

Extracting voting patterns across three Philippine senate elections using hyperspectral unmixing

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Abstract

We extract possible voting patterns by applying hyperspectral unmixing to the 2013, 2016, and 2019 Philippine elections. Hyperspectral unmixing, when applied to satellite images, extracts recurring traits or patterns found in a scene. First, data reduction determines the number of recurring patterns. Second, unmixing estimates the spectral signature of the recurring patterns. Lastly, inverting fits the obtained spectral signatures with the hyperspectral data to estimate their corresponding weights. By comparing the obtained voting patterns, we found the following recurring archetypes: opposition, conservatives, celebrities, political history, media popularity, and cultural-linguistic affiliation. The dominant archetypes for each province in each year were also calculated using their weights. We found that candidates tend to dominate their home province.

Keywords: dimension reduction, hyperspectral unmixing, voting patterns, elections

1 Introduction

Quantitative election studies often use opinion polls to extract voting patterns [1, 2]. Our proposed method finds the same voting patterns directly from precinct-level election results. Previously, we used hyperspectral unmixing to extract six voting patterns in the 2016 senate elections [3]. In this work, we extend our analysis of voting patterns to the 2013 and 2019 Philippine senate elections.

Image pixels and their corresponding spectral intensities per wavelength compose hyperspectral satellite images. Similarly, clustered precincts and their corresponding vote fractions per candidate compose Philippine election results. Given their structural similarities, hyperspectral unmixing applies to both Philippine election results and hyperspectral images with the assumption that underlying patterns can be combined to form the observed measurements. Hyperspectral unmixing decomposes the pixel spectra of an image into archetypes (recurring patterns) with distinct spectral signatures by following a three-step process: (1) dimension reduction, (2) unmixing, and (3) inversion.

Given the number of candidates in the Philippine senate elections (33 in 2013, 50 in 2016, and 62 in 2019), enumerating all possible voting combinations becomes impractical. The large number of possible combinations (60 choose 12 candidates $\approx 10^{12}$) necessitates dimension reduction to obtain fewer and more comprehensive voting patterns. The number of reduced dimensions dictates the number of archetypes in a scene. We used linear unmixing to estimate archetype spectral signatures in the 2013, 2016, and 2019 senate elections. In linear unmixing, a linear combination of the obtained archetype spectra multiplied by their weights represents each pixel spectrum. Inversion estimates the corresponding weights of each archetype. We expect that hyperspectral unmixing can also extract recurring archetypes in the Philippine 2013 and 2019 senate elections, and that their corresponding weights can be used to calculate dominant archetypes.

2 Methodology

Hyperspectral unmixing estimates \mathbf{M} and \mathbf{A} in

$$\mathbf{Y} = \mathbf{MA} + \mathbf{N}, \quad (1)$$

where \mathbf{Y} is the spectral matrix, \mathbf{M} is the mixing matrix, \mathbf{A} is the abundance matrix, and \mathbf{N} is the noise matrix [4–7]. The solution is subject to two constraints: (1) $\mathbf{A} \succeq 0$ and (2) $\mathbf{1}_p^T \mathbf{A} = \mathbf{1}_n$.

We used Hyperspectral Signal identification by minimum error (HySime), which minimizes the sum of the projection error and noise error terms, to reduce data [5]. Underestimating the subspace dimension of \mathbf{M} increases the projection error, because the reduced data lacks information from higher dimensions. Overestimating increases the noise error, because the reduced data includes information from unnecessary dimensions. Thus, minimizing the sum of projection and noise errors estimates the optimal dimension.

We used Vertex Component Analysis (VCA) [4] and Minimum Volume Simplex Analysis (MVSA) [6] to unmix and estimate \mathbf{M} . VCA assumes there are pure pixels, while MVSA doesn't. VCA takes advantage of the fact that (1) the archetypes are the vertices of the simplex (generalized n-dimension tetrahedron) spanning the data, and (2) the affine transform (preserves parallel relationships) of a simplex is also a simplex. MVSA fits a minimum volume simplex to the hyperspectral data that allows positivity constraint violations to account for noisy data.

Lastly, we used Sparse Unmixing via Variable Splitting and Augmented Lagrangian (SUnSAL) to fit linear combinations of the archetype spectral signatures obtained from unmixing to the data \mathbf{Y} . It estimates \mathbf{A} using constrained sparse regression based on the alternating direction method of multipliers [7].

The 2013 and 2016 partial election results were obtained from <http://elections.org.ph>, while the 2019 election results were scraped from the Philippine Commission on Elections website. We created a matrix \mathbf{Y} from Eqn. 1 for each year using the raw election data. Rows correspond to clustered precincts, while columns correspond to the fraction of votes with respect to the total number of ballots per clustered precinct garnered by each candidate. The MATLAB code for HySime, VCA, MVSA, and SUnSAL provided by J. Li et al. [6] were used in hyperspectral unmixing.

The obtained abundance matrix \mathbf{A} was used to calculate the dominant voting archetype per province in each year. We grouped the precincts by province, except for the 2016 elections, which was grouped by region, because it was the highest resolution available. The archetype with the highest weighted median in each province/region was deemed the dominant archetype. We used the median over the mean to increase robustness against outliers.

3 Results and Discussion

HySime determined that the optimal number of archetypes in each year (2013, 2016, 2019) are five, six, and six, respectively (summarized in Table 1). We based the correlation of candidates with high vote amplitudes (in Fig. 2) on their online profiles and news articles during their campaign year. We looked at their religion, province, party alignment, stance on social issues, and name recall. Name recall refers to the familiarity of the general public to their names through media popularity and/or political history.

Table 1: Voting archetypes per year arranged from highest to lowest mean weight

| | 2013 | 2016 | 2019 |
|---|-----------------------------------|-------------------------|--------------------------|
| 1 | opposition | popular coalitions | previous senators |
| 2 | pro-reproductive health (RH) bill | provincial politicians | conservatives |
| 3 | anti-RH bill | winners | multimedia popularity |
| 4 | joint campaign | celebrities | island group association |
| 5 | conservatives | TV news popularity | celebrities |
| 6 | | written news popularity | opposition |

The Philippine Reproductive Health (RH) Bill issue divided the country during the 2013 elections; thus, becoming a relevant topic of discussion among candidates. The Catholic Church, whose voice matters to a predominantly Catholic country, endorsed candidates opposing the RH Bill [8]. The fourth 2013 archetype dominates in the home province of candidate 12 (A in Fig. 2a), the chairman of the Philippine Red Cross. Candidate 17 and 182nd and 3rd highest vote amplitudes in fourth 2013 archetype campaigned together as friends [9].

The candidates with high vote amplitudes in the 1st 2016 archetype come from the senatorial tickets of the 2nd and 3rd most popular presidential candidates [10, 11]. Candidate 14 and 17 highest vote amplitudes in 2nd 2016 archetype served as previous politicians in the same home province (B in Fig. 2b). Candidate 9, an internationally renowned boxer, has the highest vote amplitude in the fifth 2016 archetype. Candidate 14 highest vote amplitude in last 2016 archetype owns a tabloid company that published articles about him [12].

The 2nd 2019 archetype dominates in the northern regions of the Philippines, candidate 7's hometown (D in Fig. 2c). Her family name carries heavy political history, providing her with strong name recall [13]. Candidate 17 highest vote amplitude in 3rd 2019 archetype amassed a huge following in social media sites [14]. The 6th archetype dominates in candidate 24's hometown (C in Fig. 2c).

4 Conclusions

Hyperspectral unmixing becomes more powerful the higher the data dimension by reducing huge number of combinations to fewer comprehensive patterns. We can extend our proposed method of pattern extrac-

tion to other combinations of local and national positions, and to other countries that use the popular voting mechanism. We can also apply hyperspectral unmixing to extract patterns in other quantitative social science studies that use polls and surveys with multiple parameters (high dimensions).

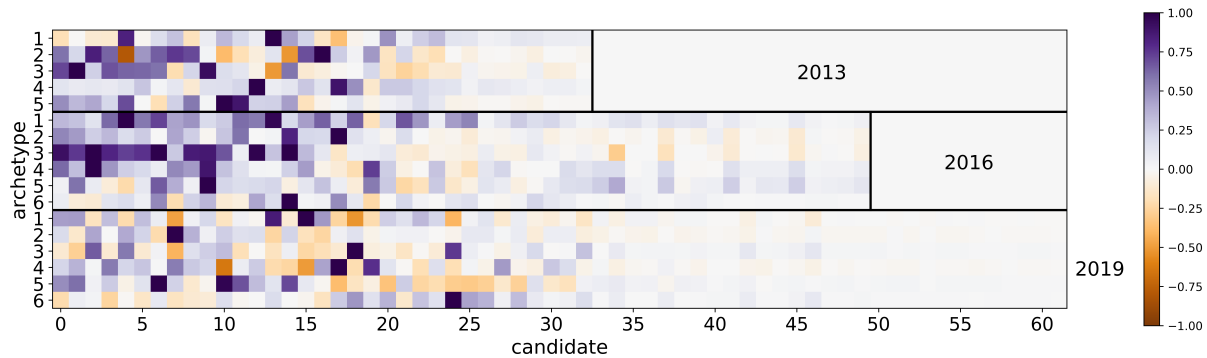


Figure 1: Vote amplitudes of archetypes per year

Acknowledgments

M.L. acknowledges the support provided by the ICTP Associateship Program. The authors received support from the Commission on Higher Education-PCARI project DARE: Data Analytics for Research and Education (IIID-2016-006). Financial support received by C. de Castro from DOST-SEI.

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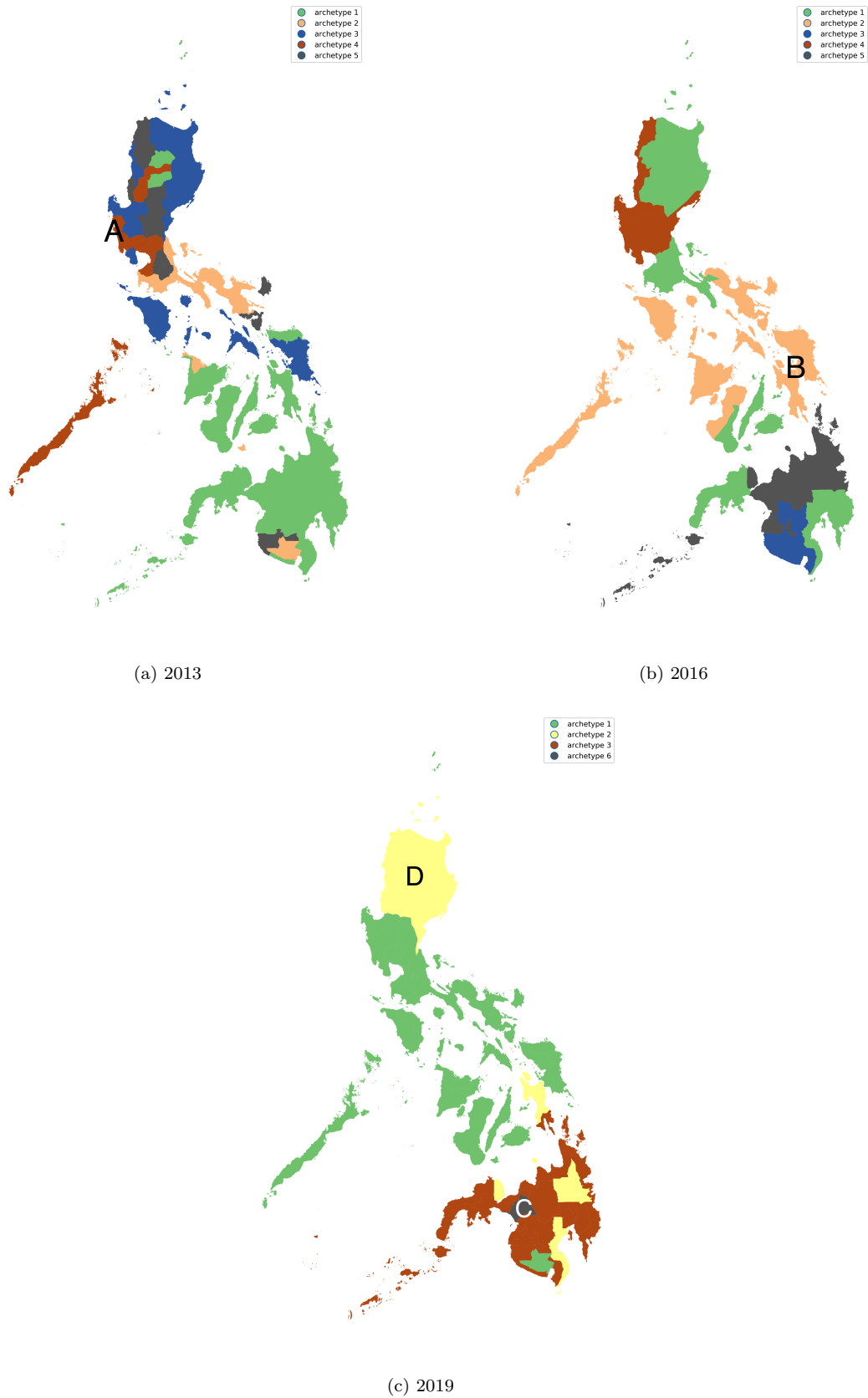


Figure 2: Dominant archetypes per year (Philippine map shapefile from <http://philgis.org>)