\mathbf{W}$, we define a diagonal *degree matrix* $\mathbf{D}$, where $d_{i,i} = \sum_j W_{i,j}$. A *combinatorial graph Laplacian matrix* $\mathbf{L}$ is $\mathbf{L} = \mathbf{D} - \mathbf{W}$ [1]. Because $\mathbf{L}$ is symmetric, one can show via the Spectral Theorem that it can be eigen-decomposed into:

$$\mathbf{L} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^T \tag{1}$$

where Λ is a diagonal matrix containing real eigenvalues λ_k, and $\mathbf{U}$ is an eigen-matrix composed of orthogonal eigenvectors $\mathbf{u}_i$ as columns. If edge weights $w_{i,j}$ are restricted to be non-negative, then one can show that $\mathbf{L}$ is *positive semi-definite* (PSD), meaning that $\lambda_k \geq 0, \forall k$ and $\mathbf{x}^T\mathbf{L}\mathbf{x} \geq 0,\ \forall \mathbf{x}$. Non-negative eigenvalues λ_k can be interpreted as *graph frequencies*, and eigenvectors $\mathbf{U}$ interpreted as corresponding graph frequency components. Together they define the *graph spectrum* for graph $\mathcal{G}$.

Unfortunately, we consider also negative edge weights $w_{i,j}$ here, and thus $\mathbf{L}$ can be indefinite. In general it is desirable to have a variational operator that is PSD. To accomplish this, we will perturb $\mathbf{L}$ with a *perturbation matrix* $\boldsymbol{\Delta}$, so that $\mathbf{L} + \boldsymbol{\Delta}$ is PSD. We will discuss how to select the optimal $\boldsymbol{\Delta}$ in the next section.

3.3. Graph-Signal Smoothness Prior

Traditionally, for graph $\mathcal{G}$ with positive edge weights, signal $\mathbf{x}$ is considered *smooth* if each sample x_i on node i is similar to samples x_j on neighboring nodes j with large $w_{i,j}$. In the graph frequency domain, it means that $\mathbf{x}$ contains mostly low graph frequency components; *i.e.*, coefficients $\boldsymbol{\alpha} = \mathbf{U}^T\mathbf{x}$ are zeros for high frequencies. The smoothest signal is the constant vector $\mathbf{1}$—the first eigenvector $\mathbf{u}_1$ for $\mathbf{L}$ corresponding to the smallest eigenvalue $\lambda_1 = 0$.

Mathematically, we can write that a signal $\mathbf{x}$ is smooth if its *graph Laplacian regularizer* $\mathbf{x}^T\mathbf{L}\mathbf{x}$ is small [5, 6]. Graph Laplacian regularizer can be expressed as:

$$\mathbf{x}^T\mathbf{L}\mathbf{x} = \sum_{(i,j)\in\mathcal{E}} w_{i,j}\left(x_i - x_j\right)^2 = \sum_k \lambda_k\, \alpha_k^2 \tag{2}$$

Because $\mathbf{L}$ is PSD, $\mathbf{x}^T\mathbf{L}\mathbf{x}$ is lower-bounded by 0, achieved when $\mathbf{x} = \mathbf{u}_1 = \mathbf{1}$.

Because we consider also negative edge weights, $\mathbf{L}$ can be indefinite, and prior $\mathbf{x}^T\mathbf{L}\mathbf{x}$ cannot be used directly. Specifically, there exists an eigenvector $\mathbf{u}_1$ where $\mathbf{u}_1^T\mathbf{L}\mathbf{u}_1 < 0$, and $\infty\mathbf{u}_1$ would be a pathological solution to a minimization problem.

To avoid numerical instability of $\mathbf{x}^T\mathbf{L}\mathbf{x}$ when $\mathbf{L}$ is indefinite, we define graph spectrum using $\mathbf{L} + \boldsymbol{\Delta}$ instead, and the corresponding regularizer is $\mathbf{x}^T(\mathbf{L} + \boldsymbol{\Delta})\mathbf{x}$. PSD $\mathbf{L} + \boldsymbol{\Delta}$ means non-negative eigenvalues (graph frequencies), and $\mathbf{x}^T(\mathbf{L}+\boldsymbol{\Delta})\mathbf{x}$ is also lower-bounded by 0. However, it is achieved when $\mathbf{x} = \mathbf{u}_1$, the lowest frequency component for $\mathbf{L}+\boldsymbol{\Delta}$, which in general is not $\mathbf{1}$. Importantly, it means that instead of the constant signal $\mathbf{1}$, the new smoothness prior will actively promote $\mathbf{u}_1$. Thus the appropriateness of low graph frequency component $\mathbf{u}_1$ for signal restoration is crucial.

For intuition, we examine the behavior of $\mathbf{u}_1$ of $\mathbf{L}$ as follows. Because $\mathbf{L}$ is a symmetric matrix, the *Rayleigh quotient* $R(\mathbf{x})$ reaches its minimum at the smallest eigenvalue $\lambda_{\min}$ when $\mathbf{x} = \mathbf{u}_1$,

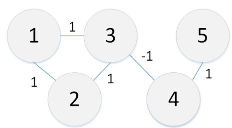
$$\lambda_{\min} = R(\mathbf{u}_1) = \frac{\mathbf{u}_1^T\mathbf{L}\mathbf{u}_1}{\mathbf{u}_1^T\mathbf{u}_1} \tag{3}$$

Note that as a unit-norm eigenvector, $\mathbf{u}_1^T\mathbf{u}_1 = 1$.

Suppose that the presence of negative edges results in $0 > \lambda_{\min}$. Then, expanding $\mathbf{u}_1^T\mathbf{L}\mathbf{u}_1$,

$$0 > \sum_{w_{i,j}>0} w_{i,j}(u_{1,i} - u_{1,j})^2 + \sum_{w_{i,j}<0} w_{i,j}(u_{1,i} - u_{1,j})^2$$

$$\sum_{w_{i,j}<0} |w_{i,j}|(u_{1,i} - u_{1,j})^2 > \sum_{w_{i,j}>0} |w_{i,j}|(u_{1,i} - u_{1,j})^2$$



(a) 5-node graph

$$\mathbf{L} = \begin{bmatrix} 2 & -1 & -1 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 \\ -1 & -1 & 2 & 1 & 0 \\ 0 & 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & -1 & 1 \end{bmatrix}$$

(b) corresponding $\mathbf{L}$

Fig. 1. Example of a 5-node graph with a negative edge.

We see that $\mathbf{u}_1$ is a *negative-edge-dominant* vector, where the connected node differences for the negative edges outweigh the differences for the positive edges.

The corollary is that, unlike a graph with only positive edges where $\mathbf{u}_1 = \mathbf{1}$ has no zero-crossings and higher frequency components have more zero-crossings (according to the nodal domain theorem [9]), the lowest frequency component $\mathbf{u}_1$ here can have one or more zero-crossing(s) at node pairs with negative edges. Thus, $\mathbf{u}_1$ is very informative—much more so than $\mathbf{u}_1 = \mathbf{1}$ for a positive-edge graph—because it contains crucial information about *which* node pairs should have opposing values in the reconstructed graph-signal. *It is thus desirable to preserve low frequencies of* $\mathbf{L}$ *even after perturbation matrix* $\mathbf{\Delta}$ *is added.*

As an example, we see in Fig. 1 a 5-node graph with a single negative edge between node 3 and 4. $\lambda_{\min} = -1.21$, and $\mathbf{u}_1 = [0.24\; 0.24\; 0.54\; -0.70\; -0.32]^T$. We see indeed that $\mathbf{u}_1$ has one zero-crossing at node pair $(3, 4)$.

4. FINDING A PERTURBATION MATRIX

We now address the problem of identifying a perturbation matrix $\mathbf{\Delta}$ such that $\mathbf{L} + \mathbf{\Delta}$ is PSD. Obviously, there exists an infinite number of feasible solutions $\mathbf{\Delta}$. Thus a well chosen criteria must be used to differentiate them.

4.1. Matrix Perturbation: Minimum-Norm Criteria

One reasonable choice is the *minimum norm criteria*, *i.e.*, find $\mathbf{\Delta}$ with the smallest norm such that $\mathbf{L} + \mathbf{\Delta}$ is PSD:

$$\min_{\mathbf{\Delta}} \|\mathbf{\Delta}\| \quad \text{s.t.} \;\; \mathbf{x}^T \left(\mathbf{L} + \mathbf{\Delta}\right) \mathbf{x} \geq 0, \; \forall \mathbf{x} \tag{4}$$

where $\|.\|$ is a *unitarily invariant norm* on $\mathbb{R}^{N \times N}$; *i.e.* $\|\mathbf{U}\mathbf{\Delta}\mathbf{V}\| = \|\mathbf{\Delta}\|$ for all orthogonal $\mathbf{U}$ and $\mathbf{V}$.

It turns out that the solution to (4) is a special case of Theorem 5.1 in [21], which we rephrase as follows. Assume that $\mathbf{L}$ has exactly p negative eigenvalues. Theorem 5.1 in [21] states that the optimal perturbation matrix $\mathbf{\Delta}$ with minimum norm $\|\mathbf{\Delta}\|$, such that $\mathbf{L} + \mathbf{\Delta}$ is PSD, is:

$$\mathbf{\Delta} = \mathbf{U} \, \text{diag}(\boldsymbol{\tau}) \, \mathbf{U}^T \tag{5}$$

where $\boldsymbol{\tau} = [\tau_1, \ldots, \tau_n]$:

$$\tau_i = \begin{cases} -\lambda_i & \text{if } 1 \leq i \leq p \\ 0 & \text{o.w.} \end{cases} \tag{6}$$

See [21] for a complete proof. We only make some important observations. First, it is clear that $\mathbf{L} + \mathbf{\Delta}$ is PSD:

$$\begin{aligned} \mathbf{L} + \mathbf{\Delta} &= \mathbf{U}\text{diag}(\lambda_1 - \lambda_1, \ldots, \lambda_p - \lambda_p, \lambda_{p+1}, \ldots, \lambda_n)\mathbf{U}^T \\ &= \mathbf{U}\text{diag}(0, \ldots, 0, \lambda_{p+1}, \ldots, \lambda_n)\mathbf{U}^T \end{aligned}$$

Since all the negative eigenvalues of $\mathbf{L}$ have been shifted to 0, $\mathbf{L} + \mathbf{\Delta}$ is PSD.

Second, due to the definition (5) of $\mathbf{\Delta}$, $\mathbf{L} + \mathbf{\Delta}$ can be spectrally decomposed using the *same* eigenvectors $\mathbf{U}$ as original $\mathbf{L}$. As discussed previously, maintaining the same eigen-space in the perturbed matrix $\mathbf{L} + \mathbf{\Delta}$ is desirable, as the low graph frequency components like $\mathbf{u}_1$ are information-rich.

Third, by shifting all negative eigenvalues of $\mathbf{L}$ to 0, the first $p+1$ eigenvectors $\mathbf{u}_1, \ldots, \mathbf{u}_p$ will all evaluate to 0 in the quadratic regularizer:

$$\mathbf{u}_i^T \left(\mathbf{L} + \mathbf{\Delta}\right) \mathbf{u}_i = 0, \;\; 1 \leq i \leq p+1 \tag{7}$$

$p+1$ because by definition $\mathbf{L}$ has eigenvector $\mathbf{1}$, and $\mathbf{1}^T(\mathbf{L} + \mathbf{\Delta})\mathbf{1}$ also evaluates to 0. Hence the regularizer expresses *no preference* among the first $p+1$ eigenvectors. This creates a problem during graph-signal restoration: though the graph structure $\mathcal{G}$ has a notion of frequencies and the original (numerically unstable) smoothness prior prefers low frequencies, the augmented regularizer does not differentiate and maps the lowest $p+1$ frequencies all to zero.

4.2. Matrix Perturbation: generalized graph Laplacian

The main problem with the minimum-norm criteria is that the differentiation among different low frequency components (eigenvectors) is removed by setting all negative eigenvalues of $\mathbf{L}$ to 0. Thus, it is desirable to maintain the frequency components of $\mathbf{L}$ in the perturbed matrix, but in a way that the frequency preferences are preserved (*i.e.*, low frequencies are still preferred over high frequencies).

To accomplish this, we define a *generalized graph Laplacian matrix* $\mathbf{L}_g$ [9] as the sum of $\mathbf{L}$ and an identity matrix $\mathbf{I}$ scaled by $-\lambda_{\min}$:

$$\begin{aligned} \mathbf{L}_g &= -\lambda_{\min}\mathbf{I} + \mathbf{L} & (8) \\ &= \mathbf{U}(-\lambda_{\min})\mathbf{I}\,\mathbf{V}^T + \mathbf{V}\mathbf{\Lambda}\mathbf{U}^T \\ &= \mathbf{U}\left(-\lambda_{\min}\mathbf{I} + \mathbf{\Lambda}\right)\mathbf{U}^T & (9) \end{aligned}$$

where $\lambda_{\min}$ is the smallest eigenvalue in $\mathbf{L}$. We see that $\mathbf{L}_g$ has the same eigenvectors $\mathbf{U}$ as $\mathbf{L}$. Further, eigenvalues $\lambda_i - \lambda_{\min}$ are non-negative, and thus $\mathbf{L}_g$ is PSD. Finally, *by shifting all eigenvalues* λ_i *by the same amount* $-\lambda_{\min}$, *the preferential order of different graph frequency components is preserved in the new prior* $\mathbf{x}^T\mathbf{L}_g\mathbf{x}$. We will thus use $\mathbf{x}^T\mathbf{L}_g\mathbf{x}$ as our graph-signal smoothness prior in the sequel.

5. GRAPH CONSTRUCTION

We now discuss our construction of the similarity graph $\mathcal{G}$ using available Twitter information and TV co-appearance data. Nodes represent Japanese public figures with active Twitter accounts, and may appear in NHK TV news segments.

We define positive and negative weights in our similarity graph between two individuals i and j as follows:

$$w^+_{i,j} = \exp\left(\frac{-d^+(i,j)^2}{\sigma_+^2}\right) \tag{10}$$

$$w^-_{i,j} = -\left(1 - \exp\left(\frac{-d^-(i,j)^2}{\sigma_-^2}\right)\right) \tag{11}$$

where $d^+(i,j)$ and $d^-(i,j)$ represent (dis)similarity distances between individual pairs, and σ_+ and σ_- are scaling parameters. We discuss how we compute $d^+(i,j)$ and $d^-(i,j)$ next.

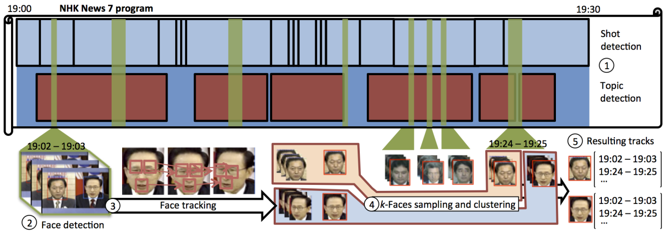


Fig. 2. Segmentation of the videos (borrowed from [3]).

To compute $d^+(i,j)$, we collected follower data of public figures' Twitter accounts. We assume that the fraction of shared followers between two individuals reflects how politically close they are. Specifically, we define

$$d^+(i,j) = \frac{|f(i) \cap f(j)|}{\min(|f(i)|, |f(j)|)} \tag{12}$$

where $f(i)$ is the set of Twitter followers for individual i. (12) basically computes the larger of two fractions of shared followers for i and j. The size of Twitter followers is $4,830,970$ [3].

To compute negative distance $d^-(i,j)$, we extracted co-occurrence information from a 12-year NHK TV news archive via face detection and tracking from the results of [3], as shown in Fig. 2. We have detected politicians in 4552 different news segments. An NHK news segment is often presented as a conflict with two views [22], and thus co-appearance of only two individuals in the same segment means likely opposing stands. Thus, we define $d^-(i,j)$ as the number of co-appearances of a pair of individuals in a TV news segment in the 12-year archive.

Finally, if both Twitter and TV co-appearance information are available for pair (i,j), we combine $w^+_{i,j}$ and $w^-_{i,j}$ linearly as follows:

$$w_{i,j} = \alpha w^+_{i,j} + \beta w^-_{i,j} \tag{13}$$

6. GRAPH-SIGNAL RESTORATION

Having constructed a similarity graph $\mathcal{G}$ as described previously, we formulate our graph-signal restoration problem given partial observation $\mathbf{y} \in \mathbb{R}^K$ (K ground truth political labels) using the graph-signal smoothness prior as follows:

$$\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2 + \mu\, \mathbf{x}^T \mathbf{L}_g \mathbf{x} \tag{14}$$

where $\mathbf{H}$ is a $K \times N$ binary matrix that selects K samples from signal $\mathbf{x}$ to compare against observation $\mathbf{y}$. μ is a weight parameter that specifies the relative importance of the fidelity term (likelihood in a MAP formulation) with the graph-signal smoothness prior.

Note that because $\mathbf{L}_g$ is PSD, $\mathbf{x}^T\mathbf{L}_g\mathbf{x} \geq 0$. If instead we use the combinatorial graph Laplacian $\mathbf{L}$ to define the smoothness prior $\mathbf{x}^T\mathbf{L}\mathbf{x}$, then because the smallest eigenvalue λ_1 can be negative, $\infty\mathbf{u}_1$ would compute to an objective value of $-\infty$ for $\mu > 0$. Hence the use of a PSD $\mathbf{L}_g$ in the smoothness prior is essential for numerical stability.

Because (14) is a simple sum of two quadratic terms, one can take the derivative with respect to $\mathbf{x}$ and equate to zero, resulting in optimal solution $\mathbf{x}^*$:

$$\mathbf{x}^* = \left(\mathbf{H}^T\mathbf{H} + \mu\mathbf{L}_g\right)^{-1} \mathbf{H}^T\mathbf{y} \tag{15}$$

7. EXPERIMENTATION

7.1. Experimental Setup

We collected data of public figures (politicians, business leaders, etc) appearing on a 12-year archive of the Japanese NHK Daily News 7 program between 2001 and 2012. The period included numerous changes in Prime Ministers (PM) and their cabinets. Japanese politics is roughly split between two leading parties—Liberal Democratic Party (LDP) and Democratic Party of Japan (DPJ)—that represent the right and left of the political spectrum. During our observed 12 years, there were four different LDP PMs and three different DPJ PMs.

Beyond construction of the positive and negative edges in the similarity graph based on Twitter followers and TV news co-appearances as described in Section 5, we also connect observed sample pairs of same party members with edge weight 1 and observed sample pairs of opposing party members with -1.

We assign sample values -1 and 1 to the DPJ and LDP PMs respectively to construct observation $\mathbf{y}$. We then estimate political leanings (left or right) of the remaining individuals by solving $\mathbf{x}$ using (15); sign($\mathbf{x}$) gives an estimate of party affiliation. Of course, our ultimate goal is to estimate the *political leanings* of politicians. However, our ground truth is limited to party affiliations, though some notable individuals allow for more fine-grained interpretations of the estimated sample values x_i, as we will discuss later when interpreting our obtained estimates.

For our experiment, we use parameters $\mu = 20$, $\sigma = 1$, and $\alpha = \beta = 0.5$. We have in total 18 labeled politicians between DPJ (10) and LDP (8), and 9 additional unlabeled individuals.

The US political landscape is much more polarized than the one of Japan. In the electoral period of the end 2016, this polarization is even more amplified, and the data from Twitter should somehow reflect this situation. This context makes it a perfect occasion for testing our methodology. For samples, we include US politicians who are currently state governors (as of Oct. 2016). We choose observations $\mathbf{y}$ as the presidential election candidates and their running-mates since 2000, while assigning -1 for Democrats and 1 for Republicans. The only parameter that was changed is $\mu = 0.02$.

7.2. Japanese Politics Experimental Results

We first ran an experiment on the 18 individuals. Using only positive weights computed from Twitter data, our method resulted in 4 errors in estimated party affiliations compared to the ground truth. This shows that Twitter alone—where many politicians share followers for a variety of reasons—is not sufficiently informative or

[3]Because only 65% of followers share the opinion of the politicians they follow [10], we extract *partisan* followers for our experiments: those who only following minister(s) of a single party. This subset total $1,145,153$.

reliable for political leaning estimation. We observed also that the variance of estimated $\mathbf{x}$ has small standard deviation (SD) 1.10^{-2}; the estimated difference in political leanings is small. We next added negative edges obtained from TV news data also, resulting in only two erred political affiliations, while SD (0.6) is also larger. Looking closer, the two erred predictions had the two smallest magnitude in x_i: 0.016 and -0.012. The first error was for *I. Ozawa*, a politician also infamously known as "The Shadow Shogun" [23], labeled as DPJ. Though he was a member of DPJ during the tested period, he coordinated several coalitions against his own party, and left to form a new one in the end. The second politician is *S. Kamei*, who actually rebelled against LDP, switched party twice before becoming independent.

We removed these two politians from the graph, and we achieved 0 error on our new dataset (Fig. 3, $SD = 0.6$). Interestingly, the prediction with the smallest magnitude in LDP was *M. Suzuki*, who was disgraced and convicted 1 year in prison after taking bribes.

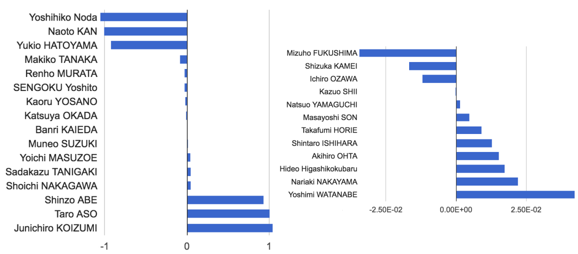


Fig. 3. Left: Results of the 16 people dataset. Observation individuals are the ones with highest confidence. Right: Results of unlabeled people of the 27 people dataset).

We extended our experiment with LDP and DPJ members as ground truth to all unlabeled public figures in our dataset, in order to predict political leaning more broadly. The results are well in accordance with our own knowledge (Fig. 3). For example, *Y. Watanabe*, former LDP member though currently independent, is a known right-wing politician close to LDP. New Komeito's *A. Ohta* and *N. Yamaguchi* are correctly placed on the right side also, as their party has an alliance with LDP.

We also compared to a label propagation method that propagates known labels in the graph to unlabeled nodes greedily. We observed 6 errors in the case of 18 politicians and 5 errors after removal of the two ambiguous cases. When testing with the larger case, we obtain 6 errors with 3 dubious cases (extreme-left classified as LDP, and an LDP-supported independent classified as DPJ).

7.3. US Politics Experimental Results

Since we do not have large-scale US TV news archive, the following experiment was conducted only following Twitter data. It sets 63 politicians having an official Twitter account, including 13 presidential election candidates and running-mates, with a total of 27,130,455 followers[4].

As observations $\mathbf{y}$, we have 13 presidential candidates and running-mates (6 Republicans and 7 Democrats), and 50 governors (with 18 Democrats and 32 Republicans). Only 3 governors are neither labeled Democrat nor Republican but Independent or Democratic Farmer Labor (DFL). In this electoral context, the most followed politicians are by far *H. Clinton* (10M), *D. Trump* (13M), and *B. Obama* (18M).

If we use only positive edges on the dataset, then our method results in 7 errors ($SD = 0.102$) in estimated affiliation compared to the ground truth. The label propagation method returns 4 erred politicians. With negative edges, we drop down to one error, with a larger $SD = 0.152$.

The erred politician is *C. Baker* ($\mathbf{x}_i = -0.030$), governor of Massachusetts—known to be a historically Democratic state. He is an unusual moderate Republican and notably took anti-Trump positions during the campaign.

The three politicians not affiliated with Democratic and Repubican parties are all placed on the Democratic side ($\mathbf{x}_i < 0$). It is confirming *M. Dayton*'s alignment since he is from the DFL ($\mathbf{x}_i = -0.039$). It is more surprising for the two independent politicians, *K. Mapp* ($\mathbf{x}_i = -0.037$), gov. of the Virgin Islands, and *W. Walker* ($\mathbf{x}_i = -0.016$), gov. of Alaska, who are ex-Republican politicians. They actually have relatively very few Twitter followers, with 152 for *K. Mapp* and 1,394 partisans for *W. Walker*. This provides minimal reliable information from which we could derive similarity information.

As for the outliers, the furthest left is Democrat *T. McAuliffe* ($\mathbf{x}_i = -0.065$), who has very close ties with the Clintons, and the furthest left Republican is *L. Hogan* ($\mathbf{x}_i = 0.002$), who publicly disavowed D. Trump.

8. CONCLUSION

We study the problem of estimating political leanings of public figures by extracting and analyzing patterns in mass media. Specifically, we first construct a similarity graph with nodes representing individuals. We then construct positive edges based on shared Twitter followers, and negative edges based on NHK evening news co-appearances. We define a new graph-signal smoothness prior based on a derived generalized graph Laplacian matrix that is positive semi-definite. We formulate a graph-signal restoration problem, solvable in closed form. Experimental results show reliable estimates of political affiliations, and detection of outlier politicians in both the Japanese and the US political media-landscapes.

9. REFERENCES

[1] D. I. Shuman, S. K. Narang, P. Frossard, A. Ortega, and P. Vandergheynst, "The emerging field of signal processing on graphs: Extending high-dimensional data analysis to networks and other irregular domains," in *IEEE Signal Processing Magazine*, May 2013, vol. 30, no.3, pp. 83–98.

[2] Norio Katayama, Hiroshi Mo, Ichiro Ide, and Shinichi Satoh, "Mining large-scale broadcast video archives towards inter-video structuring," *Advances in Multimedia Information Processing-PCM 2004*, vol. 1, no. 1, pp. 489–496, 2005.

[3] Benjamin Renoust, Tetsuro Kobayashi, Thanh Duc Ngo, Duy-Dinh Le, and Shin'Ichi Satoh, "When face-tracking

[4] 20,970,613 once counting only the *partisan* followers.

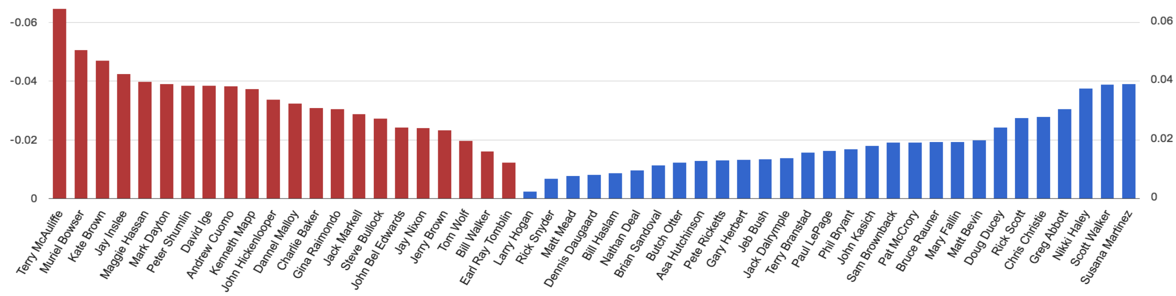


Fig. 4. All USA governors (without observations), only *C. Baker* is erred (negative values in red).

meets social networks: a story of politics in news videos," *Applied Network Science*, vol. 1, no. 1, pp. 1–25, 2016.

[4] Ellis S Krauss, *Broadcasting politics in Japan: NHK and television news*, Cornell University Press, 2000.

[5] J. Pang, G. Cheung, W. Hu, and O. C. Au, "Redefining self-similarity in natural images for denoising using graph signal gradient," in *APSIPA ASC*, Siem Reap, Cambodia, December 2014.

[6] J. Pang, G. Cheung, A. Ortega, and O. C. Au, "Optimal graph Laplacian regularization for natural image denoising," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, Brisbane, Australia, April 2015.

[7] W. Hu, G. Cheung, and M. Kazui, "Graph-based dequantization of block-compressed piecewise smooth images," in *IEEE Signal Processing Letters*, February 2016, vol. 23, no.2, pp. 242–246.

[8] P. Wan, G. Cheung, D. Florencio, C. Zhang, and O. Au, "Image bit-depth enhancement via maximum-a-posteriori estimation of AC signal," in *IEEE Transactions on Image Processing*, June 2016, vol. 25, no.6, pp. 2896–2909.

[9] T. Biyikoglu, J. Leydold, and P. F. Stadler, "Nodal domain theorems and bipartite subgraphs," in *Electronic Journal of Linear Algebra*, November 2005, vol. 13, pp. 344–351.

[10] Jennifer Golbeck and Derek Hansen, "Computing political preference among twitter followers," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2011, pp. 1105–1108.

[11] Elanor Colleoni, Alessandro Rozza, and Adam Arvidsson, "Echo chamber or public sphere? predicting political orientation and measuring political homophily in twitter using big data," *Journal of Communication*, vol. 64, no. 2, pp. 317–332, 2014.

[12] Felix Ming Fai Wong, Chee Wei Tan, Soumya Sen, and Mung Chiang, "Quantifying political leaning from tweets and retweets.," *ICWSM*, vol. 13, pp. 640–649, 2013.

[13] F. M. F. Wong, C. W. Tan, S. Sen, and M. Chiang, "Quantifying political leaning from tweets, retweets, and retweeters," *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 8, pp. 2158–2172, 2016.

[14] Esther David, Maayan Zhitomirsky-Geffet, Moshe Koppel, and Hodaya Uzan, "Utilizing facebook pages of the political parties to automatically predict the political orientation of facebook users," *Online Information Review*, vol. 40, no. 5, pp. 610–623, 2016.

[15] X. Liu, G. Cheung, X. Wu, and D. Zhao, "Inter-block soft decoding of JPEG images with sparsity and graph-signal smoothness priors," in *IEEE International Conference on Image Processing*, Quebec City, Canada, September 2015.

[16] Y. Mao, G. Cheung, and Y. Ji, "Image interpolation during DIBR view synthesis using graph Fourier transform," in *3DTV-Conference*, Budapest, Hungary, July 2014.

[17] Y. Mao, G. Cheung, and Y. Ji, "On constructing z-dimensional dibr-synthesized images," in *IEEE Transactions on Multimedia*, August 2016, vol. 18, no.8, pp. 1453–1468.

[18] S. Chen, A. Sandryhaila, J. M. F. Moura, and J. Kovacevic, "Signal denoising on graphs via graph filtering," in *IEEE Global Conference on Signal and Information Processing*, Austin, TX, December 2014.

[19] S. Chen, A. Sandryhaila, J. Moura, and J. Kovacevic, "Signal recovery on graphs: Variation minimization," in *IEEE Transactions on Signal Processing*, September 2015, vol. 63, no.17, pp. 4609–4624.

[20] A. Sandryhaila and J. Moura, "Discrete signal processing on graphs," in *IEEE Transactions on Signal Processing*, April 2013, vol. 61, no.7, pp. 1644–1656.

[21] N. Higham and S. H. Cheng, "Modifying the inertia of matrices arising in optimization," in *ELSEVIER Linear Algebra and its Applications*, May 1998, vol. 275-279, pp. 261–279.

[22] Holli A Semetko and Patti M Valkenburg, "Framing european politics: A content analysis of press and television news," *Journal of communication*, vol. 50, no. 2, pp. 93–109, 2000.

[23] Isaac Meyer, "The History of Japan podcast, Episode 82: The Shadow Shogun, Redux," 2014.