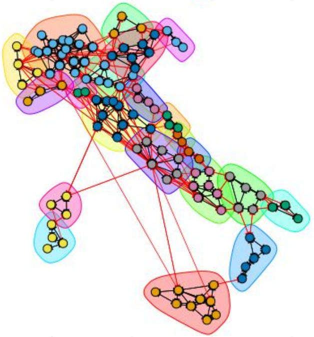
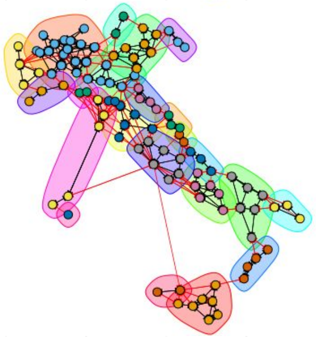
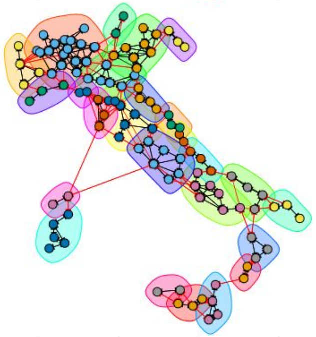




DATA SCIENCE & SCIENTIFIC COMPUTING

Impact of Italy's COVID-19 Lockdown on National Mobility Networks

Final project for the Social Network Analysis course

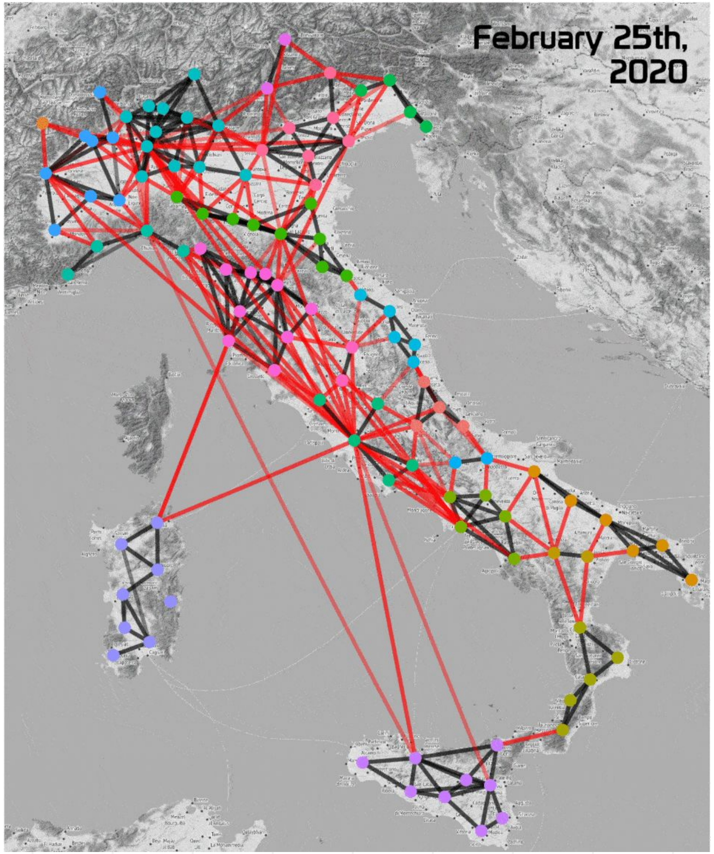
Gabriele Sarti and Enrico Fallacara, University of Trieste, Academic Year 2020/2021

The **goal** of this project is to analyze how Italian mobility trends have shifted during the three phases of the 2020 lockdown, focusing on three specific dates:

1. **First lockdown** (February 21st, 2020)
2. **National lockdown** (March 10th, 2020)
3. **Reopening of inter-regional travel** (May 5th, 2020)

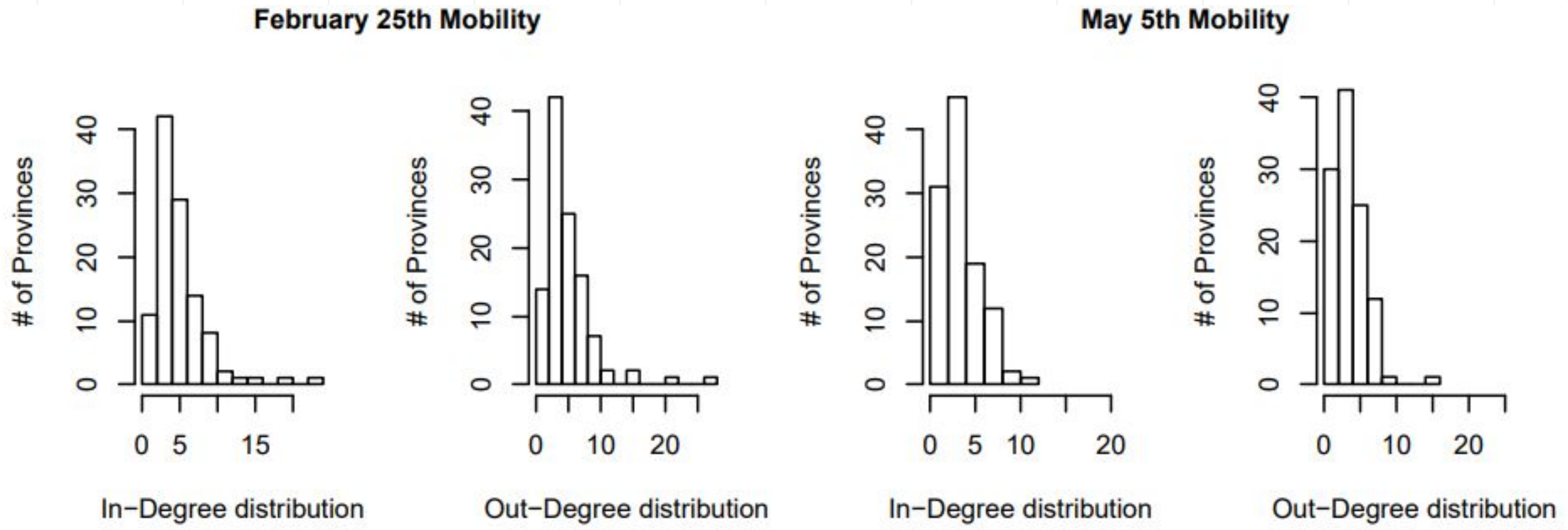
We used **Movement Range Maps data** published by Facebook on the Humanitarian Data Exchange platform, considering only raw estimated movements at the provincial level.

We focus mostly on the analysis of **inter-provincial movements**, that we deem as most interesting.

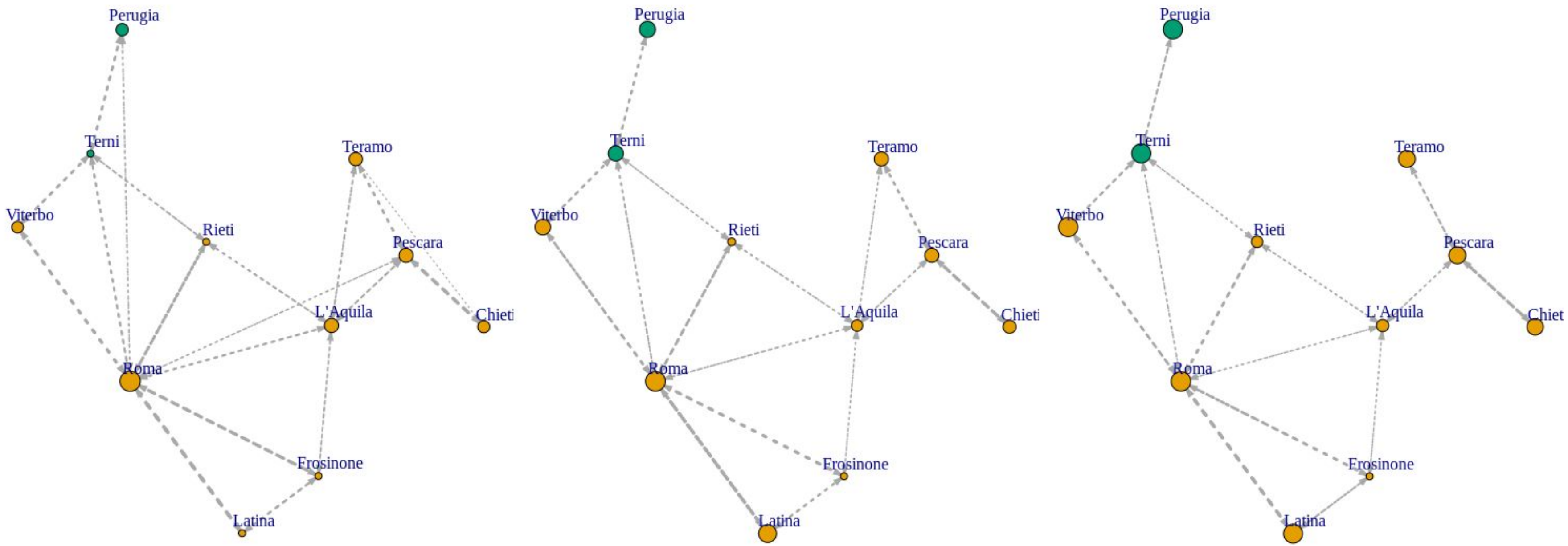


1. Diachronic Descriptive Analysis

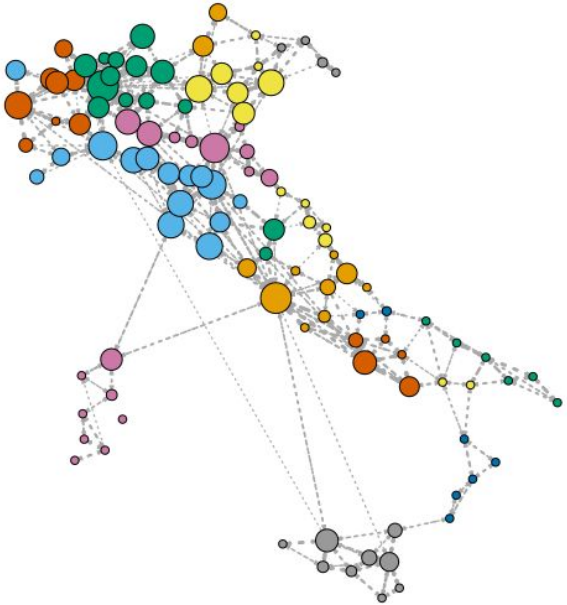
In all three dates, mobility networks are **directed**, **weighted** (according to the raw mobility weight value), and **disconnected**. We observe drastic mobility reduction for most well-connected provinces.



	Feb. 25th	Mar. 10th	May 5th
# of provinces	110	110	110
# of edges	600	478	434
# of movements	119065	85258	68515
% mobility decrease	-	30%	43%
Density	.050	.040	.036
Diameter	.306	.506	.843
Dyad census (MAN)	279/42/5674	230/18/5747	206/22/5767
# of triangles	918	492	423
Assortativity by degree	.134	.251	.326
Global transitivity	.386	.405	.417
Transitivity sub. upper	.171	.206	.272
Transitivity sub. lower	.315	.317	.345
Transitivity k-cores	.796	.613	.611

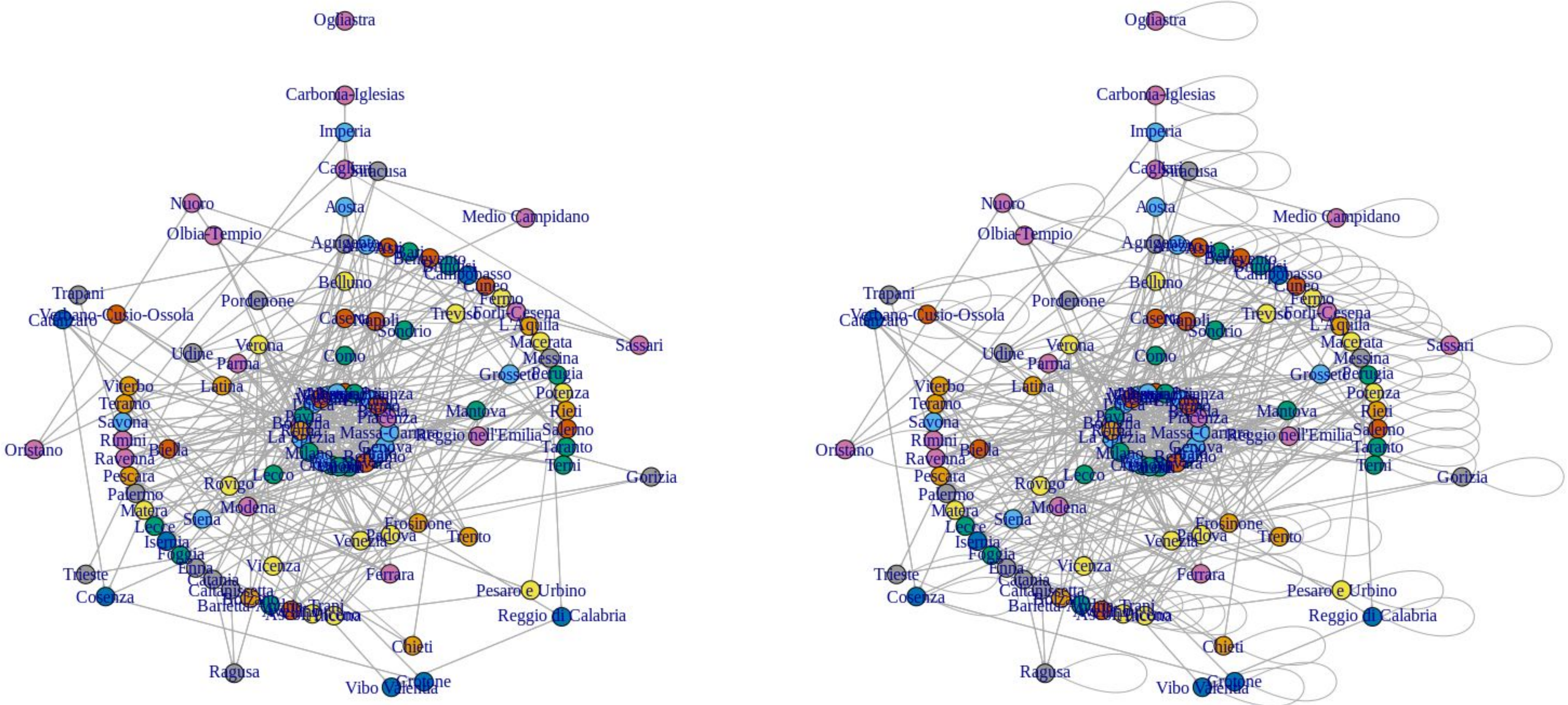


Mobility situation of provinces belonging to Lazio, Umbria, and Abruzzo. Edge size represents the number of raw movements, while vertex size represents the **betweenness** of nodes in the total network.

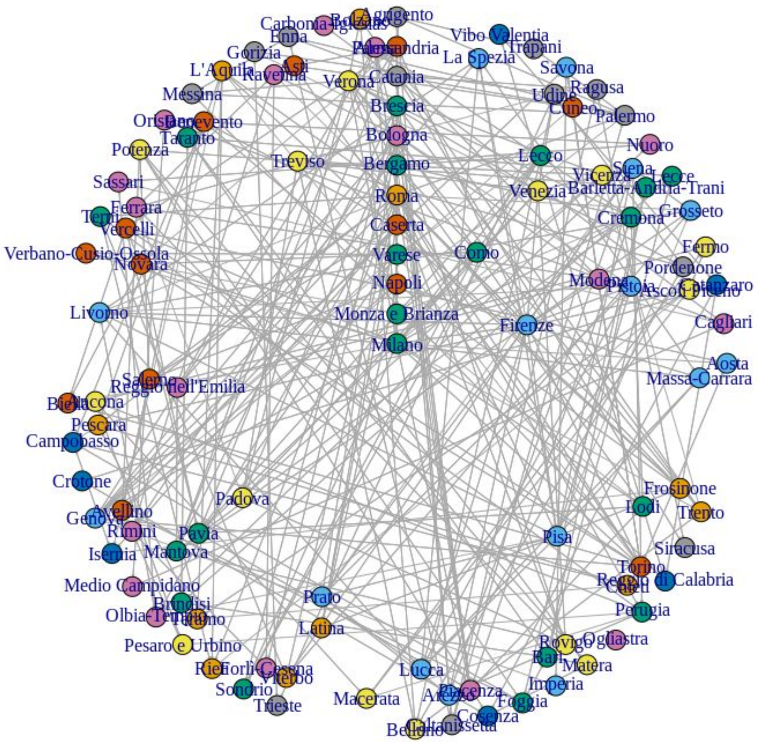


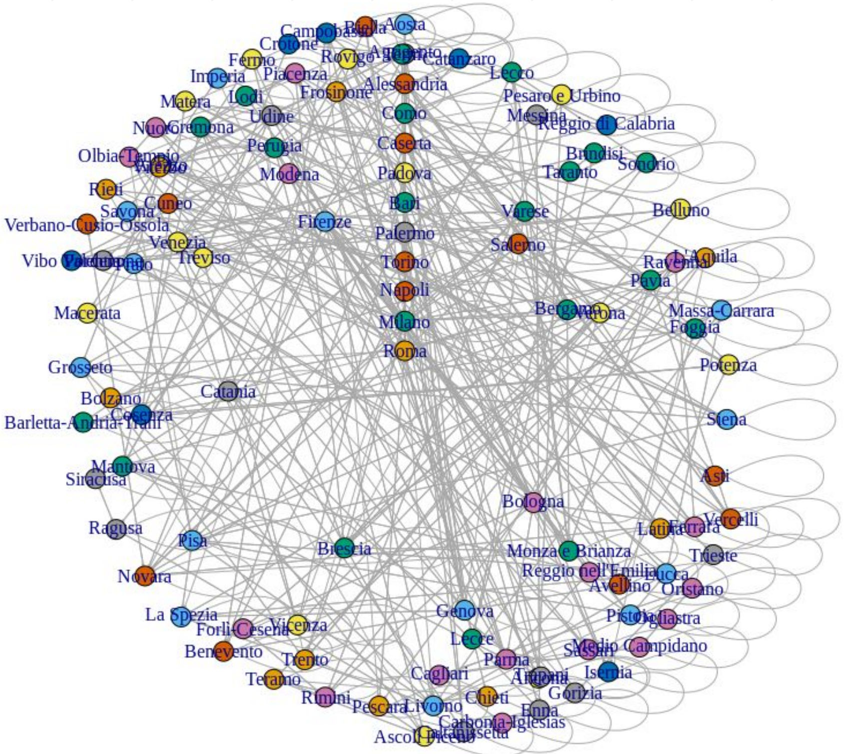
Mobility for provinces on the whole territory. Edge size represents the number of raw movements, while vertices sizes and colors represent the **eigenvector centrality** and the regional membership of nodes in the network.

2. Analyzing Mobility Communities

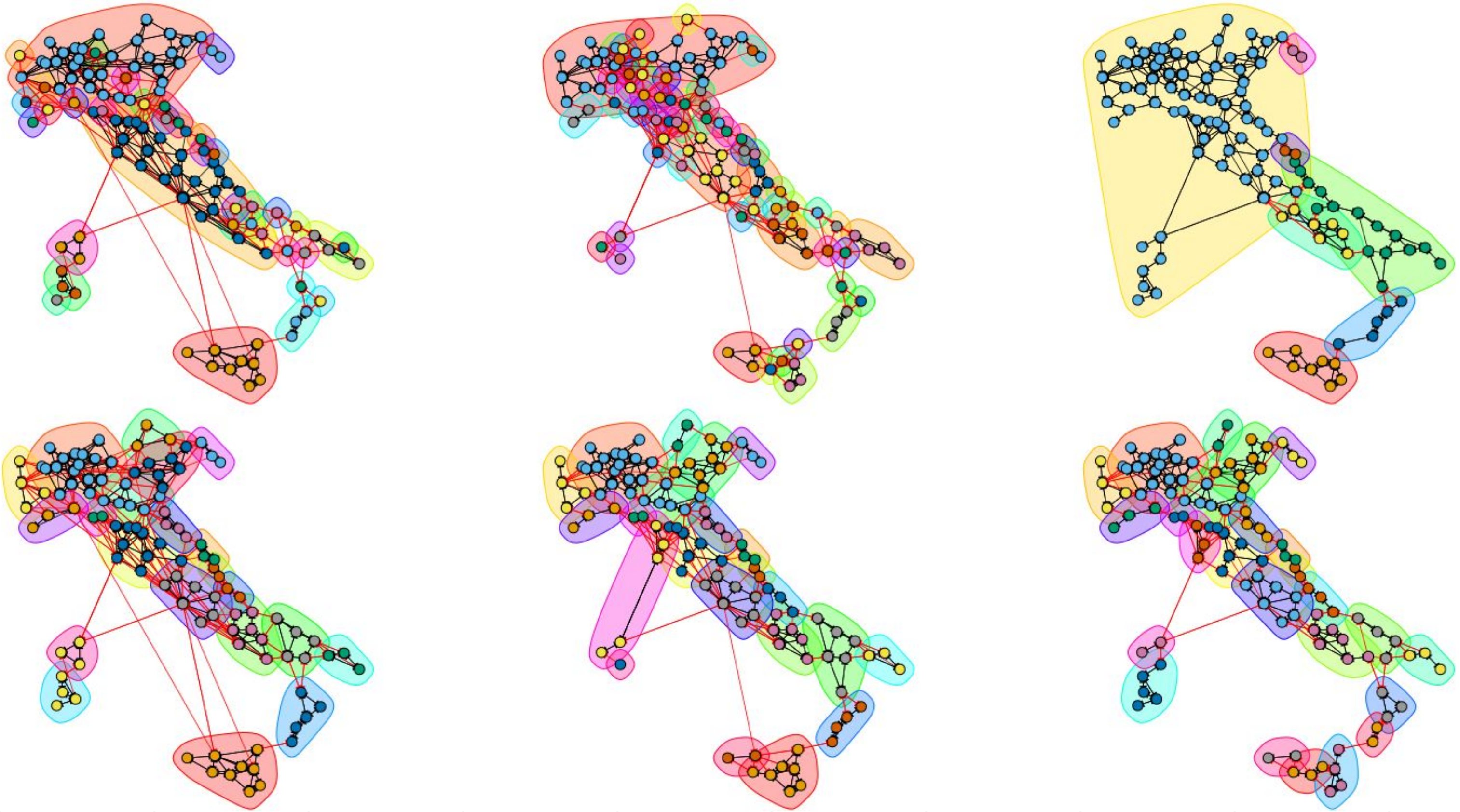


Coreness values of provinces (February 25th), for inter-provincial movements only (left) and all movements (right).





Weighted coreness values of provinces in the mobility network (February 25th), respectively for inter-provincial (left) and all movements (right)



Communities highlighted by the **Girvan-Newman** (top) and the **Label Propagation** (bottom) clustering algorithms.

Community detection results produced by **Girvan-Newman** and **Label Propagation** algorithms:

	Girvan-Newman			Label Propagation		
	Feb. 25th	**Mar. 10th**	**May 5th**	**Feb. 25th**	**Mar. 10th**	**May 5th**
# communities	36	60	7	22	22	24
modularity Q	.39	.25	.39	.51	.57	.59
δ_{int}	.19 (.38)	.12 (.31)	.54 (.37)	.78 (.21)	.68 (.25)	.73 (.23)
δ_{ext}	.07 (.05)	.08 (.04)	.01 (.01)	.04 (.03)	.03 (.01)	.03 (.01)
Gini index	.96 (.18)	.97 (.14)	.66 (.37)	.78 (.22)	.76 (.22)	.80 (.21)

We could not easily apply hierarchical modularity optimization approaches since the network is directed.

3. Modeling Mobility Patterns

To achieve a better quality of fit on our networks, we used some **auxiliary data** that can provide additional useful information to the model:

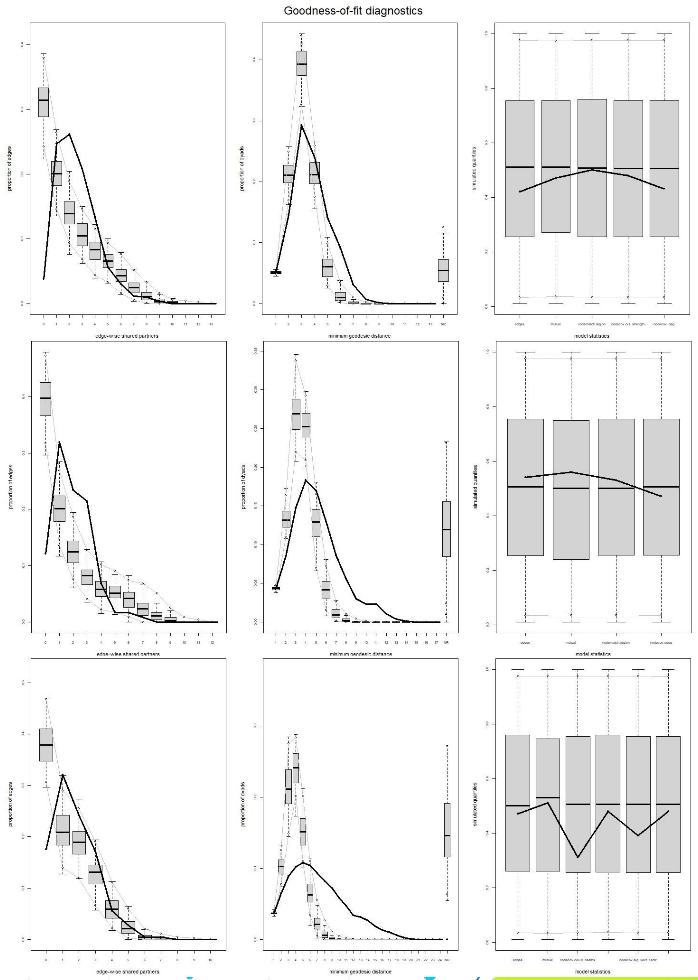
- Province d'Italia data (Wikipedia) , that contains informations about **population**, **population density**, **surface** and **municipalities** at provincial level.
- COVID-19 Italy official data , which contains information about the number of **COVID cases** at province level and the number of **COVID-related fatalities** at regional level.

After adding these variables, we start by specifying and estimating three **ERGM models**, one for each analyzed day.

```
mod.feb <- ergm(feb.net ~ edges + mutual + nodematch('region', diff=F) + nodecov('ideg') +
                    nodecov('out_strength'))
mod.mar <- ergm(mar.net ~ edges + mutual + nodematch('region', diff=F) + nodecov('odeg'))
mod.may <- ergm(may.net ~ edges + mutual + nodematch('region', diff=F) + nodecov('ideg') +
                    nodecov('eig_vect_centr') + nodecov('covid_deaths'))
```

ERGM models show some sort of **performance decay**, where the goodness-of-fit diagnostics for the MCMC procedure worsen over time for different configurations, despite remaining quite acceptable for our purposes.

We observe how the best model fitted on May 5th data badly mimics geodesic distances and some network attributes.

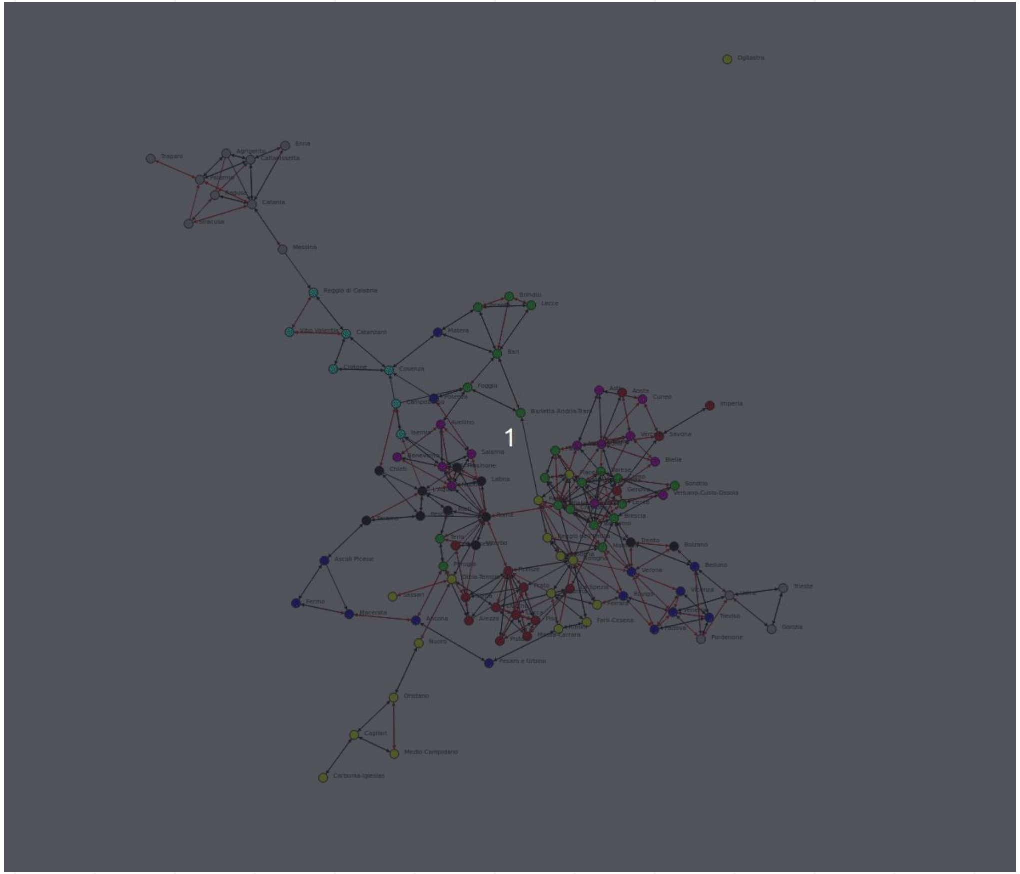


Moving to a **dynamic mobility network**, using **STERGM,** is highly desirable since it allows us to focus our analysis on **tie dynamics** (both formation and dissolution of edges) and **attribute dynamics** (e.g. change in nodes inbound and outbound strengths).

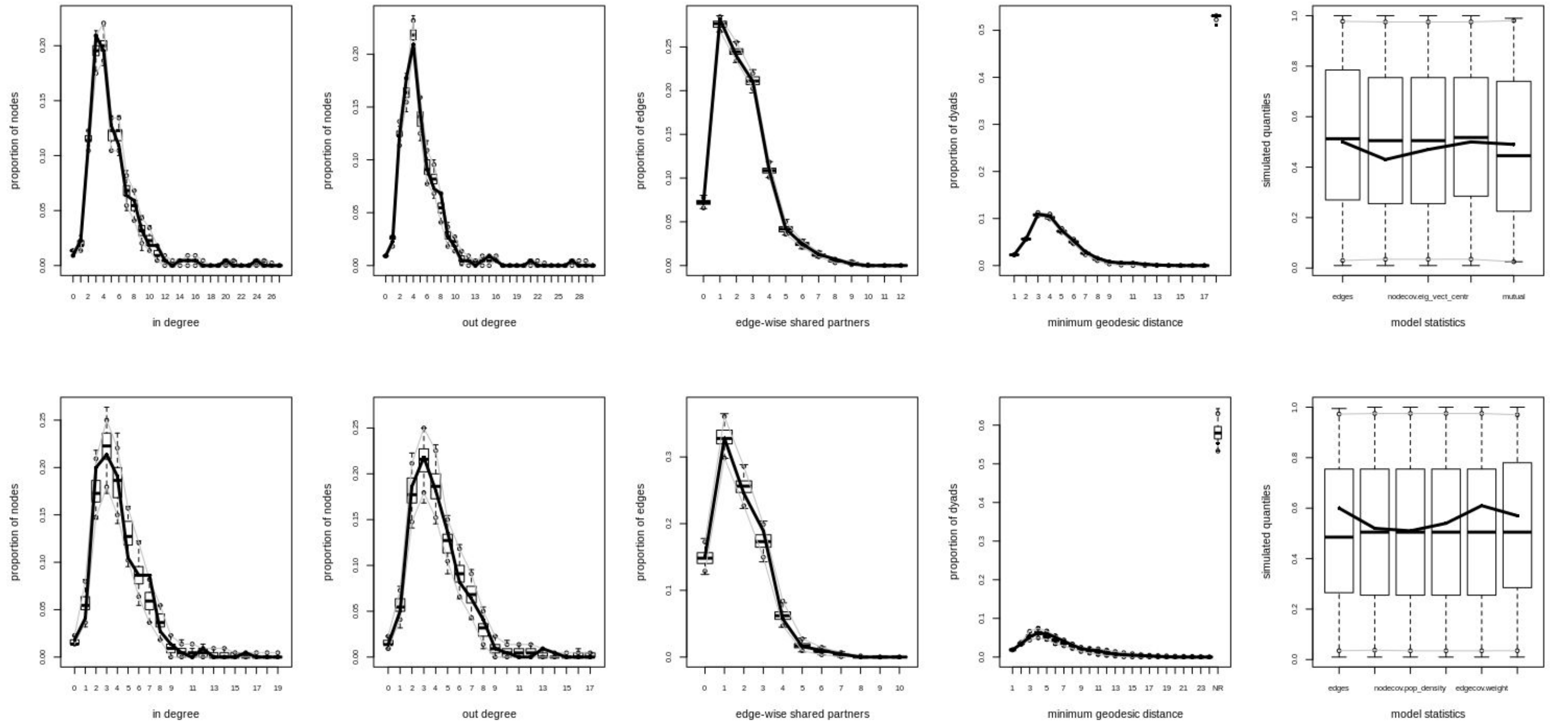
```
mob.nets <- list(feb.net, mar.net, may.net)
stergm.fit <- stergm(mob.nets,
                     formation= ~ edges + gwesp(0.25, fixed=T) + mutual +
                       nodecov('eig_vect_centr') + nodematch('region', diff=F),
                     dissolution = ~ edges + mutual + nodecov('covid_deaths') +
                        nodecov('pop_density') + edgecov('length_km') +
                        edgecov('weight'),
                     targets="formation", estimate = "CMLE")
```

STERGMs are composed by a model for **tie formation** and one for **tie dissolution** that are assumed as independent from each other. We use MCMC for fitting the models, using conditional maximum likelihood estimation (CMLE) as fitting procedure.

Simulating Network Temporal Evolution with a STERGM Model



	ERGMs			TERGM	
	Feb. 25th	**Mar. 10th**	**May 5th**	**Generation**	**Dissolution**
edges	-6.92^{***}	-7.50^{***}	-7.64^{***}	-9.62^{***}	-2.36^{***}
mutual	7.21^{***}	8.69^{***}	8.15^{***}	4.17^{***}	3.31^{***}
gwesp fix 0.25	-	-	-	0.92^{**}	-
in-degree	0.11^{***}	-	1.76^{***}	-	-
out-degree	-	0.10^{***}	-	-	-
eigen. centrality	-	-	-0.43^{***}	1.40^{*}	-
region	2.31^{***}	2.18^{***}	2.36^{***}	2.89^{***}	-
pop. density	-	-	-	-	-3^{*}_{e-4}
covid deaths	-	-	-3.95^{***}_{e-5}	-	$-1^{\cdot}_{e-3}$
edge weight	-	-	-	-	$.08^{***}$
edge length (km)	-	-	-	-	4^{***}_{e-3}
AIC	1795	1360	1293	174.1	416.8
BIC	1831	1390	1338	214.3	446.7

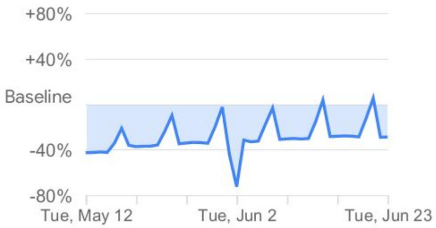


STERGMs provide a much better goodness of fit for the mobility network at all times.

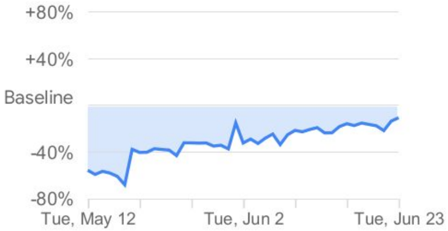
Conclusion

We conclude by comparing our results with **Google Global Mobility Report**, which measures daily visitors counts for specific location categories (e.g. train stations, workplaces, residential areas) and compares shifts in mobility as variations relative to a baseline day before the pandemic outbreak.

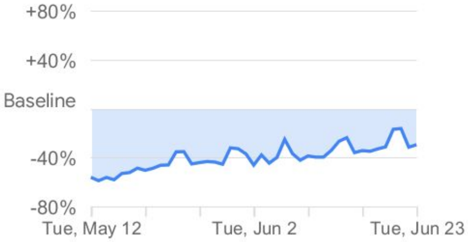
Focusing on the **Italy report**, we can see that the **reduction of movements** towards workplaces, for retail and recreation and towards transit stations estimated for May 12th (**roughly 40-50%**) is very similar to the results obtained from our mobility network (**43%**). This coherence in empirical observations acts as further support to the validity of our findings. The current situation seems to be improving ever since.



Workplaces



Retail & recreation



Transit stations

“

This analysis was by no means intended to cover all the interesting phenomena underlying such monumental shifts in mobility trends. We believe, instead, this research might be interesting to better understand the behavior of the Italian mobility network, and possibly make it more robust to counter future adversities.

THANK YOU FOR YOU ATTENTION!

Repository of the project at:

https://github.com/gsarti/lockdown-mobility-analysis