# Mobility effect on the spread of COVID-19 epidemics and restrictions efficacy on mobility

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- In the second part we want to study the real effectiveness of the restrictions on the human mobility, and eventually infer the time after which the the restriction became effective.

# Apple Mobility Data

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- Subsequent analysis highlighted coherence between the two types of mobility. Walking mobility data are missing for smaller region as Aosta Valley. For the sake of brevity and consistency we focused our analysis just on the driving mobility.

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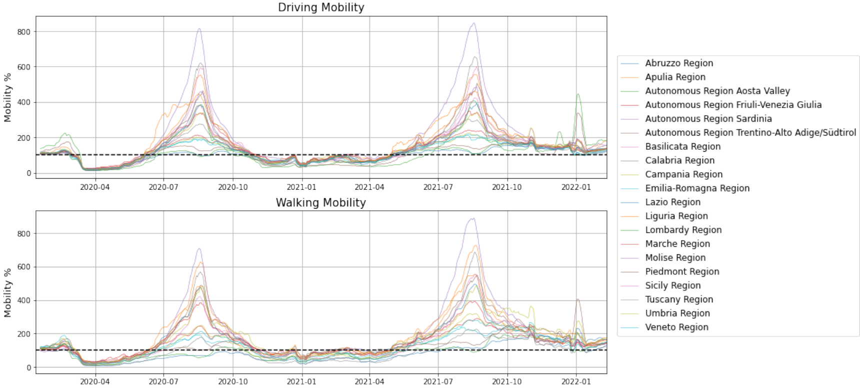
- To prevent spurious correlation due to the weekly periodicity of those data we performed a rolling average over 7 days.

# Visualization



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- Google acquired these data from users who have opted-in to Location History for their Google Account. As the AMD, this dataset is representative of a sample of users.

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- Again, to remove spurious correlations we performed a rolling average on time window of 7 days.

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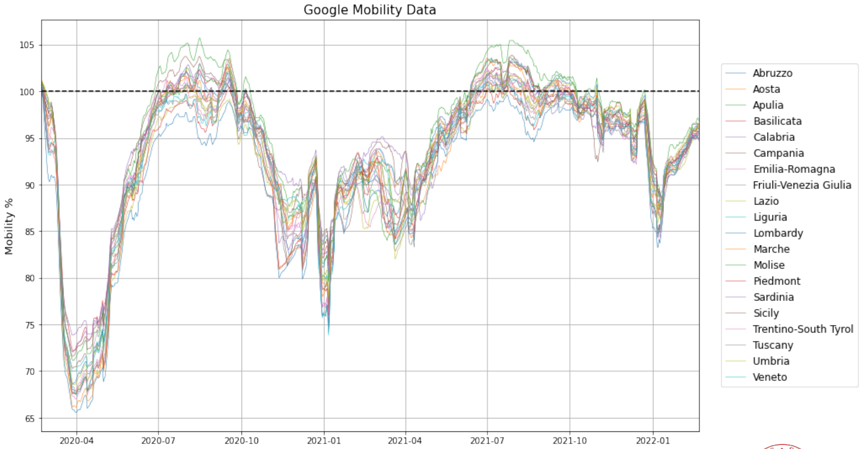
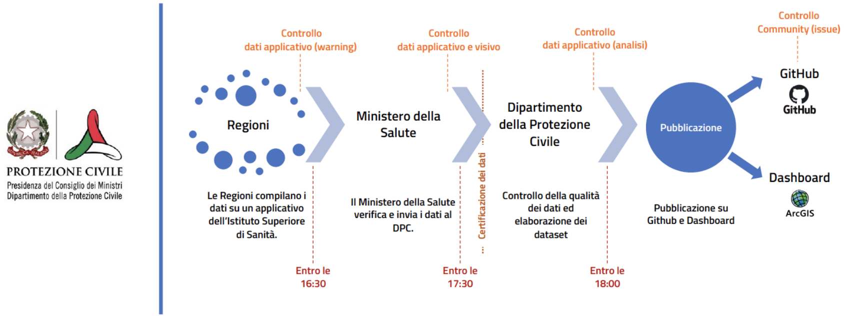


# Protezione Civile



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- Unfortunately significant trends such as "new cases with symptoms" and "daily hospitalized" are not present.

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- Also in this case we performed a moving average on a 7-days window.

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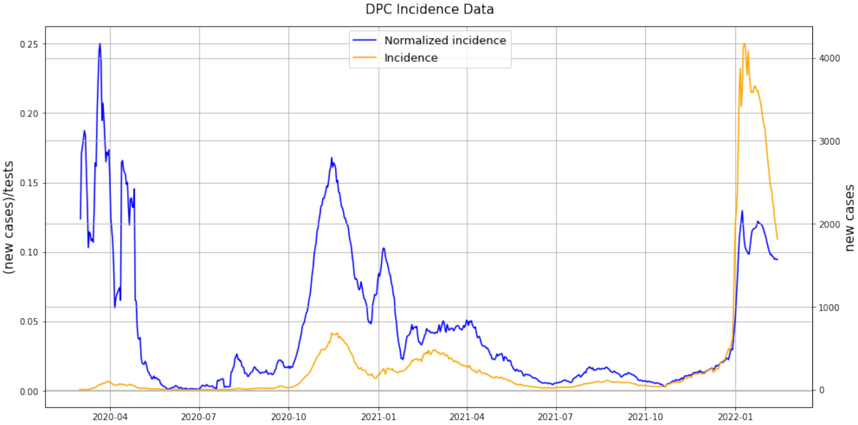

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  - 2020-05-19 to 2020-10-12: The "summer period" that goes until mandatory mask and the first measures to limits gatherings.
  - 2020-10-13 to 2020-11-05: The last windows before the regional restrictions based on colors.

# Macro Time Windows

In order to better organize all the different temporal frames we individuated four different macro time windows, that will be also helpful in further visualization:

1) 02/2020-10/2020. After the first outbreaks the lockdown started for 10 municipalities and gradually the regions started to close the schools and the Universities. Further restrictions were applied trying to contain the spread of the virus. From April 26 the government start to loose the restrictive measures. In the summer the contagions dropped even more and the restrictions became even more mild.

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# Scope

2) 10/2020-03/2021. Mask is mandatory in public and color zones are imposed over Italy, a curfew is applied and many stores are limited for their opening during the day. Furthermore during Christmas holidays Italy is put in a national red/orange zone for holidays and orange/yellow for weekdays.

# Scope

3) 03/2021-06/2021. After positives started again to increase yellow zone is abolished while a red zone is set during Easter holidays. Vaccines start to spread over people and COVID-19 green certification is established

# Scope

4) 07/2021-02/2022. The state of emergency is extended until 31 December 2021 and the contexts in which, starting from 6 August, the green COVID-19 certification is mandatory are extended; in addition, the parameters for the differentiation of the Regions in epidemiological scenarios change, this time on the basis of the employment rate of intensive care units and medical areas.

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- We know that the the effects of a contagion is visible after a certain period of time, comprehensive of the incubation period and the reporting time.
- We want to perform a lag-time analysis in order to see how the correlation changes with respect to the window we use to shift the incidence curve.

# Methods

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- We are then interested in a rank correlation coefficient, which can assess monotonic relationship (a looser assumption than the linear relationship)
- We choose to exploit Kendall's $\tau$ over the Spearman's $\rho$ due to the easier interpretation.

# Methods

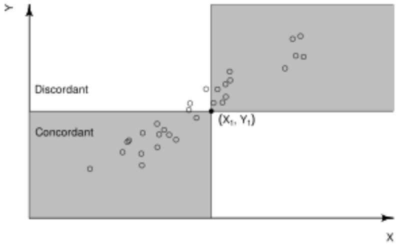
The Kendall $\tau$ is defined as:

$$\tau = \frac{(\#\text{of concordant pairs}) - (\#\text{of discordant pairs})}{\binom{n}{2}}$$

where a pair of observations $(x_i, y_i)$ and $(x_j, y_j)$ with $i < j$ are said to be concordant if:

- $x_i > x_j$ and $y_i > y_j$, or
- $x_i < x_j$ and $y_i < y_j$

with $i = 1, \ldots, n$.



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- We subdivided the data based on certain time windows: they could be either the period a certain region stayed of a certain color (ie. Abruzzo stayed orange from 2021-04-06 to 2021-04-26) or a notable time windows before color-restriction were established (ie. the first generalized lock-down from 2020-03-10 to 2020-05-18).

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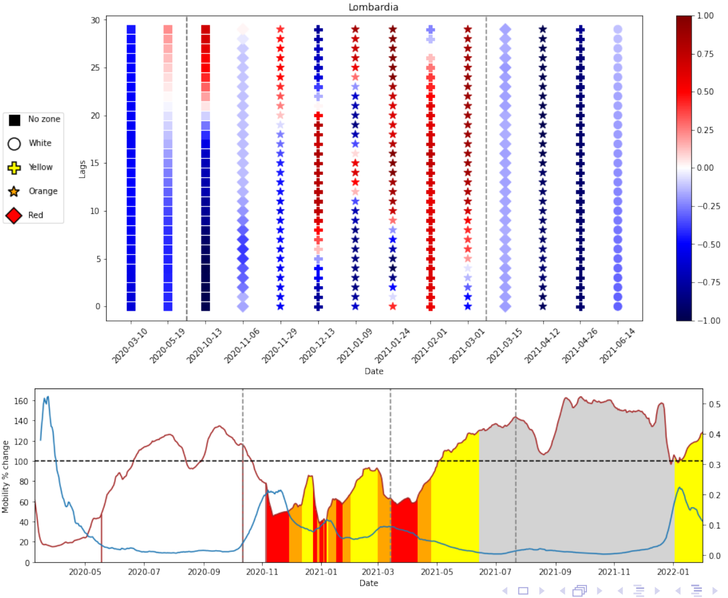
- We performed the lag-time analysis calculating the correlation between the mobility associated to the previously mentioned time windows and the correspondent incidence translated by the lag, for various values of lag.
- We repeated this analysis for every region and every correspondent time windows.

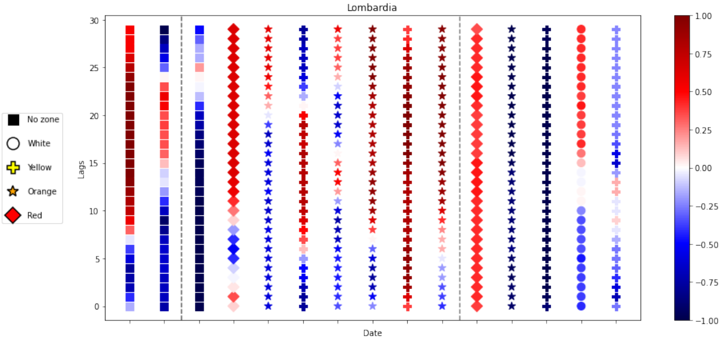
# AMD Results



Lombardia
No zone
White
Yellow
Orange
Red
Lags
Date
2020-03-10
2020-05-19
2020-10-13
2020-11-06
2020-11-29
2020-12-13
2021-01-09
2021-01-24
2021-02-01
2021-03-01
2021-03-15
2021-04-12
2021-04-26
2021-06-14
Mobility % change
Date

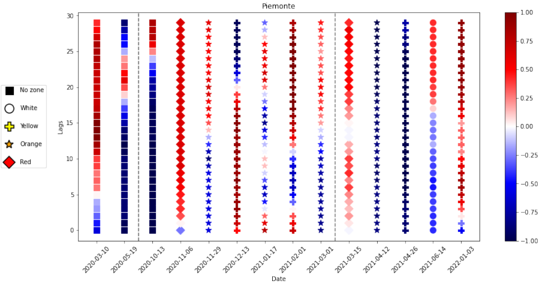
# AMD Results

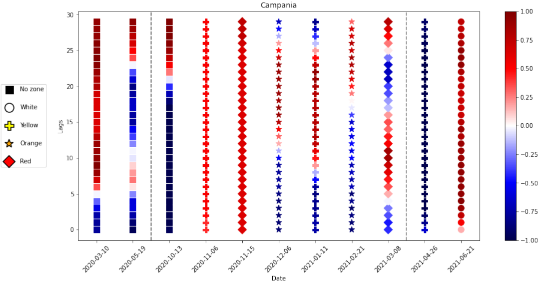
We need to point out that for each correlation analysis we are considering very different time windows. To be more consistent we can repeat the analysis considering just the first 10 days after a certain time window starts.



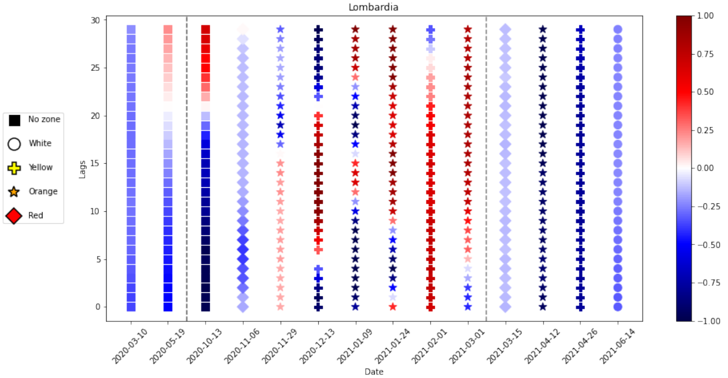
# AMD Results

It can be see that considering a smaller time windows we obtain similar results also for the other regions.



# GMD Results



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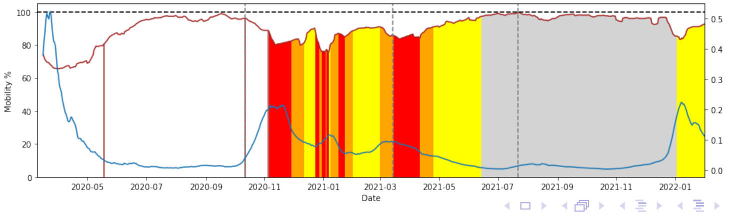
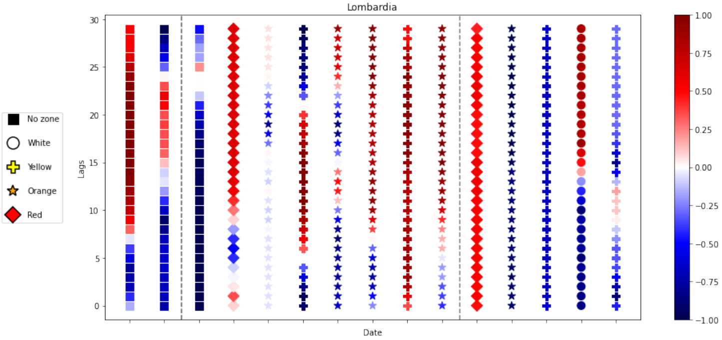
2021-01-24
2021-02-01
2021-03-01
2021-03-15
2021-04-12
2021-04-26
2021-06-14
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

Mobility %
Date
2020-05
2020-07
2020-09
2020-11
2021-01
2021-03
2021-05
2021-07
2021-09
2021-11
2022-01

# GMD Results

Also for Google's mobility data we repeat the analysis on a smaller time windows. Again we are considering just the first 10 days after a certain time window starts.



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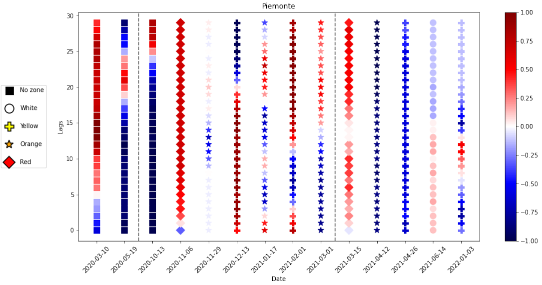


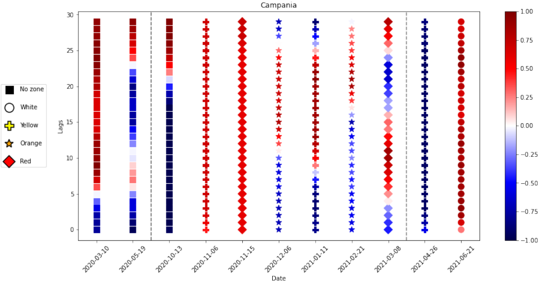

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- Considering the whole time windows associated to a certain color of a region bring inconsistency in the comparison, due to the fact these windows size can vary a lot.

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- Anyways, supposing that the sum of the incubation and reporting period lies in a range between 15-20 days is seems consistent with our result: for that lag range most of the $\tau$ curves are positively correlated!

# Further Considerations

- This analysis turned out more challenging then what we expected. It could have been useful to have access to the dataset of the "newly infected with symptoms" utilized by ISS in their estimation of the $R_t$, but unfortunately that data were not public.

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- It is worth mentioning also that the Mobility dataset are far from precise and are base on a certain sample population, that of course could not be representative of the whole.

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- Time series for the color change of each region in the time window 11/2020 – 02/2022.

Specifically we want to discover how many days people spend on average to adapt to the issue of restrictions, meaning what is the lag in time between restrictions emanation and their actual application.

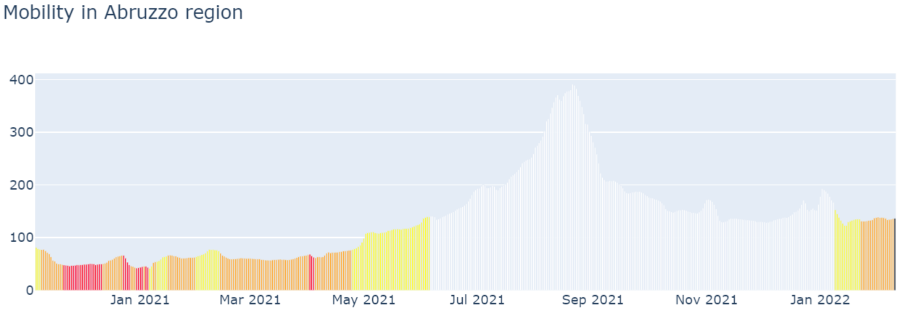
# Scope

- After we apply this procedure for all regions it would be useful to try to find a trend concerning how lag is distributed over time and over different time windows.

- We decide to take into account each time window when a region stays in a certain color and the last three larger time windows mentioned at the beginning of the presentation.

# One example

If we plot the colors time windows and mobility for one region (e.g. Abruzzo) we notice that the first mentioned are directly reflected into a change of mobility. For this reason we want to discover whether in the other regions the behavior is the same or not.



# Methods

We should first find an agreement to follow for detecting when restrictions have a certain efficacy on the mobility of population.
We would like to see when and within how many days a color change corresponds to a lighting or weighting of restrictions in mobility.
Let's consider mobility differences:

# Methods

- Positive points correspond to an increment, with as magnitude the height of the column, of mobility while negative ones correspond to a decrement of mobility w.r.t the previous day;

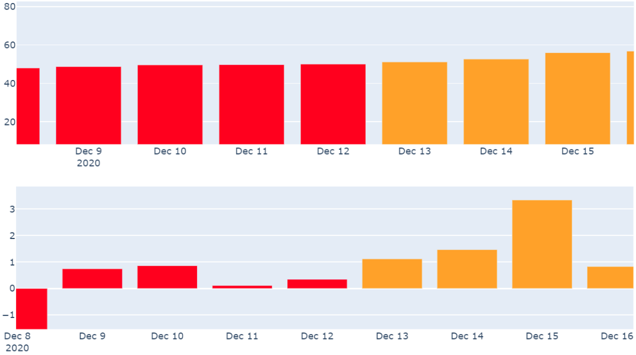



Figure: From top to bottom example of mobility and mobility differences

# Methods

- Differences of mobility differences represent the positive or negative velocity of variations in mobility. It means that if two consecutive points in mobility differences are both positive, then they both reflect an increment of mobility, but if the second is higher than the first then its mobility has changed faster than the first one.

$$\Delta(M(t+1)) - \Delta(M(t)) > 0 \longrightarrow \Delta[\Delta(M(t))] > 0$$

# Criteria for detecting the application of restrictions

We are interested in those change of colors that strengthen the restrictions, why?

- If a region moves from a color to a lighter one people might be influenced in moving more but it does not imply that they would move less, "violating" then the restrictions, since there are no stronger restrictions issued. It means that if we want to detect whether a restriction is respected or not we should consider those changes that reinforce limitations instead of lowering them.

# Criteria for detecting the application of restrictions

There could be four cases:

1. Mobility difference is positive before and after the color change;
2. Mobility difference is positive before the color change and negative after;
3. Mobility difference is negative before the color change and positive after;
4. Mobility difference is negative before the color change and negative after.

# Criteria for detecting the application of restrictions

If a color changes into a darker one we would expect a lower value in mobility in the next day or within a certain range of days.

Case **one** is pathological since mobility after the restrictions continues to increase even if with a lower rate.

In case **four**, when signs of mobility differences are both negative, we consider a good case the one where mobility still continues to follow a shrinking trend but from one day to another its decrease is higher than the day before the change in color.

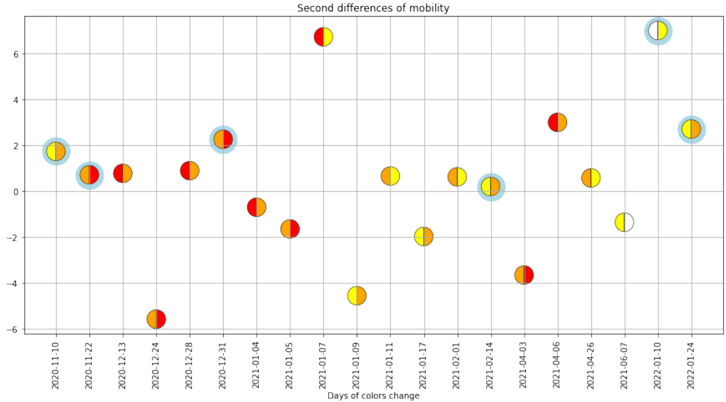
# Criteria for detecting the application of restrictions

Case **two** will be always a good one (for an instantaneous change in mobility or with lag) since after the color change mobility starts to decrease while before it was increasing.

Case **three** should be detected as a pathological one since mobility was decreasing before the color change but after that it starts to increase again

# Instantaneous effect on mobility hypothesis

Assume that we expect a "sudden" change in mobility when a region moves to a darker color. The only pathological case is when moving from one point to the successive one the mobility differences increment ($\Delta[\Delta(M)] > 0]$), meaning **third** case and the bad ones of **four**.



# Instantaneous effect on mobility hypothesis

In this way all those other points whose second differences are negative are assumed to manifest an instantaneous effect on mobility when a color changes. From this point we should have analyzed separately each pathological point and detect how many days after the application of the restriction mobility decreases or increases more slowly and then changes trend.

However the assumption of instantaneous change is wrong for those colors where, even if mobility second differences are negative, they could represent a slower increment in mobility but however an increment, and the day after mobility difference increases and sets a different trend.

# General filters

It's better to consider a series of filters that are to apply to all darkening colors change time windows. They should:

- take into account the behavior of the color zone the region came from with a memory of a certain number of days before the color change;

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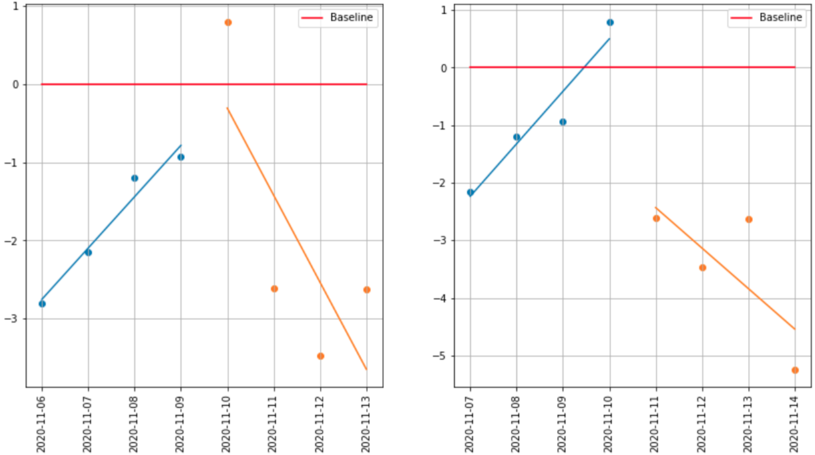
- take into account the behavior of the color zone the region came from with a memory of a certain number of days before the color change;
- consider a window of days after the restriction in order to have a mobility trend prediction after the color change.
- relax the condition on the velocity of mobility variation that detected as bad cases those in the second difference of mobility plot.

An example with Abruzzo region with two iterations of the filter:



# Time lag estimation

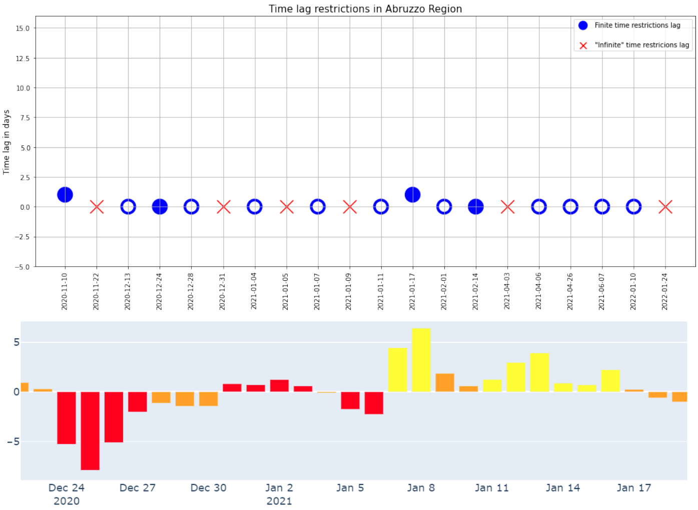
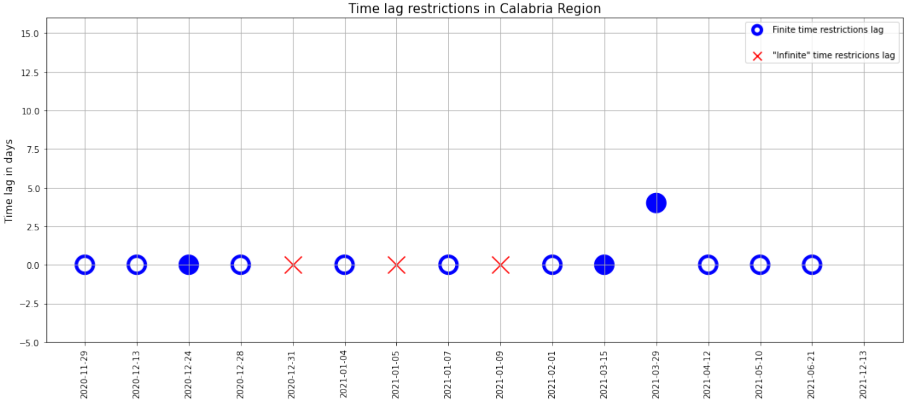
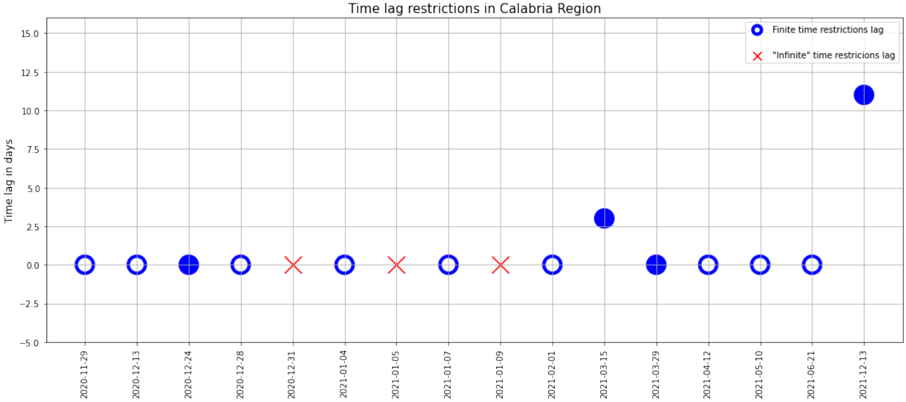



Figure: From the top: Abruzzo restrictions time lag distribution, Abruzzo mobility difference for Christmas holidays.

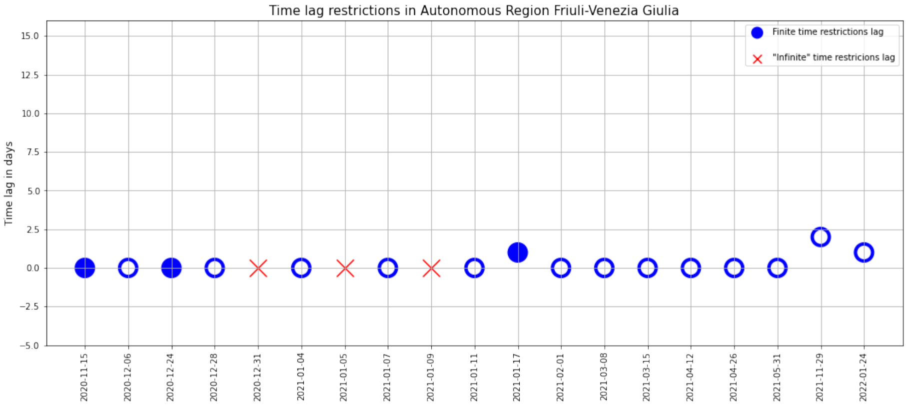
# Results: time lag distribution Apple mobility



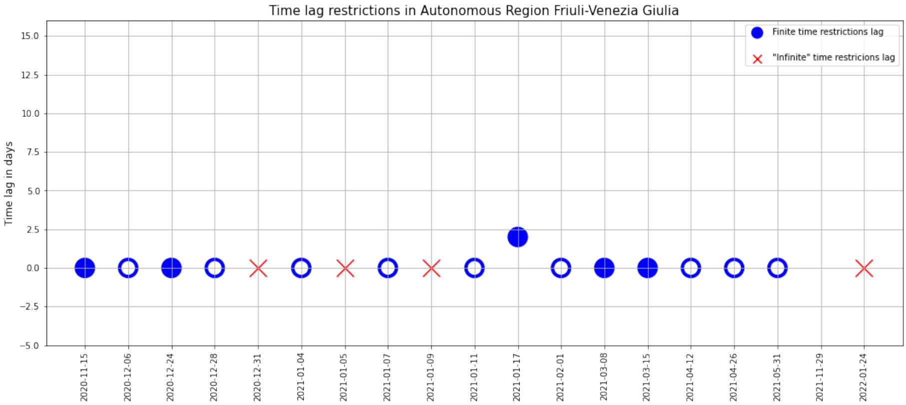
# Results: ime lag distribution Google mobility



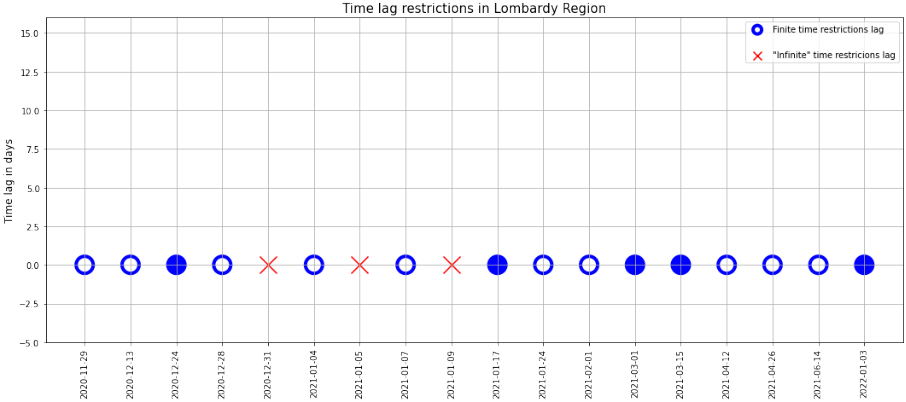
# Results: time lag distribution Apple mobility



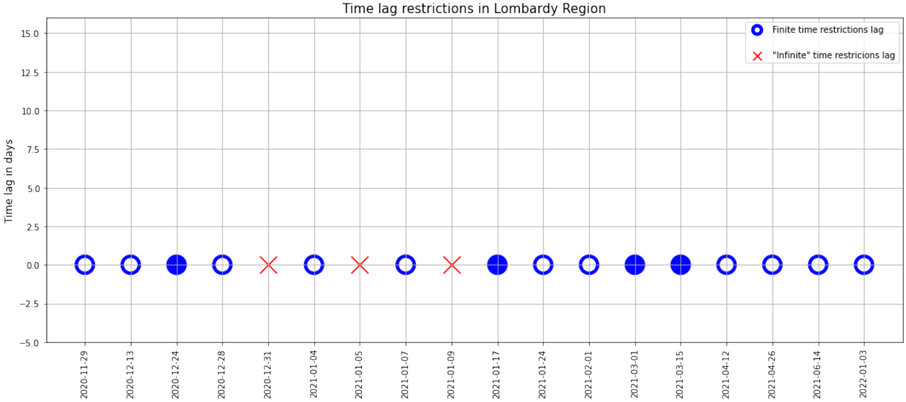
# Results: time lag distribution Google mobility



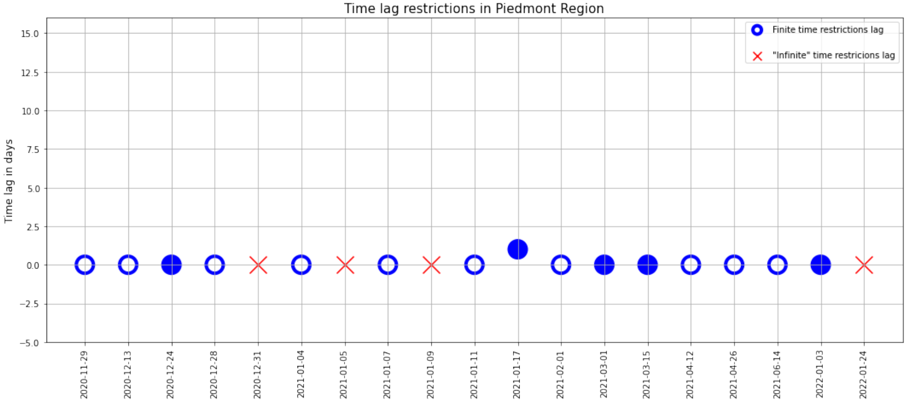
# Results: time lag distribution Apple mobility



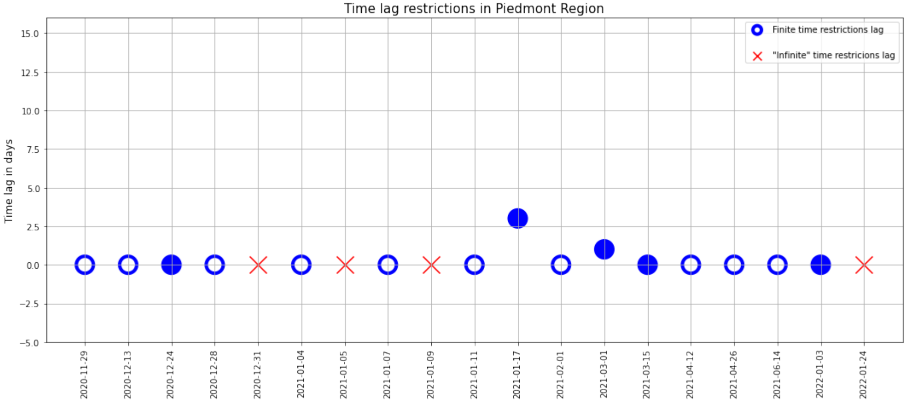
# Results: time lag distribution Google mobility



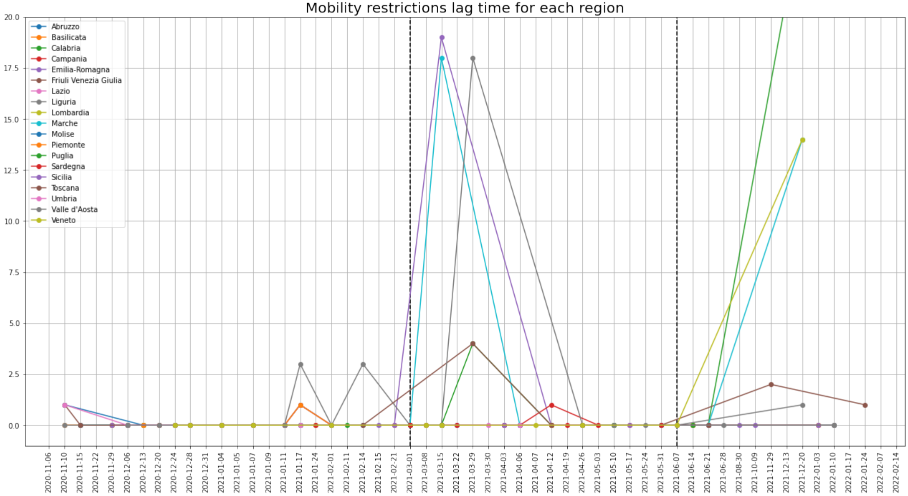
# Results: time lag distribution Apple mobility



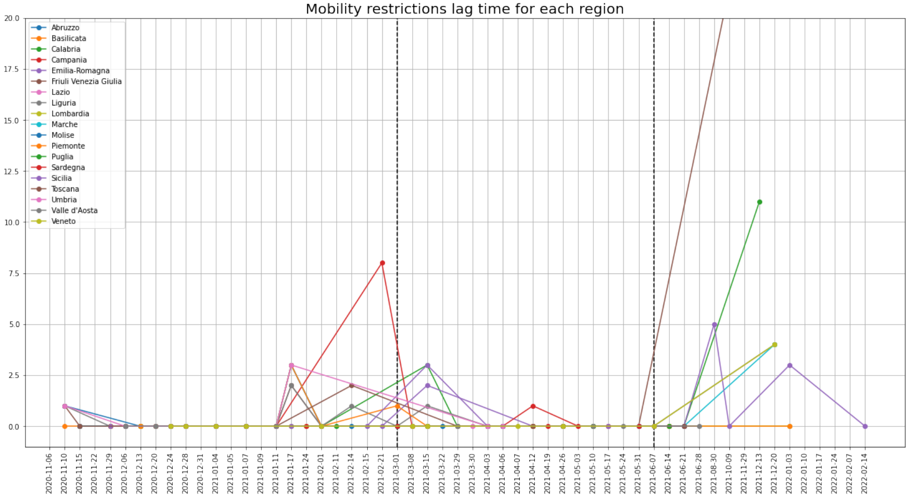
# Results: time lag distribution Google mobility



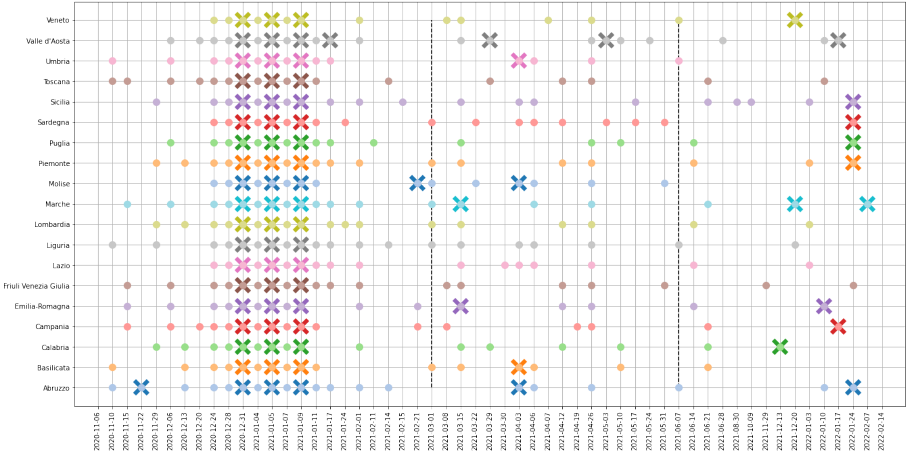
# Results: all regions time lag distribution Apple mobility



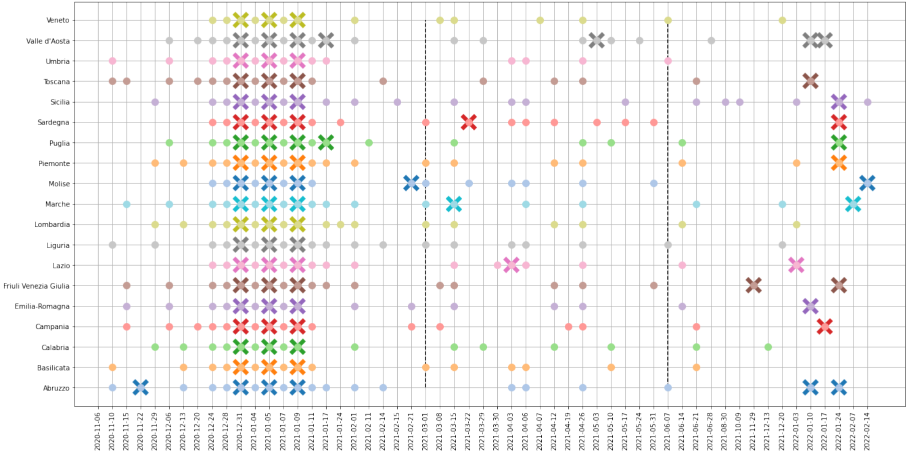
# Results: all regions time lag distribution Google mobility



# Results: restrictions efficacy Apple mobility



# Results: restrictions efficacy Google mobility



# Conclusions and further considerations

- we can see that time lags in the application of restrictions strictly depends on the duration of each color zone;
- overall time lag distribution presents a trend such that when approaching the present date time lags increase and restrictions become less effective;
- lags for each region are strongly related to the time window chosen during the filtering procedure;
- during Christmas holidays restrictions seems to be really ineffective since color changes happen one day after each other and our detection filter deprecates all those color zones that range less than four days.

Thanks for your attention!