Towards New Metrics Assessing Air Traffic Network Interactions

Silvia Zaoli

Salzburg 6 of December 2018

Founding Members

EUROPEAN UNION EUROCONTROL

Domino Project

Aim: assessing the impact of innovations in the European ATM system

Innovations change the actions and the behaviour of agents of the ATM system (airlines, airports, Network manager, AMAN, DMAN, ….)

- 4D Trajectory adjustment (delay management strategies of airlines)
- Flight Prioritization (exchange of departure slots between flights)
- Flight arrival coordination (tactical management of arrival to reduce reactionary delays)

Domino Project

Innovations will be implemented in an Agent Based Model (ABM)

- simulates one day of operations (pre-tactical and tactical phases) in different scenarios

- scenarios implement the mechanisms at different levels (current operation to maximum innovation)

- simulates the action and interactions of a massive number of agents: the airlines, airports, Network manager, passenger etc.

  -> captures the phenomena emerging from these complex interactions

Effects of innovations

How do we assess and quantify the impact of innovations in a certain scenario at the global level from the results of the ABM?

Air traffic is naturally described as a networked system

→ Network science provides us with tools to study the interaction of network elements, the role of topology in the propagation of signals (e.g. delay or congestion) and in the network functioning

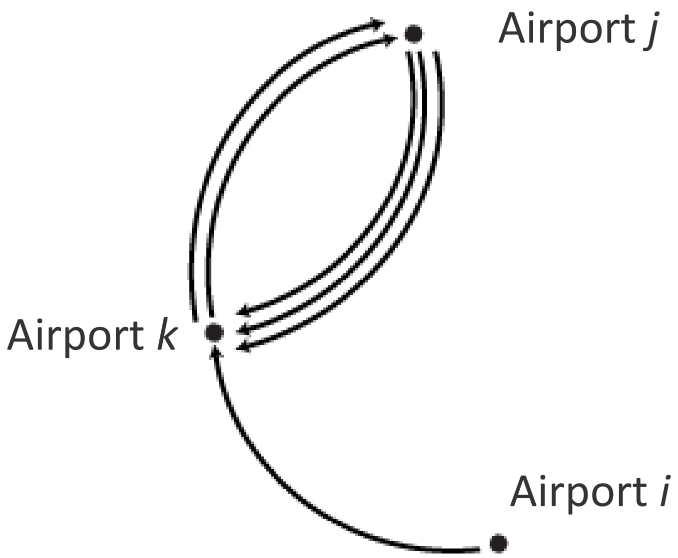
We consider two types of effects of innovations:

- Preservation of possible passengers' itineraries (connectivity of network of airports and flights)

- Tightening/weakening of interdependence of the systems' elements (e.g. of airports, of airlines, or of all agents)

Preservation of connectivity

Network of airports (nodes) and flights (directed links)



A walk of length *n* from *i* to *j* is a sequence of n flights that brings from *i* to *j*

Centrality metrics (Katz, PageRank) measure the connectivity of a node in terms of its number of incoming or outgoing walks:

$kc_i = \alpha \times$ (#walks of length 1) + $\alpha^2 \times$ (#walks of length 2) + … $\quad \alpha \leq 1$

(longer walks contribute less)

Preservation of connectivity

Let us compare two networks:

Scheduled network	Realized network
Scheduled flights (with scheduled departure and arrival times)	Realized flights (with realized departure and arrival times, possibly cancelled)
	Some possible itineraries lost

If walks represent possible passengers' itineraries, the loss of centrality between the scheduled and the realized network measures the loss of connectivity of an airport due to delays

→ Innovations make the systems more robust if they preserve the centralities of airports (between the scheduled and the realized network)

If innovations are implemented locally (only in specific airports), is the benefit local or does it extend?

Preservation of connectivity

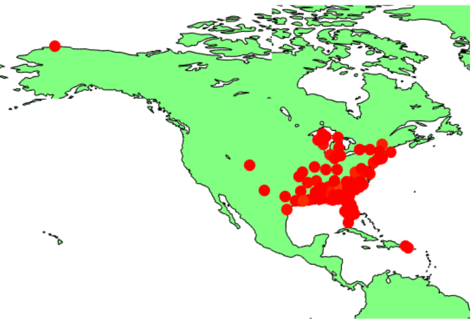
Do walks represent possible passengers' itineraries?

- Standard centrality metrics apply to STATIC, SINGLE-LAYER networks
- Walks on the static, single-layer network do not represent itineraries that can be actually traveled! And delays do not affect walks

Comparison of two days with different delay situations

US airspace, 3 and 9 April 2015

Few, small delays



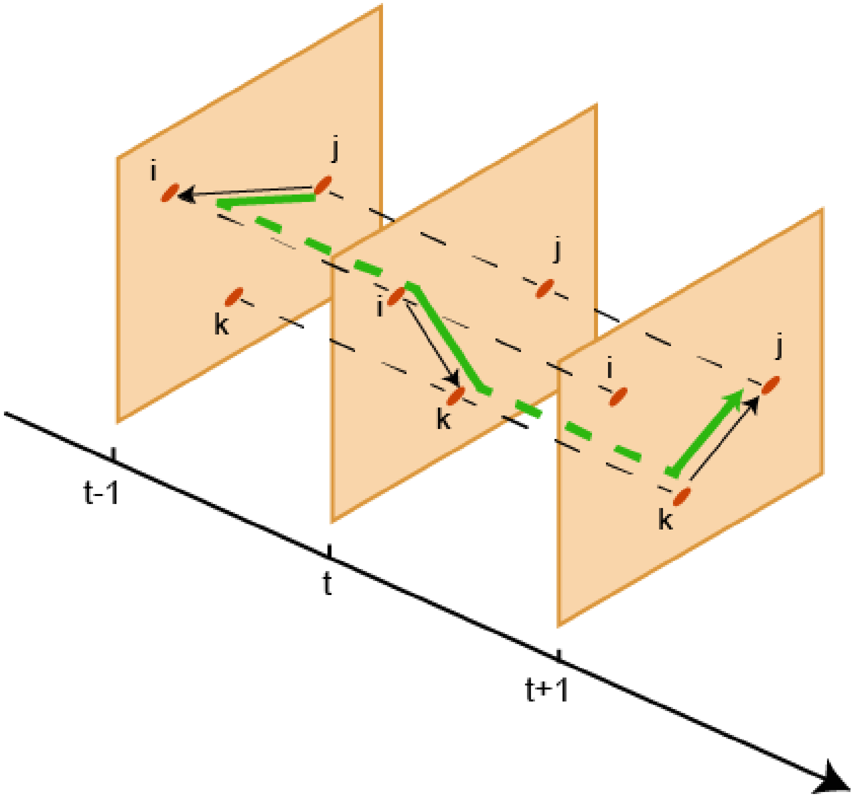
Many, large delays

The ranking of airports according to their centralities changes very little between the scheduled and the realized network!

day 1: τ=0.995
day 2: τ=0.985

Preservation of connectivity

The network of airports and flight is a TEMPORAL MULTIPLEX

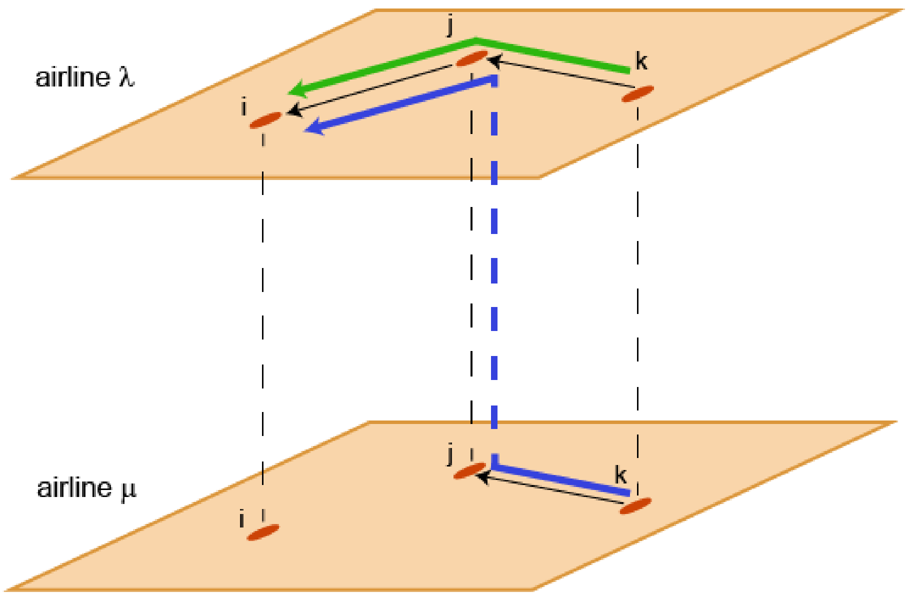


Temporal network

- The network changes at each time step
- Walks are time-oriented

Preservation of connectivity

The network of airports and flight is a TEMPORAL MULTIPLEX



Multiplex

- One layer per airline
- Walks can be intra- or inter-layer

Preservation of connectivity

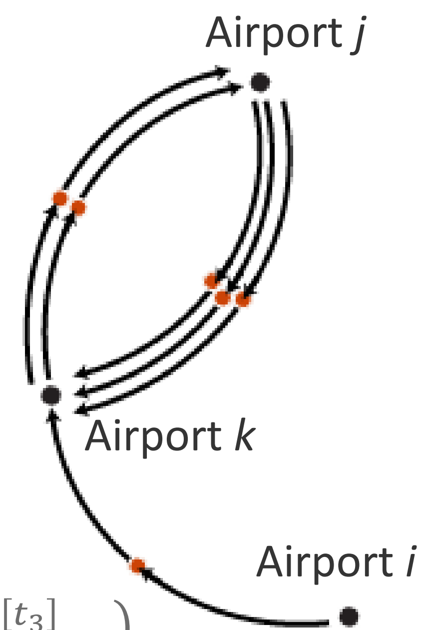
We need to define new centrality metrics for temporal multiplexes, where walks represent itineraries that can actually be traveled

Standard Katz Centrality $kc_i^{out} = \sum_{n=1}^{\infty} \sum_j \alpha^n A_{ij}^n$

A_{ij} adjacency matrix of the network
A_{ij}=1 if there is a link from *i* to *j*

Trip Centrality tc_i^{out}

- Adjacency matrix $A^{[t]}$ depends on time
- Introduction of secondary nodes ensures that walks respect schedules
- A copy of each airport per layer, each inter-layer jump has a cost ε (the walk weights less)

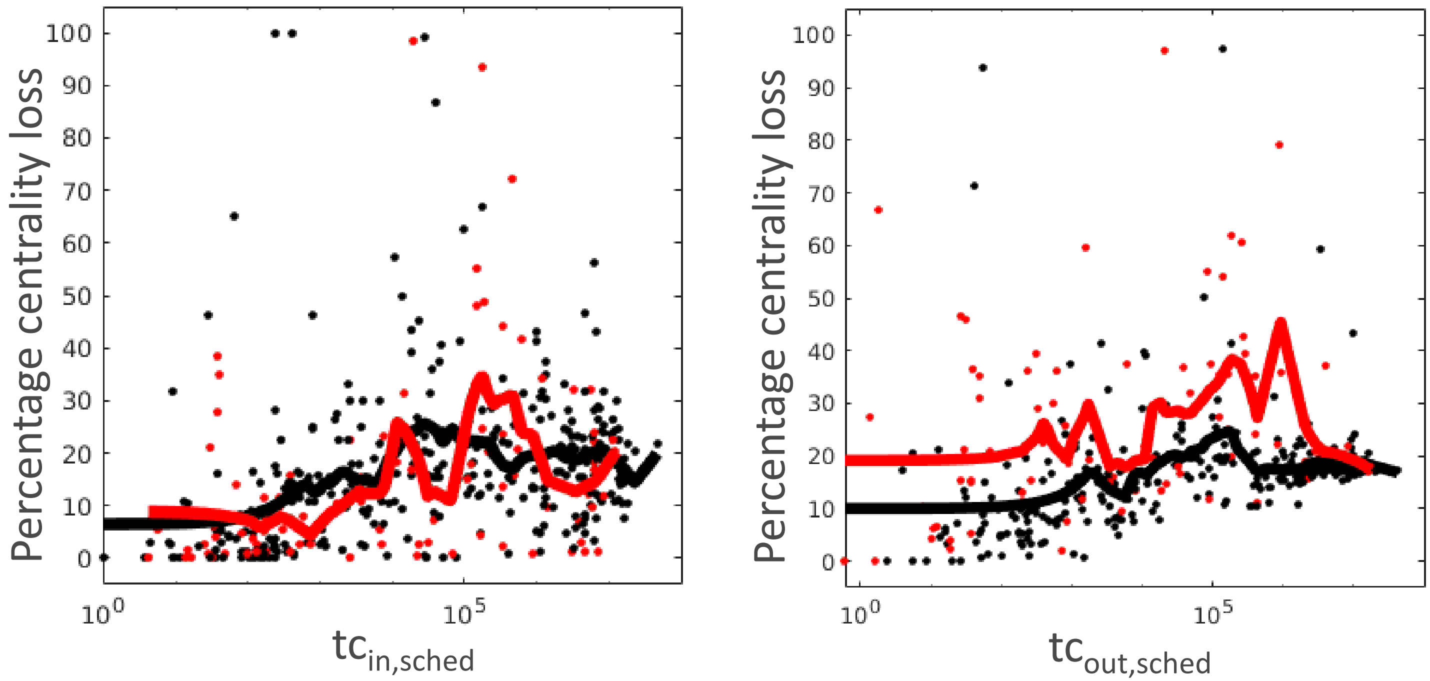


To obtain tc_i^{out} I sum contributions of the form $\left(\alpha A^{[t_1]} K \alpha A^{[t_2]} K \alpha A^{[t_3]} \ldots\right)_{ij}$ where $K = K(\varepsilon)$ and $t_1 < t_2 < t_3 \ldots$

Preservation of connectivity

Application to data: 1 September 2017, ECAC airspace

Percentage of centrality lost:



Each dot is an airport
Red dots are airports with many departing flights with large departure delays

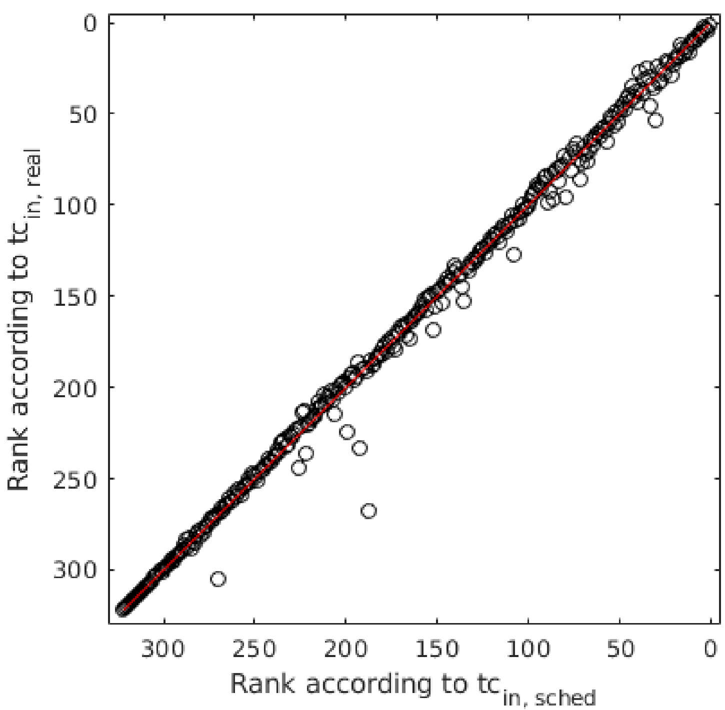
Not all airports with many delayed flights lose centrality, and vice versa

Centrality loss quantifies something different with respect to delays, because disrupted itineraries do not depend trivially on the delays

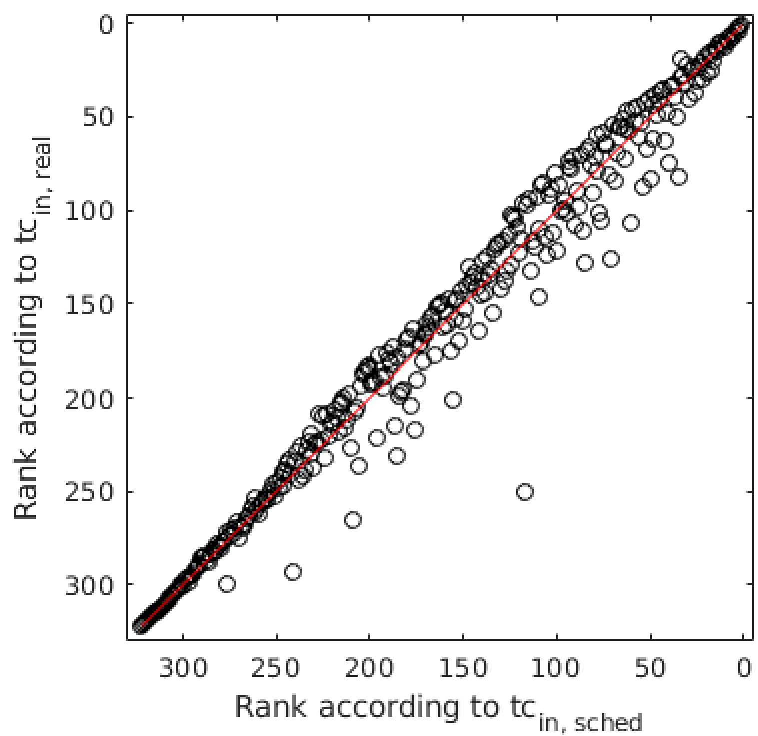
Preservation of connectivity

Application to data: 3 and 9 April 2015, US airspace

Day 1: τ=0.97

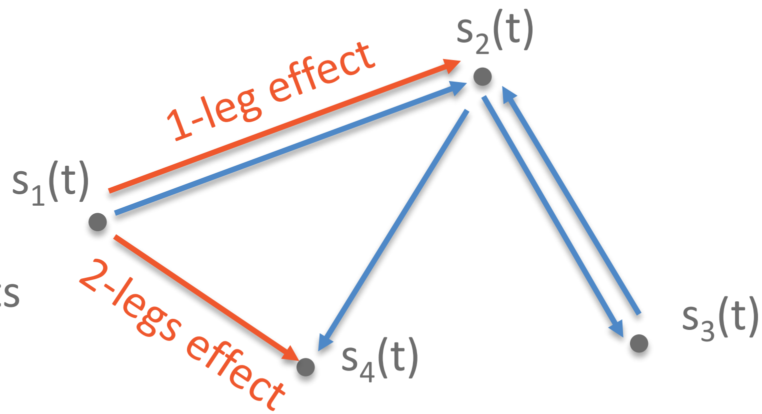


Day 2: τ=0.94



Interdependence of elements

- The interaction of the system's elements fosters the transmission of signals on the network, like e.g. delays or congestions
- Let us focus on the network of airports and flights (although the method is more general).
- Each airport is characterized by its "state of delay", the average departure delay of its flights (suitably detrended for daily seasonality)
- Does $s_2(t)$ influence $s_1(t)$? (is there a causal relation?)



- A causal relation between two airports could arise, e.g., when they are connected by direct flights because of reactionary delays (1-leg effect) but also when they are not connected directly (2- or more-legs effect)
- Once pairwise causal relations are detected, we can build a second network where links are the casual relations
- Characterizing this network informs us on the delay propagation patterns

How do we detect causal relations?

Causality relations

Granger causality in mean

- Well established statistical test to detect causality between time series [Granger, C. W. (1969)
- A time series $s_2(t)$ causes $s_1(t)$ if the knowledge about the past observations of s_2 helps forecasting the future observations of s_1

$$s_1(t) = \varphi_0^1 + \sum_{j=1}^{p} \varphi_j^{11} s_1(t-j) + \sum_{j=1}^{p} \varphi_j^{12} s_2(t-j) + \epsilon_t^1$$

VAR(p) model

  - Test null hypothesis that the φ_j^{12} are null
  - If rejected, there is a causal relation between $s_2(t)$ and $s_1(t)$

  - Every possible couple of airports is tested, and a “causality network” is built with the resulting links [Zanin et al. (2017)]

Granger, “Investigating causal relations by econometric models and cross-spectral methods”, Econometrica, 1969
Zanin et al. “Network analysis of chinese air transport delay propagation”, Chinese Journal of Aeronautics 30(2), 2017

Causality relations

Improving the existing method

The test assumes linear dependence, which might not apply to delay, and treats small delays with the same importance as large delays

→ We consider, instead, only extreme delay events, and test causality on those (GRANGER CAUSALITY IN TAIL).

Extreme delay events: in the tail of the forecasted delay distribution.
New time series $\tilde{s}(t)$ =1 if the state of delay is extreme, zero otherwise.
Does $\tilde{s}_2(t)$ help predicting $\tilde{s}_1(t)$?

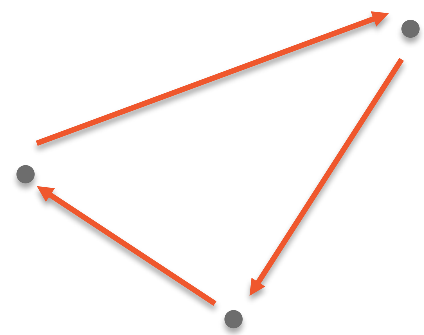
Causality relations

Application to data: Jan-Mar 2015, US air space

Overexpression of feedback loops and mutual linkages in the causality network (both in mean and in tail) with respect to the corresponding random case, enhancing delay propagation

the decrease of these patterns due to innovations would represent an improvement

Mutual linkage



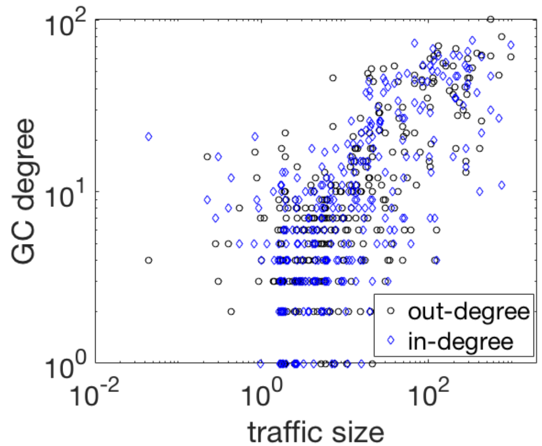
Feedback loop

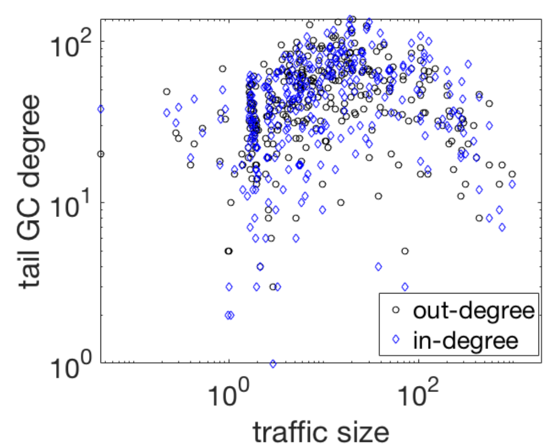
Causality relations

Application to data: Jan-Mar 2015, US air space

- With Granger causality in mean, larger airports tend to have more causality links, and these tend to overlap with flight-links (i.e., many 1-leg effects)
- With Granger causality in tail, middle sized airports have the most causality links, but small overlap with flights (2- or more legs effects dominate)

→ Large airports seem more important in the propagation of average delay (including small ones), but middle sized airports seem more important in the propagation of extreme delays, through 2- or more legs effects





GC degree= # causality links

Conclusions

We identified the following metric to assess innovations:

- Loss of Trip centrality between the scheduled and the realized network
  - on average for the entire network
  - for a specific airport
  - for a specific airline

- Density of links in causality network (the smallest, the better)
  - using delays of all airlines
  - using airline specific delays -> multi-layer causality network

- Feedback loops and mutual links (the less, the better)

This work was done with …

Piero Mazzarisi (Università di Bologna)

Fabrizio Lillo (Università di Bologna)

Gérald Gurtner (University of Westminster)

Luis Delgado (University of Westminster)

Towards New Metrics Assessing Air Traffic Network Interactions

Thank you very much for your attention!

This project has received funding from the SESAR Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement No 783206.

SESAR JOINT UNDERTAKING

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Bonferroni correction

- Multiple-hypothesis testing produces many false-negatives (false causal relations)

→ Need for a correction limiting these cases

Bonferroni correction: to obtain a significance level α on M tests, I use a corrected significance level α /M

- Applying the correction o the US data, the link density decreases from 45% to 5%

→ Many of the causality relation detected without the correction are not significant