Reconstructing collaborations between political parties from bill cosponsorship networks

Mirko Signorelli[1,2] and Ernst C. Wit[1]

1: Johann Bernoulli Institute for Mathematics and Computer Science, University of Groningen
2: Department of Statistical Sciences, University of Padova

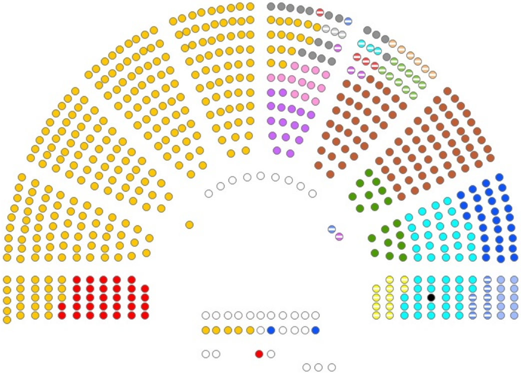
rijksuniversiteit groningen
Università degli Studi di Padova

Number of political groups in some Parliaments

Country	Lower ("main") Chamber	# political groups*	% MPs of 2 main parties
USA	Congress	3	98%
Germany	Bundestag	4	80%
France	National Assembly	7	85%
Italy	**Chamber of Deputies**	**10**	**62%**
UK	House of Commons	12	86%

* Including "independents" (USA, UK) / "not registered" MPs (FR) / "mixed group" (IT).

Party affiliation of the deputies



Current composition of the Chamber:

- 630 deputies;
- 10 (9+1) parties.

...Which parties are more alike / collaborate more?

Majority: PD + CD + SC + AP (+ a few other MPs...).

Bill cosponsorship networks

In the (Italian) Chamber of Deputies, each bill can be

- sponsored by a single deputy;
- cosponsored by more than one deputy.

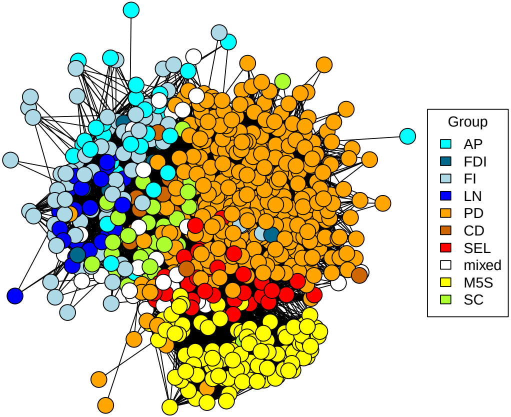
Cosponsorship = **proxy for ideological agreement**.

Bill cosponsorship network

An edge-valued, undirected graph $\mathcal{G} = (V, E)$ where

- each **node** $v_i \in V$ is a **deputy**;
- a weighted **edge** e_{ij} displays the **number of bills** that deputies v_i and v_j have cosponsored together during a legislature.

Example: current legislature



Bill cosponsorship network of the XVII legislature (2013-15).
Colors denote parliamentary groups. Edge weights not shown.

Purpose

Derive a model that can answer these questions:

1. which parties are politically more active?
2. **which collaborations exist between parties**?
3. what other factors affect bill cosponsorship choices?

Network generating process

Idea

$\mathcal{G}$ arises from a multivariate Poisson process, stopped at time T.

Steps

1. Associate a Poisson process $\{N_{ij}(t),\ t \geq 0\}$ with rate λ_{ij} to every pair (i, j) of nodes.
2. $N_{ij}(t) \sim \text{Poi}(\lambda_{ij} t)$.
3. Stop the process at $T \Rightarrow a_{ij} = N_{ij}(T)$.
4. p_1 modelling assumption: $N_{ij}(t) \perp\!\!\!\perp N_{kl}(t)$, $(i, j) \neq (k, l)$.

Stochastic blockmodels

Each deputy belongs to only one parliamentary group
$\Rightarrow$ a **partition** of deputies into p groups ("blocks") is **available**.

Stochastic blockmodel (Holland et al., 1983)

If i and k belong to same block, any probability statement on the graph is left unchanged by interchanging e_{ij} with e_{kj}.

Blockmodel assumption: interaction rates λ_{ij} are homogeneous within each pair of blocks (r, s), i.e.,

$$\lambda_{ij} = \zeta_{rs} \ \forall i \in \text{group } r, \ \forall j \in \text{group } s.$$

Initial stochastic blockmodel

Conditional on group memberships of nodes $i \in r$ and $j \in s$,

$$a_{ij} | (i \in r, j \in s) \sim \text{Poi}(\mu_{rs} = T\zeta_{rs}).$$

Decomposition of μ_{rs}:

$$\log(\mu_{rs}) = \theta_0 + \alpha_r + \alpha_s + \phi_{rs}.$$

- θ_0: overall network density;
- α_r, $r \in \{1, ..., p\}$: cosponsorship activity of party r;
- ϕ_{rs}, $r \leq s \in \{1, ..., p\}$: collaboration (+) or repulsion (-) between deputies in parties r and s.

Our (extended) stochastic blockmodel

- Extension that allows **inclusion of covariates** x_{ij} associated to (v_i, v_j):

$$a_{ij}|(i \in r, j \in s, x_{ij}) \sim \text{Poi}(\mu_{ij}),$$

$$\log(\mu_{ij}) = \theta_0 + x_{ij}\beta + \alpha_r + \alpha_s + \phi_{rs}.$$

- **Identifiability conditions**:

$$\sum_{r=1}^{p} \alpha_r = 0 \text{ and } \sum_{s=1}^{p} \phi_{rs} = 0 \;\; \forall r = 1, ..., p,$$

where (for ease of notation) we write $\phi_{sr} = \phi_{rs}$.

Penalized inference

The model includes $q = p(p+1)/2 + dim(\beta)$ parameters:

$$\theta = (\theta_0,\ \beta,\ \alpha_2,\ \dots,\ \alpha_p,\ \phi_{12},\ \phi_{13},\ \dots,\ \phi_{p-1,p})\,.$$

- Number of parameters increases quickly with p!
  - E.g., if $dim(\beta) = 4$ and $p = 5 \Rightarrow q = 20$;
  - if $p = 10 \Rightarrow q = 60$, if $p = 15 \Rightarrow q = 125$...
- Why do we resort to penalized inference?
  - We seek a parsimonious solution;
  - Some ϕ_{rs} could be 0 ("indifference" between parties r and s).

The adaptive Lasso

Adaptive Lasso (Zou, 2006)

$$\hat{\theta} = \underset{\theta}{\text{argmax}} \; \log L(\theta) - \delta \sum_{j=1}^{q} w_j |\theta_j|,$$

where $L(\theta)$ = likelihood, δ = tuning parameter, w_j = weight.

Let θ^* be a consistent estimator of θ and $N = n(n-1)/2$: if

1. $w = 1/|\theta^*|^\gamma$
2. $\delta/\sqrt{N} \to 0$
3. $\delta N^{(\gamma-1)/2} \to \infty$

then $\hat{\theta}$ is consistent in variable selection.

Weight vector and interpretation

Definition of the weight vector w:

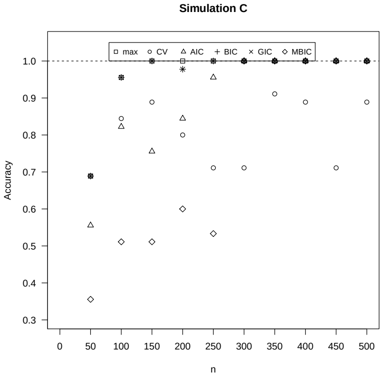
- $w_j = 0$ for θ_0 and α_r (unpenalized);
- $w_j = 1/|\theta_j^*|^\gamma$, with $\theta_j^* =$ MLE & $\gamma = 2$, for β and ϕ_{rs}.

Interpretation of α and ϕ

$$\hat{\alpha}_r = \begin{cases} > 0 & \text{deputies} \in r \text{ cosponsor more than average} \\ < 0 & \text{deputies} \in r \text{ cosponsor less than average} \end{cases} .$$

$$\hat{\phi}_{rs} = \begin{cases} > 0 & \text{deputies in } (r, s) \text{ tend to collaborate} \\ < 0 & \text{deputies in } (r, s) \text{ tend to avoid collaborations} \\ = 0 & \text{indifference between collaboration / no coll.} \end{cases} .$$

Selection of tuning parameter δ



- We simulate networks with different model complexity (q) and betamin condition strength.
- We compare the accuracy[1] of models selected by CV, AIC, BIC, GIC[2] and MBIC[3].
- RESULTS: AIC, CV, MBIC often inaccurate; BIC and GIC outperform them.

[1] % of correctly detected null / non-null ϕ_{rs}.
[2] Fan and Tang (2013). [3] Chand (2012).

The data

Ingredients:

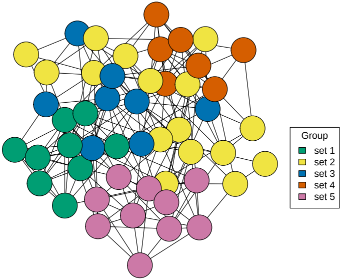
1. bill cosponsorship networks for the Italian Chamber of Deputies (Briatte, 2016), 4 legislatures:
   - XIV (2001-2006) $\rightarrow$ **8** parties;
   - XV (2006-2008) $\rightarrow$ **13** parties;
   - XVI (2008-2013) $\rightarrow$ **8** parties;
   - XVII (2013-2015) $\rightarrow$ **10** parties.
2. personal details of Deputies (dati.camera.it):
   - gender;
   - age;
   - electoral constituency;
   - parliamentary group.

Covariates (x_{ij})

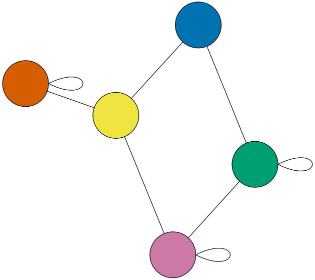
Covariate	Legislature			
	XIV	XV	XVI	XVII
Intercept (θ_0)	-2.49	-3.05	-2.53	-3.60
Female-Male (FM)	0.251	0.170	0.174	0.198
Female-Female (FF)	0.998	1.00	0.662	0.606
Age difference	0	0	-0.010	-0.002
Same electoral constituency	0.522	0.490	0.514	0.553

- $\hat{\theta}_0$ lower for shorter legislatures (XV & XVII).
- Cosponsorship more frequent if at least one sponsor is female.
- No age effect.
- Collaborations based on geographic proximity.
- Effects (roughly) similar over time.

Relations between blocks: the reduced graph



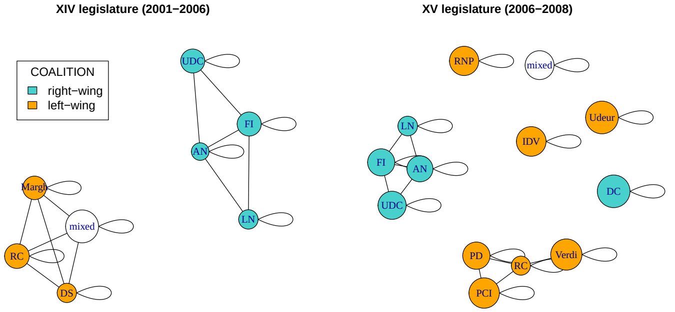
Original graph



Reduced graph

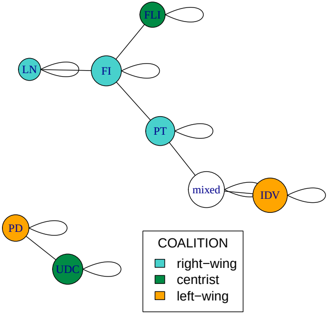
- Anderson et al. (1992): draw an edge between blocks r and s if $\hat{\pi}_{rs} > c$ (= blocks highly connected).
- Instead, we draw an edge if $\hat{\phi}_{rs} > 0$ (= collaboration!).

XIV and XV legislatures (2001-2008)



- 2 coalitions of parties (left & right) + stable majorities.
- **Strong polarization**: collaborations almost exclusively within parties and between parties in the same coalition.

XVI legislature (2008-2013)

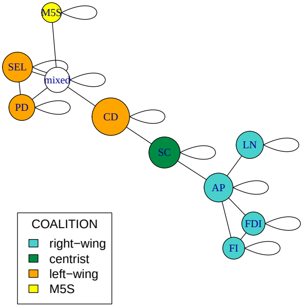


Three different majorities:

1. FI + LN + PT + FLI;
2. FI + LN + PT;
3. FI + FLI + UDC + PD.

- Reduced graph: reflects division majority/opposition of the first half of the legislature (1).
- Why? Cosponsorship is more likely to take place at the very beginning of each legislature!

XVII legislature (data until dec. 2015!)



- Four “coalitions” (left-wing, right-wing, Scelta Civica & Mov. 5 Stelle).
- “Composite” majority (PD + CD + SC + AP + partly FI).
- Main collaborations:
  - within the same party;
  - between right-wing parties;
  - centrist parties: SC-CD and SC-AP;
  - two main left-wing parties (PD-SEL);
  - ...M5S isolated?

Extensions and alternatives

- We have used `glmnet` (great for sparse matrices!).
- Interesting extension: introduce **nodal random effects** to model unobserved sources of heterogeneity.
  - Italian Chamber: available covariates might not be enough.
  - Other Parliaments: no covariates / difficult to retrieve.
- Problem: **how to combine efficiently ℓ_1 penalty and random effects** (`glmmLasso` cannot handle sparse X!)?
- Alternative approach: `latentnet`
  - does not use group membership & provides latent space representation of Deputies;
  - leads to similar results;
  - drawbacks: no penalization + considerably slower.

Summary

- Bill cosponsorship $\approx$ ideological agreement between deputies.
- Stochastic blockmodel: how do parties collaborate?
- Adaptive lasso (consistent in variable selection).

Results:

- strong ideological polarization from 2001 to 2008;
- increasing political fragmentation from 2008 to 2015;
- female deputies more active in bill cosponsorship;
- geographic proximity relevant, age difference irrelevant.

Preprint: Signorelli & Wit, *A penalized inference approach to stochastic blockmodelling of community structure in the Italian Parliament*. arXiv:1607.08743.

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