

# APPROCHE CAUSALE : UNE CLÉ POUR COMPRENDRE LES TRANSFORMATIONS SOCIÉTALES



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# Introduction



- Les actuaires doivent affiner leur compréhension des phénomènes complexes face aux transformations sociétales et à l'émergence de nouveaux risques
- **Inférence causale et graphes acycliques dirigés (DAG)** permettent de représenter et d'analyser les relations entre événements.
- Réduisent les biais d'interprétation  
Renforcent la robustesse des modèles

## Buts de l'atelier

- Introduire ces concepts à travers des exemples concrets.
- Illustrer l'exploitation de l'IA générative et des données textuelles pour produire des graphes de connaissance causaux.

# Plan



1. L'inférence causale : un levier pour une meilleure analyse des risques
2. Les graphes acycliques dirigés (DAG) et IA générative au service de la causalité : quelques applications concrètes
3. Opportunités et limites de l'approche causale

# 1. Inférence causale



**claim 1** a paradigm shift is necessary

- “ What if we introduced usage-based telematics discounts—how much would that actually reduce accident rates? ”
- “ What if we offered pay-as-you-go payment plans—do they truly increase policy retention and reduce lapses? ”

See Lyon and Popov (2020), *the power of what if...*

**RISK ASSESSMENT**  
Peer-Reviewed

## THE POWER OF WHAT IF Assessing & Understanding Risk

By Thomas Lyon and Leonid Popov

**FIGURE 1**  
COMPARISON OF HAZARD ANALYSIS, RISK ANALYSIS & RISK ASSESSMENT

**FIGURE 2**  
WHAT IF RISK REDUCTION PROCESS

**FIGURE 3**  
TRADITIONAL WHAT IF HAZARD ANALYSIS EXAMPLE

**FIGURE 4**  
WHAT IF HAZARD ANALYSIS WORKSHEET

**FIGURE 5**  
SEMIOQUANTITATIVE RISK ASSESSMENT MATRIX EXAMPLE (3 x 3)

**FIGURE 6**  
RISK SCORING LEVELS & ACTION EXAMPLE

**FIGURE 7**  
CONNECTION AREA

**FIGURE 8**  
DISTANCE BETWEEN FILL LINES

**FIGURE 9**  
UNIFORM FILL LINE SHAPES & SIZES

**FIGURE 10**  
DATA OF CASE STUDY

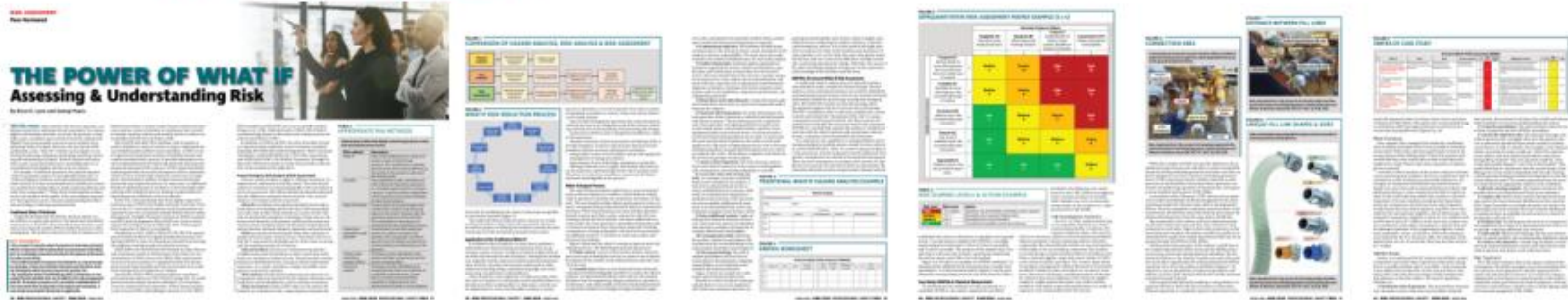
# 1. Inférence causale



**claim 1** a paradigm shift is necessary

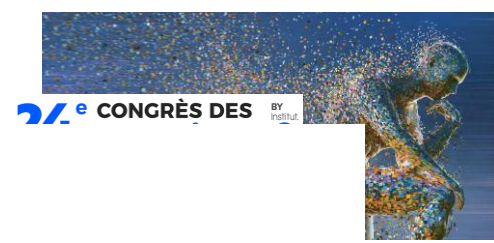
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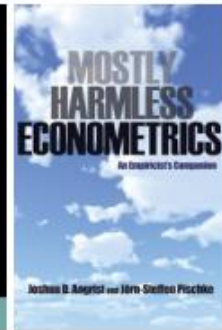
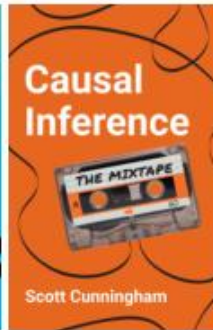
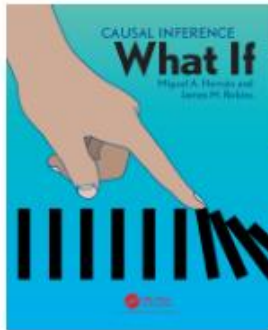
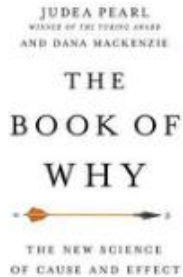


# 1. Inférence causale

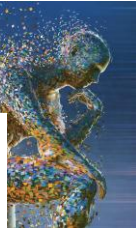


**claim 1** a paradigm shift is necessary

- “correlation does not imply causation”
- $\mathbb{E}[Y \mid \text{no treatment}] \stackrel{?}{=} \mathbb{E}[Y \mid \text{treatment}] \leftarrow$  regression or machine learning
- $\mathbb{E}[Y \mid \text{do}(\text{no treatment})] \stackrel{?}{=} \mathbb{E}[Y \mid \text{do}(\text{treatment})]$
- *do(...)* operator, formalized in Pearl (1994) *a probabilistic calculus of actions*



# 1. Inférence causale



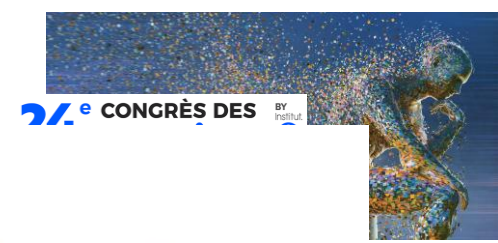
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- $\text{do}(\dots)$  operator, formalized in Pearl (1994) *a probabilistic calculus of actions*

**claim 2** there are simple methods for more relevant answers

- difference in differences
- regression discontinuity
- potential outcomes, counterfactuals (with causal graphs)
- matching, counterfactuals
- bias correction and re weighting

# 1. Inférence causale



**claim 1** a paradigm shift is necessary

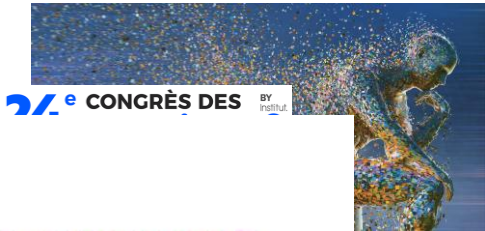
- “What if we introduced usage-based telematics discounts—how much would that actually reduce accident rates”
- “What if we offered pay-as-you-go payment plans—do they truly increase policy retention and reduce lapses”

**claim 1'** time travel is still not possible



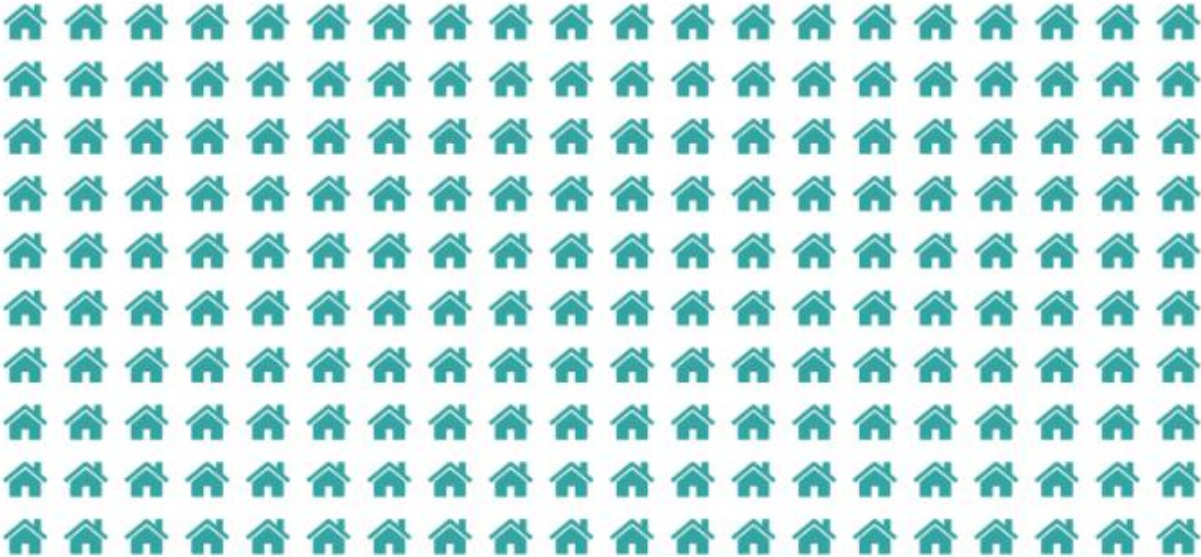


# 1. Inférence causale



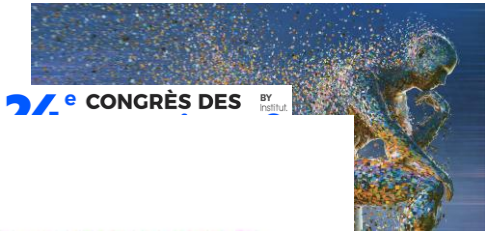
## Motivation

Does hospital recovery improve survival outcomes compared to home recovery?



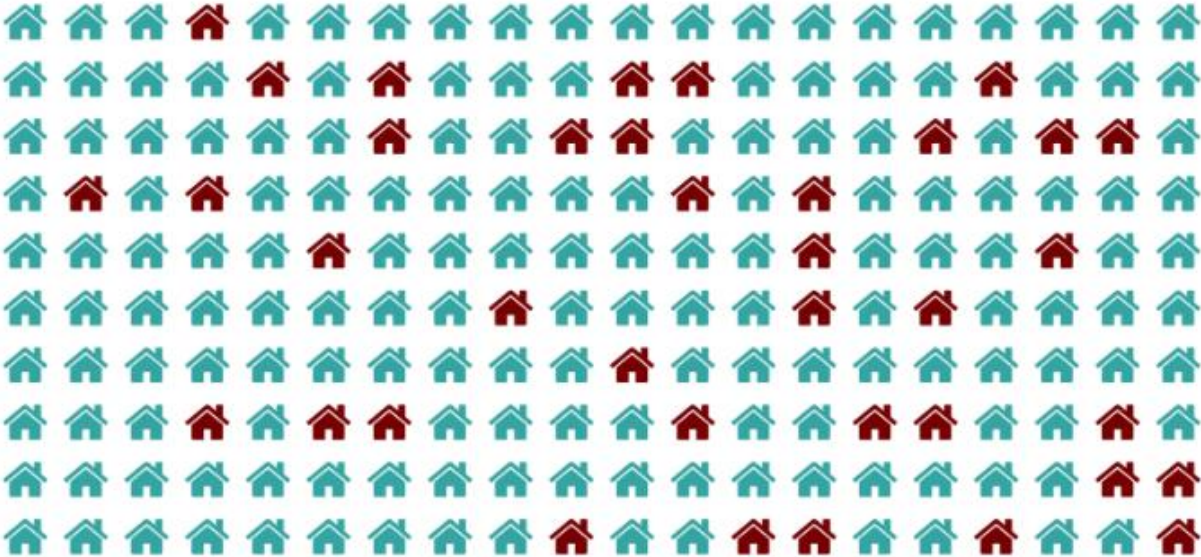
Initial situation, no treatment (home recovery for all patients)

# 1. Inférence causale



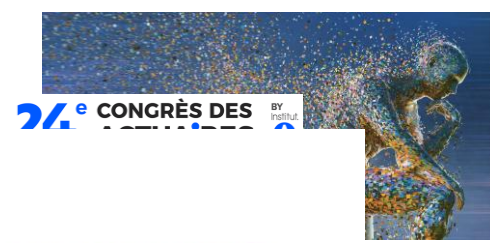
## Motivation

Does hospital recovery improve survival outcomes compared to home recovery?



Initial situation, no treatment,  $\mathbb{P}[Y = 1 \mid \text{no treatment}] \sim 20\%$

# 1. Inférence causale



## Motivation

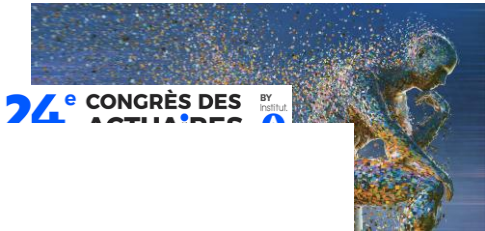
Does hospital recovery improve survival outcomes compared to home recovery?



Suppose we could **get back in time, treatment,** (hospital recovery for all patients)



# 1. Inférence causale



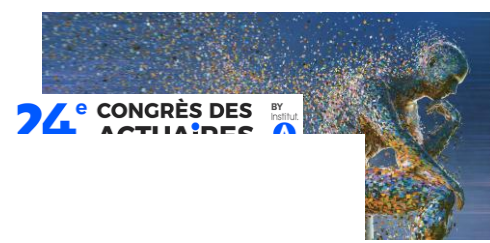
## Motivation

Does hospital recovery improve survival outcomes compared to home recovery?



Suppose we could get back in time,  $\mathbb{P}[Y = 1 | \text{treatment}] \sim 10\%$

# 1. Inférence causale



## Motivation

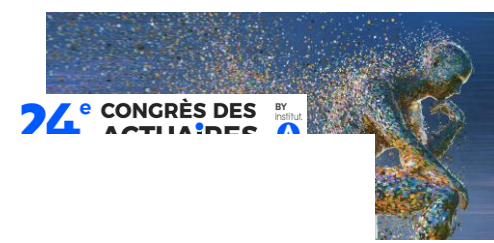
Does hospital recovery improve survival outcomes compared to home recovery?



Solution? split the population in two, control v.s. treatment



# 1. Inférence causale



## Motivation

Does hospital recovery improve survival outcomes compared to home recovery?



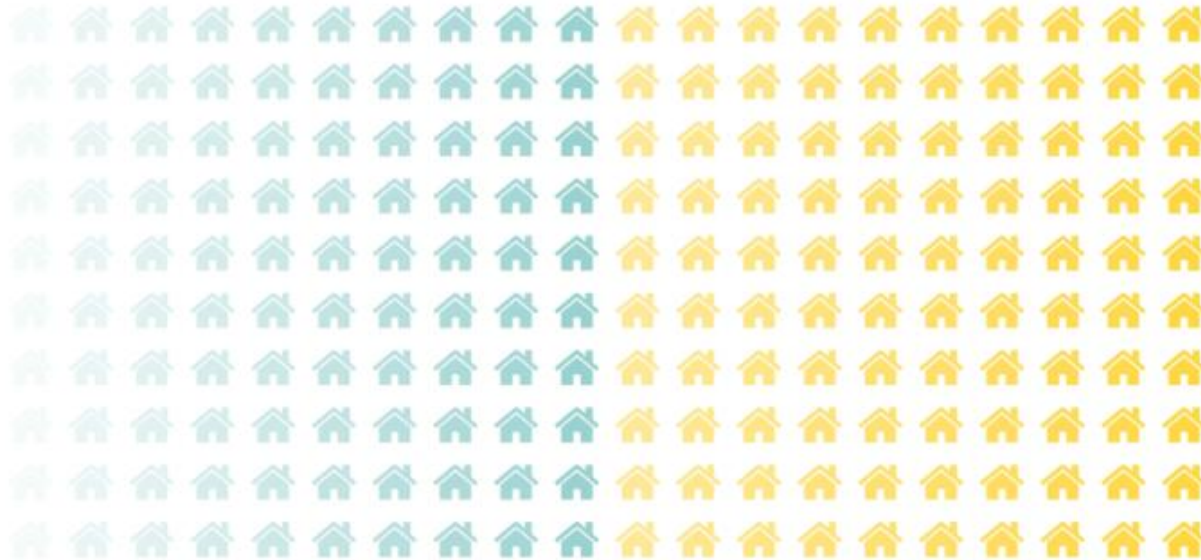
Compare:  $\mathbb{P}[Y = 1 \mid \text{no treatment}] \stackrel{?}{=} \mathbb{P}[Y = 1 \mid \text{treatment}]$

# 1. Inférence causale



## Motivation

Does hospital recovery improve survival outcomes compared to home recovery?



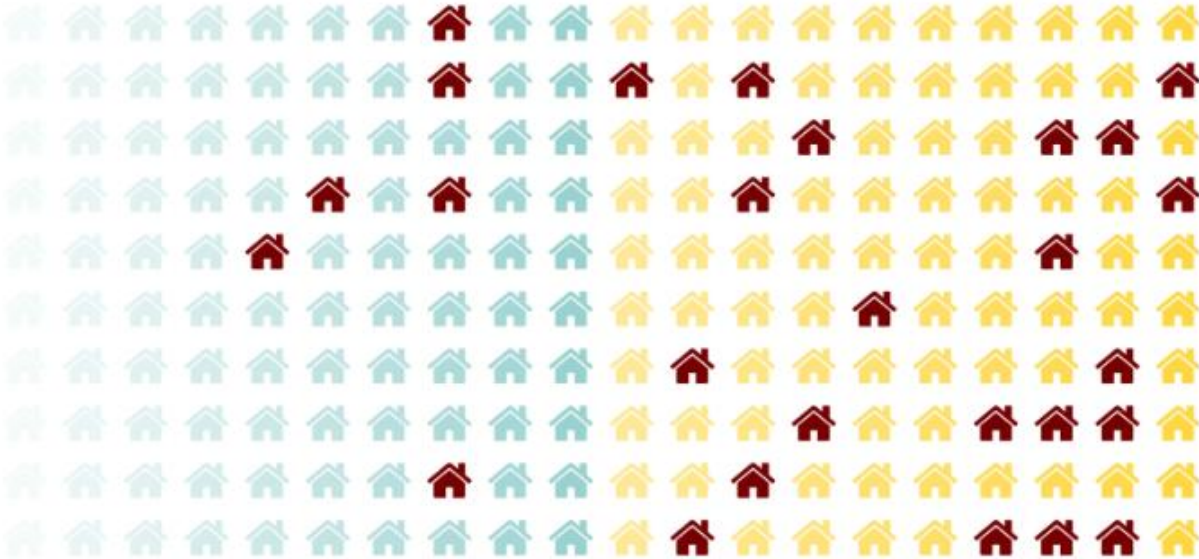
What if groups (**control** v.s. **treatment**) are related to ...?

# 1. Inférence causale



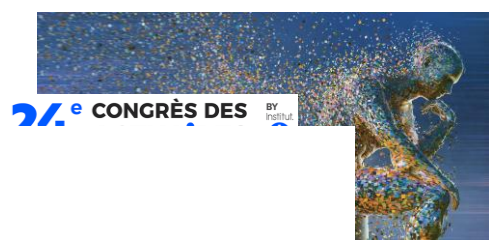
## Motivation

Does hospital recovery improve survival outcomes compared to home recovery?



What if groups (control v.s. treatment) are related to ...?

# 1. Inférence causale



## Motivation

- Group should be “as random as possible” (**randomized trial**)
- In many applications, we deal with **observational data** (not a real experiment)
- What we care about is not difference in (**conditional probabilities**),

$$\mathbb{P}[Y = 1 \mid \text{no treatment}] \stackrel{?}{=} \mathbb{P}[Y = 1 \mid \text{treatment}]$$

- We are looking for something more complicated, related to (**intervention**),

$$\mathbb{P}[Y = 1 \mid \text{do}(\text{no treatment})] \stackrel{?}{=} \mathbb{P}[Y = 1 \mid \text{do}(\text{treatment})]$$

or

$$\mathbb{P}[Y(\text{no treatment}) = 1] \stackrel{?}{=} \mathbb{P}[Y(\text{treatment}) = 1]$$

where  $Y(\text{no treatment})$  and  $Y(\text{treatment})$  are **potential outcomes**



# 1. Inférence causale

## Cas 1 - Intervention

“No causation without manipulation,” Holland (1986)

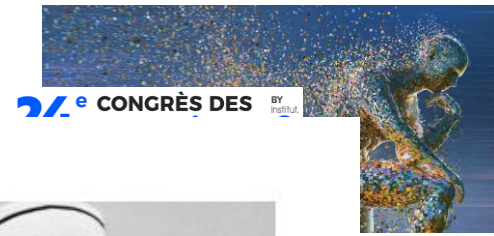
→ **Randomized Control Trial** (RCT)

- Check that key demographics and other confounders are balanced
- Find difference in average outcome in treatment and control groups
- Use statistical significance to test for effects

RCT considered a **Golden Standard**

See Jonas Salk's polio vaccine in the 50's, Meldrum (1998)

But doesn't fix attrition problem





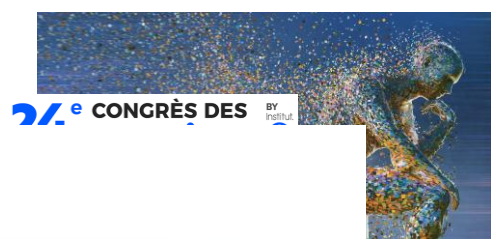
# 1. Inférence causale

## Cas 1 - Intervention

If the study is too short, the effect might not be detectable yet; if the study is too long, attrition becomes a problem (people might drop out because of the treatment, or because they got/didn't get into the control group)

- Hawthorne effect, observing people makes them behave differently
- John Henry effect, control group works hard to prove they're as good as the treatment group
- Spillover effect, control groups naturally pick up what the treatment group is getting

see also [Yeh et al. \(2018\)](#)



**RESEARCH**

**OPEN ACCESS**

**Check for updates**

**Parachute use to prevent death and major trauma when jumping from aircraft: randomized controlled trial**

Robert M Yeh,<sup>1</sup> Linda R Voldstad,<sup>2</sup> Michael W Vohs,<sup>3</sup> Changyu Shen,<sup>4</sup> Daniel R Kramer,<sup>1</sup> Jordan B Simon,<sup>5</sup> Eric A Secomsky,<sup>6</sup> Joanne L Hasty,<sup>7</sup> Robert M Dornier,<sup>8</sup> Orlin S Kain,<sup>9</sup> Bratislava K Rybalova<sup>10</sup> On behalf of the PARACUTE investigators

**ABSTRACT**

**OBJECTIVE**  
To determine if using a parachute prevents death or major traumatic injury when jumping from an aircraft.

**DESIGN**  
Randomised controlled trial.

**SETTING**  
Private or commercial aircraft between September 2017 and August 2018.

**PARTICIPANTS**  
57 aircraft passengers aged 18 and over were screened for participation. 23 agreed to be enrolled and were randomised.

**INTERVENTIONS**  
Jumping from an aircraft (parachute or helicopter) with a parachute versus an empty backpack (helicopter).

**MAIN RESULTS**  
Composite of death or major trauma: Injury (defined as an injury severity score over 10) upon impact with the ground: Resuscitated immediately after landing.

**RESULTS**  
Parachute use did not significantly reduce death or major injury (0% for parachute v 0% for control, P=0.5). This finding was consistent across multiple subgroups. Compared with individuals screened but not enrolled, participants included in the study were on aircraft at significantly lower altitude (mean of 0.6 m for parachute v mean of 314 m for non-participants, P<0.001) and lower velocity (mean of 0 km/h v mean of 882 km/h, P<0.001).

**CONCLUSIONS**  
Parachute use did not reduce death or major traumatic injury when jumping from aircraft in the first randomised evaluation of this intervention. However, the trial was only able to enroll participants on small commercial aircraft on the ground, suggesting cautious interpretation to high altitude jumps. When heli-

reporting the effectiveness of an intervention such as this commercial, randomised trials might selectively enroll individuals with a lower potential for death, thus distorting the applicability of the results to real practice.

**Introduction**  
Parachutes are routinely used to prevent death or major traumatic injury among individuals jumping from aircraft. However, evidence supporting the efficacy of parachutes is weak and guideline recommendations for their use are primarily based on anecdotal testimony and expert opinion.<sup>1-3</sup> Despite the widely held yet unsubstantiated belief of efficacy, many studies of parachutes have suggested injuries related to their use in both military and recreational settings,<sup>4,5</sup> and parachute injuries are broadly recognised in the World Health Organization's ICD-10 International Classification of Diseases, 10th revision.<sup>6,7</sup> This could cause concern for supporters of evidence-based medicine, because numerous medical interventions believed to be useful have ultimately failed to show efficacy when subjected to properly selected randomised clinical trials.<sup>8</sup>

Previous attempts to evaluate parachute use in a randomised setting have not been randomised owing to both ethical and practical concerns. Lack of evidence could inhibit recruitment of participants in such a trial. However, whether pre-existing beliefs about the efficacy of parachutes would, in fact, impact the randomisation of participants in a clinical trial has not been formally evaluated. To address these important gaps in evidence, we conducted the first randomised clinical trial of the efficacy of parachutes in reducing death and major injury when jumping from an aircraft.

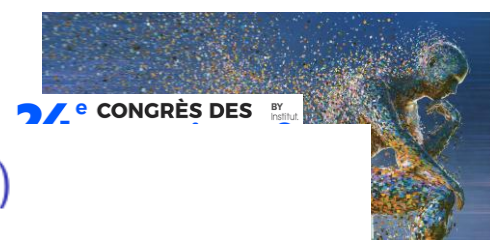
**Methods**

**Study protocol**  
Between September 2017 and August 2018, individuals were screened for inclusion in the PARACUTE or SHAREDHEALTH Study. Consented by study staff before flight<sup>9</sup> Lack of Treatment Eligible (SUSCRIPTIVE) trial. Prospective participants were approached and consented by study investigators on commercial or private aircraft.

The randomised aircraft, listed was related to trips the investigators were scheduled to take for business or personal reasons unrelated to the present study. Typically, passengers seated close to the study investigators (especially not known circumstances) would be approached and flight, between the time of initial seating and time of exiting the aircraft. The

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# 1. Inférence causale



## Case 2a - Double différences (ou différence des différences)

**"Difference in differences"** (DID), studying the differential effect of a treatment on a 'treatment group' versus a 'control group' in a natural experiment, Angrist and Pischke (2009)

Example minimum wages and employment, Card and Krueger (1994) and Imai (2022)

What happens if you raise the minimum wage?

Economic theory says there should be fewer jobs

New Jersey in 1992 \$4.25 → \$5.05

Average number of jobs per fast food restaurant in NJ

$\left\{ \begin{array}{l} \text{before (NJ)} : 20.44 \\ \text{after (NJ)} : 21.03 \end{array} \right.$

$\Delta = 0.59$ : Is this the causal effect?

### Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania

By DAVID CARD AND ALAN B. KRUEGER\*

*On April 1, 1992, New Jersey's minimum wage rose from \$4.25 to \$5.05 per hour. To evaluate the impact of the law we surveyed 410 fast-food restaurants in New Jersey and eastern Pennsylvania before and after the rise. Comparisons of employment growth at stores in New Jersey and Pennsylvania (where the minimum wage was constant) provide simple estimates of the effect of the higher minimum wage. We also compare employment changes at stores in New Jersey that were initially paying high wages (above \$5) to the changes at lower-wage stores. We find no indication that the rise in the minimum wage reduced employment. JLEL, 33(6), 323*

How do employers in a low-wage labor market respond to an increase in the minimum wage? The prediction from conventional economic theory is unambiguous: a rise in the minimum wage leads perfectly competitive employers to cut employment (George J. Stigler, 1966). Although studies in the 1970s based on aggregate teenage employment rates usually confirmed this prediction,<sup>1</sup> earlier studies based on comparisons of employment at affected and unaffected establishments often did not (e.g., Richard A. Lester, 1966, 1964). Several re-

cent studies that rely on a similar comparative methodology have failed to detect a negative employment effect of higher minimum wages: Analyses of the 1990-1991 increases in the federal minimum wage (Lawrence F. Katz and Krueger, 1992; Card, 1992a) and of an earlier increase in the minimum wage in California (Card, 1992b) find no adverse employment impact. A study of minimum-wage floors in Britain (Stephen Machin and Alan Manning, 1994) reaches a similar conclusion.

This paper presents new evidence on the effect of minimum wages on establishment-level employment outcomes. We analyze the experiences of 410 fast-food restaurants in New Jersey and Pennsylvania following the increase in New Jersey's minimum wage from \$4.25 to \$5.05 per hour. Comparisons of employment, wages, and prices at stores in New Jersey and Pennsylvania before and after the rise offer a simple method for evaluating the effects of the minimum wage. Comparisons within New Jersey between initially high-wage stores (those paying more than the new minimum rate prior to its effective date) and other stores provide an alternative estimate of the impact of the new law.

In addition to the simplicity of our empirical methodology, several other features of

\*Department of Economics, Princeton University, Princeton, NJ 08544. We are grateful to the Institute for Research on Poverty, University of Wisconsin, for partial financial support. Thanks to Orlin Ashenfelter, Charles Brown, Richard Lerman, Gary Solon, two anonymous referees, and seminar participants at Princeton, Michigan State, Iowa State, University of Michigan, University of Pennsylvania, University of Chicago, and the NBER for comments and suggestions. We also acknowledge the expert research assistance of Susan DeJans, Chris Burns, Geraldine Harris, and Jonathan Ohsuga.

<sup>1</sup>See Charles Brown et al. (1982, 1983) for surveys of this literature. A recent update (Alison J. Welfington, 1992) concludes that the employment effects of the minimum wage are negative but small: a 10-percent increase in the minimum is estimated to lower teenage employment rates by 0.56 percentage points.

# 1. Inférence causale



## Case 2a - Double différences (ou différence des différences)

	pre	post
control	$a$ (never treated)	$b$ (never treated)
treatment	$c$ (not yet treated)	$d$ (treated)

	pre	post	$\Delta$
Pennsylvania	$a = 23.33$	$b = 21.17$	$a - b$
New Jersey	$c = 20.44$	$d = 21.03$	$c - d$

Causal effect

$$\Delta = \begin{cases} (d - c) - (b - a) = (0.59) - (-2.16) = 2.76 \\ (d - b) - (c - a) = (-2.89) - (-0.14) = 2.76 \end{cases}$$

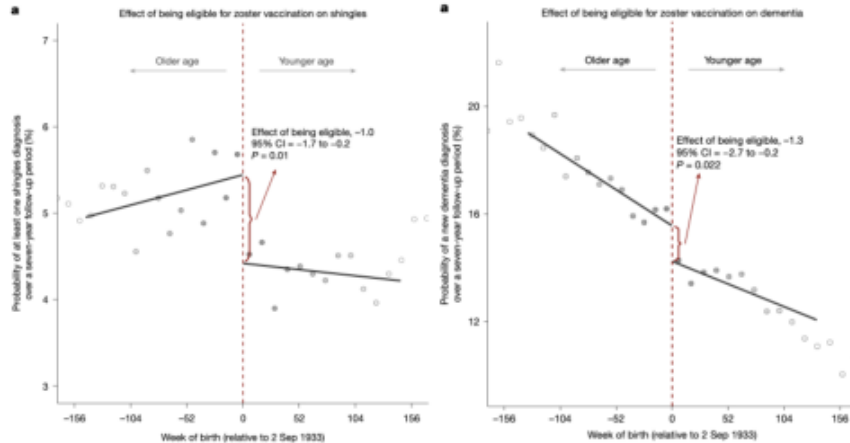
	pre	post
control	$a$	$a + \beta$
treatment	$a + \gamma$	$a + \gamma + \beta + \Delta$



# 1. Inférence causale

## Cas 2b - Régression sur discontinuité

“In Australia, starting Nov. 1, 2016, live attenuated HZ vaccination was provided free to individuals aged 70 to 79 years. Thus, individuals whose 80th birthday was just a few weeks before Nov. 1, 2016, never became eligible,”  
Eyting et al. (2025)



### Article

## A natural experiment on the effect of herpes zoster vaccination on dementia

<https://doi.org/10.1038/s41586-025-08800-x>

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Neurotropic herpesviruses may be implicated in the development of dementia<sup>1</sup>. Moreover, vaccines may have important off-target immunological effects<sup>2</sup>. Here we aim to determine the effect of live attenuated herpes zoster vaccination on the occurrence of dementia diagnoses. To provide causal as opposed to correlational evidence, we take advantage of the fact that, in Wales, eligibility for the zoster vaccine was determined on the basis of an individual's exact date of birth. Those born before 2 September 1933 were ineligible and remained ineligible for life, whereas those born on or after 2 September 1933 were eligible for at least 1 year to receive the vaccine. Using large-scale electronic health record data, we first show that the percentage of adults who received the vaccine increased from 0.03% among patients who were merely 1 week too old to be eligible, to 47.2% among those who were just 1 week younger. Apart from this large difference in the probability of ever receiving the zoster vaccine, individuals born just 1 week before 2 September 1933 are unlikely to differ systematically from those born 1 week later. Using these comparison groups in a regression discontinuity design, we show that receiving the zoster vaccine reduced the probability of a new dementia diagnosis over a follow-up period of 7 years by 3.5 percentage points (95% confidence interval (CI) = 0.4–7.1,  $P = 0.009$ ), corresponding to a 20.0% (95% CI = 6.5–33.4) relative reduction. This protective effect was stronger among women than men. We successfully combine our findings in a different population (England and Wales's combined population), with a different type of data (death certificates) and using an outcome (deaths with dementia as primary cause) that is closely related to dementia, but less reliant on a timely diagnosis of dementia by the healthcare system<sup>3</sup>. Through the use of an unique natural experiment, this study provides evidence of a dementia-preventing or dementia-delaying effect from zoster vaccination that is less vulnerable to confounding and bias than the existing associational evidence.

Recently, evidence has grown that neurotropic herpesviruses may have a role in the pathogenesis of dementia<sup>1</sup>. One approach to targeting herpesviruses in vaccination. However, vaccines are also increasingly being recognized as eliciting broader immune responses that can have important off-target effects, particularly in the case of live-attenuated vaccines<sup>2</sup>. Such effects have frequently been observed to differ strongly by sex<sup>4</sup>.

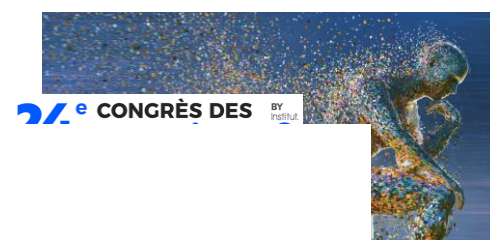
To date, studies in cohort and electronic health record data on the effect of vaccination receipt on dementia have simply compared the occurrence of dementia among those who also received zoster vaccination and those who did not<sup>5</sup>. These studies have to assume that all characteristics that are different between those who are vaccinated and those who are not (and that are also related to dementia) have been

rigorously well measured and modelled in the analysis, such that no factors confound the relationship between vaccination receipt and dementia<sup>6</sup>. This assumption of no confounding has often implausible because it has to be assumed that the study has detailed data on factors that are difficult to measure, such as personal motivation or health literacy<sup>7</sup>. It is also an assumption that cannot be empirically verified.

We used a fundamentally different approach that takes advantage of the fact that, in Wales, starting on 1 September 2013, those born on or after 2 September 1933 were eligible for herpes zoster vaccination for at least 1 year, while those born earlier never became eligible<sup>8</sup>. Using detailed large-scale electronic health record data, we were able to compare adults who were ineligible for the vaccine because they were born immediately before the eligibility cut-off date with those born

<sup>1</sup>Division of Human Genetics and Population Health, Department of Medicine, Stanford University, Stanford, CA, USA. <sup>2</sup>Labri Institute for Precision Research (LIPRI), Portland and Reno, Oregon. <sup>3</sup>Faculty of Law and Economics, Johannes Kepler University Linz, Austria. <sup>4</sup>Department of Health, Behavior, and Society, Harvard Medical School, Boston, MA, USA. <sup>5</sup>Department of Epidemiology and Population Health, Stanford University, Stanford, CA, USA. <sup>6</sup>The PRF authors have rights related to their respective roles in the UK Intellectual Property Office. <sup>7</sup>Department of Epidemiology and Population Health, Stanford University, Stanford, CA, USA. <sup>8</sup>The Welsh Health Research Authority. \*Equal contributors. ✉Correspondence: P.O. Box 247800, San Francisco, CA, USA. The authors contributed equally: Markus Eyring, Min Xia. ✉e-mail: p.odierkoue@stanford.edu

# 1. Inférence causale



## Cas 2b - Régression sur discontinuité

Does extra time in the hospital improve health outcomes?

See also [Howe et al. \(2016\)](#), that estimate the effect of playing Pokémon GO on the number of steps taken daily up to six weeks after installation of the game.

**"Regression discontinuity design"** (RDD), [Thistlethwaite and Campbell \(1960\)](#) or [Imbens and Lemieux \(2008\)](#)

See also [Imai \(2022\)](#)

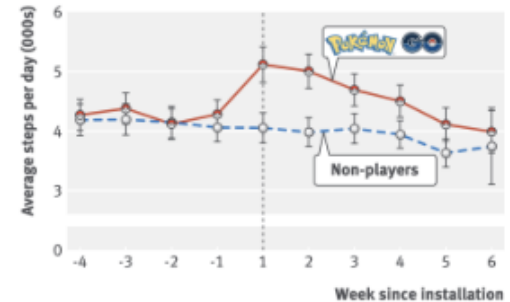
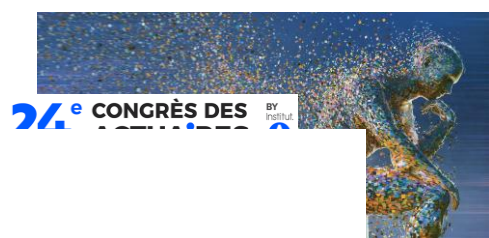


Fig 1 | Average number of daily steps and 95% confidence intervals by week before and after installation of Pokémon GO (median 8 July 2016)



# 1. Inférence causale



## Case 3 - Résultats Potentiels et Countrefactuels

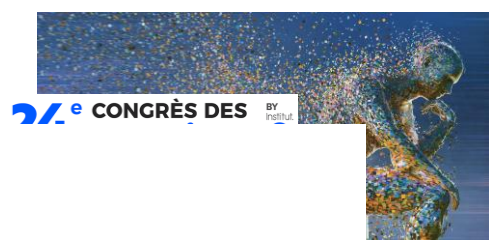
	Gender	Name	Treatment		Outcome (Weight)				Height	...
			$t_i$	0 1	$y_i$	$y_i^*(0)$	$y_i^*(1)$	TE	$x_i$	...
1	H	Alex	0	<input checked="" type="checkbox"/> <input type="checkbox"/>	75	75	?	?	172	...
2	F	Betty	1	<input type="checkbox"/> <input checked="" type="checkbox"/>	52	?	52	?	161	...
3	F	Beatrix	1	<input type="checkbox"/> <input checked="" type="checkbox"/>	57	?	57	?	163	...
4	H	Ahmad	0	<input checked="" type="checkbox"/> <input type="checkbox"/>	78	78	?	?	183	...

If we define **potential outcomes** as:

$$\begin{cases} y_i(1) = \text{Outcome if unit } i \text{ receives treatment } (t_i = 1) \\ y_i(0) = \text{Outcome if unit } i \text{ receives control } (t_i = 0) \end{cases}$$

then the **individual treatment effect** is:  $TE_i = y_i(1) - y_i(0)$ .

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## Case 3 - Résultats Potentiels et Countrefactuels

But in real life:

$$TE_i = \begin{cases} y_i(1) - ??? & \text{if } t_i = 1 \\ ??? - y_i(0) & \text{if } t_i = 0 \end{cases}$$

We never observe both potential outcomes for any individual — **no counterfactuals**

Since we can't observe individual treatment effects, we turn to averages,

$$\overline{TE} = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] = \tau_{ATE}$$

only works if the treated and control groups are comparable (i.e., balanced on covariates). Otherwise, use designs or statistical methods that adjust for confounding

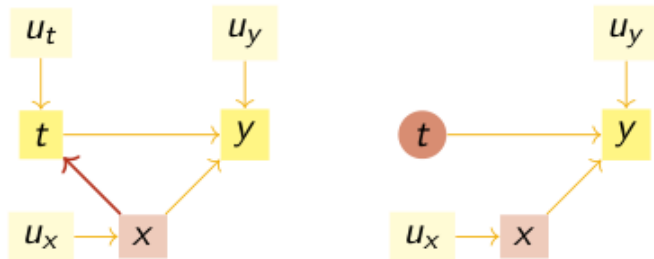
See **causal model from Neyman-Rubin** Neyman (1923), Rubin (1973, 1974), see also Sekhon (2009) and textbooks Angrist and Pischke (2009, 2014).

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## Case 3 - Potential Outcomes and Counterfactuals

Sewall Wright introduced **directed acyclical graphs** (DAG) to represent probabilistic cause and effect relationships among a set of variables (see [Wright \(1921, 1934\)](#))



When you *do*( $t$ ), delete all arrows into  $t$  confounders don't influence treatment.

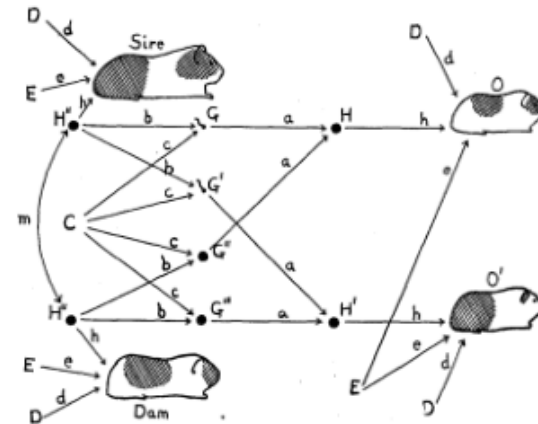
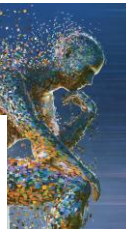


FIGURE 2.—A diagram illustrating the relations between two mated individuals and their progeny.  $H, H', H''$  and  $H'''$  are the genetic constitutions of the four individuals.  $G, G', G''$  and  $G'''$  are four germ-cells.  $E$  and  $D$  represent fungible external conditions and chance irregularities as factors in development.  $C$  represents chance at segregation as a factor in determining the composition of the germ-cells. Path coefficients are represented by small letters.

# 1. Inférence causale



## Case 4 - Méthodes d'appariement, ou "matching"

We have two sets of observations

$$\begin{cases} t = 0 : \{(y_1, \mathbf{x}_1), \dots, (y_i, \mathbf{x}_i), \dots, (y_{n_0}, \mathbf{x}_{n_0})\} \\ t = 1 : \{(y_1, \mathbf{x}_1), \dots, (y_j, \mathbf{x}_j), \dots, (y_{n_1}, \mathbf{x}_{n_1})\} \end{cases}$$

Given treated observation  $(y_j, \mathbf{x}_j)$

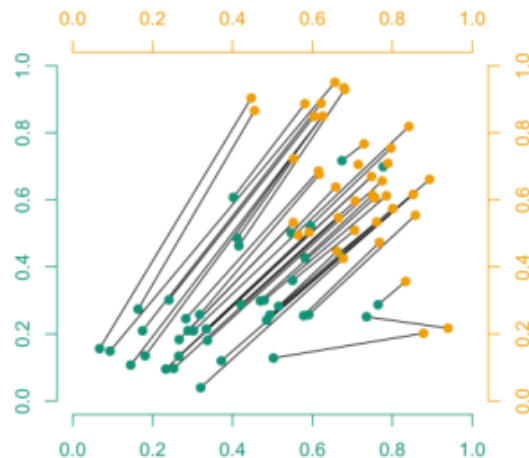
find a plausible untreated counterfactual  $(y_{i^*}, \mathbf{x}_{i^*})$

**Nearest neighbour matching (1-1)**,  $d(\mathbf{x}_{i^*}, \mathbf{x}_j)$

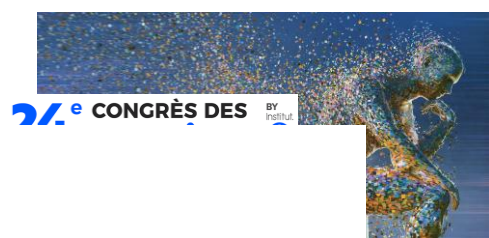
find a plausible counterfactual

Find untreated observations that are very close/similar to treated observations based on confounders

Lots of mathy ways to measure distance (e.g., use Optimal Transport instead)



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## Case 5 - Poids et correction de biais

Use **Inverse probability weighting** (IPW), as Rosenbaum and Rubin (1983)

- Estimate Propensity Scores

Predict the probability of treatment assignment using logistic/probit regression or machine learning:

$$e(\mathbf{x}) = \mathbb{P}(T = 1 \mid \mathbf{X} = \mathbf{x})$$

- Weight Observations

Assign higher weights to individuals whose treatment assignment is unlikely.

We want to estimate the Average Treatment Effect  $\tau_{ATE} = \mathbb{E}[Y(1) - Y(0)]$

Estimated potential outcome means,

$$\mathbb{E}[Y(1)] \approx \mathbb{E}\left[\frac{TY}{e(\mathbf{X})}\right] \text{ and } \mathbb{E}[Y(0)] \approx \mathbb{E}\left[\frac{(1-T)Y}{1-e(\mathbf{X})}\right]$$



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## Case 5 - Poids et correction de biais

- IPW Estimator of ATE, quite naturally

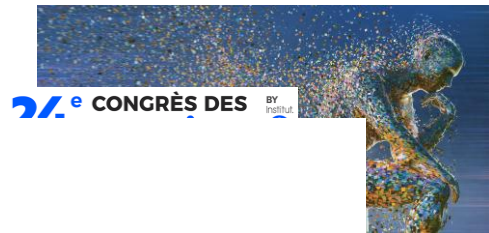
$$\hat{\tau}_{ATE}^{IPW} = \frac{1}{n} \sum_{i=1}^n \left[ \frac{t_i y_i}{\hat{e}(\mathbf{x}_i)} - \frac{(1 - t_i) y_i}{1 - \hat{e}(\mathbf{x}_i)} \right]$$

- Assumptions for consistency
  - **Unconfoundedness:**  $Y(0), Y(1) \perp\!\!\!\perp T \mid \mathbf{X}$
  - **Positivity:**  $0 < \hat{e}(\mathbf{x}_i) < 1$  for all  $i$
- AIPW Estimator of ATE

$$\hat{\tau}_{ATE}^{AIPW} = \frac{1}{n} \sum_{i=1}^n \left[ \left( \frac{t_i}{\hat{e}(\mathbf{x}_i)} - \frac{1 - t_i}{1 - \hat{e}(\mathbf{x}_i)} \right) (y_i - \hat{\mu}_{t_i}(\mathbf{x}_i)) + \hat{\mu}_1(\mathbf{x}_i) - \hat{\mu}_0(\mathbf{x}_i) \right]$$

Units with low probability of receiving the treatment they got are upweighted,  
Mimics a randomized experiment by rebalancing the covariates.

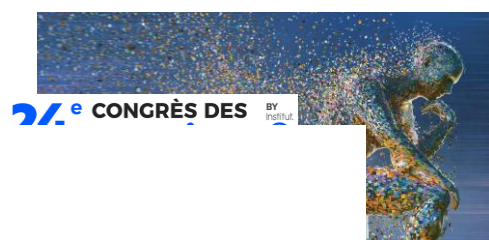
# 1. Inférence causale



## Classical references

- **Donohue and Levitt (2001)**: how legalized abortion led to fewer unwanted births and a subsequent decline in crime rates roughly eighteen years later, using cross-state variation and crime data.
- **Card and Krueger (1994)**: difference-in-differences design comparing fast-food employment in New Jersey (which raised its minimum wage) and Pennsylvania (which did not), finding no adverse employment effects.
- **Cornfield et al. (1959)**: epidemiological evidence linking smoking to lung cancer and introduces sensitivity analysis techniques to assess how unmeasured confounding could affect that conclusion.
- **Hill (1965)**: nine criteria—such as strength, consistency, temporality, and biological gradient—for judging whether an observed association can be interpreted as causal.

# 1. Inférence causale



## Classical references

- **Rosenbaum and Rubin (1983)**: propensity score (the probability of treatment given covariates) and shows that conditioning on it balances covariates, enabling unbiased estimation of causal effects in observational studies.
- **Imbens and Angrist (1994)**: instrumental-variables methods in a potential-outcomes framework, defining the Local Average Treatment Effect (LATE) and demonstrating how it can be identified and estimated using instruments that affect compliance.

**Rubin (1974)**: formalizes the “Rubin Causal Model,” defining treatment-assignment mechanisms and potential outcomes, and proposes methods for estimating causal effects in both randomized and observational settings.

**Holland (1986)**: clarifies the potential-outcomes framework, distinguishes causal effects from associations, and discusses identification and estimation of causal parameters under various assignment mechanisms.

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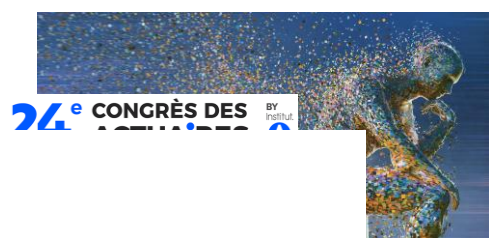


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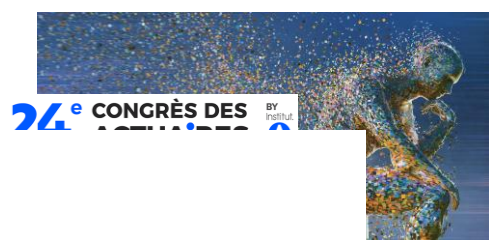
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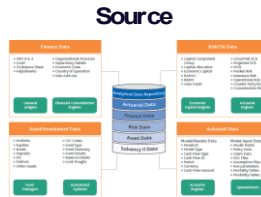
# 2.1 Contexte

Plusieurs aspects limitent la bonne compréhension des risques :

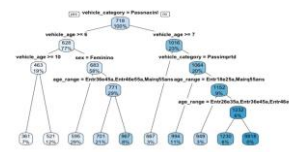
- + L'organisation de la connaissance
- + Son exploitation dans les outils actuariels
- + Son interopérabilité entre équipes

L'utilisation d'IA Gen permet de mieux représenter les phénomènes notamment via :

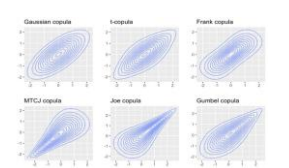
- + Le traitement multi modal de corpus documentaires
- + La formalisation d'un modèle de données standardisé, typé et évolutif
- + L'emploi de LLMs pour structurer l'information en DAG et les causes



## Multi-dimensionalité



## Corrélation & chronologie



## Inaltérabilité

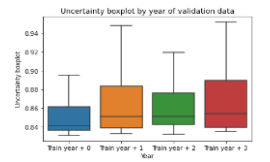


Figure: exemple de rapport de sinistre

```
{
  "type": "claim",
  "id": "claim_123456789",
  "status": "open",
  "description": "Water damage in living room",
  "date": "2023-10-26T08:30:00",
  "location": "Paris",
  "severity": "medium",
  "cause": "water",
  "owner": "John Doe",
  "address": "123 Rue de la Paix, Paris",
  "contact": "01 23 45 67 89"
}
```

Figure: exemple de modèle JSON

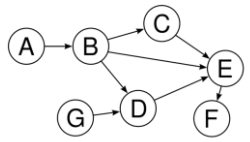


Figure: exemple de structure DAG

# 2.2 Approches



## Données

- + Exemple sur 2K rapports de sinistres
- + Un modèle de données de +96 attributs.
- + Des attributs particuliers sur les nodes et edges pour la causalité

## Modèles

- + LLM (Claude 3.5/4, Llama 3 8B/ 70B) et Embedding (gte-large)
- + Déduplication programmatique, standard via Clustering
- + Algorithme dichotomique pour traiter l'agrégation

## Evaluations

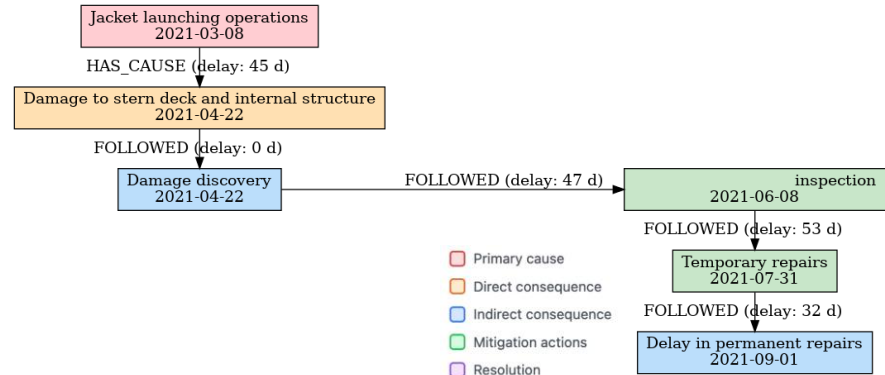
- + Evaluation techniques des couts, temps d'inférence, nombre de nodes, de edges, déduplication, compression, agrégation, etc.
- + Evaluation de la qualité : précision, exhaustivité, consistance, etc.
- + Système HIL

## Pré-traitements

- + OCR Textract, Deduplication, Fixed chunking
- + Text to markdown et Image to text
- + Sentence spanner

## Processus

- + Création de DAG par chunk par UCR
- + Agrégation des DAG pour un UCR donné
- + Standarisation et agrégation dans un graphe commun



# 2.3 Résultats

## Temps

+ 1min par dossier

## Coûts

+ 1 à 5€ par dossier

## Evaluations

+ Peu de défaut

+ 30 attributs en moyenne

+ Agrégat par UCR limité à 2 ou 3 comp  
tenu de la taille des chunk

## Graphes

+ 1 à 5 graphes par claims

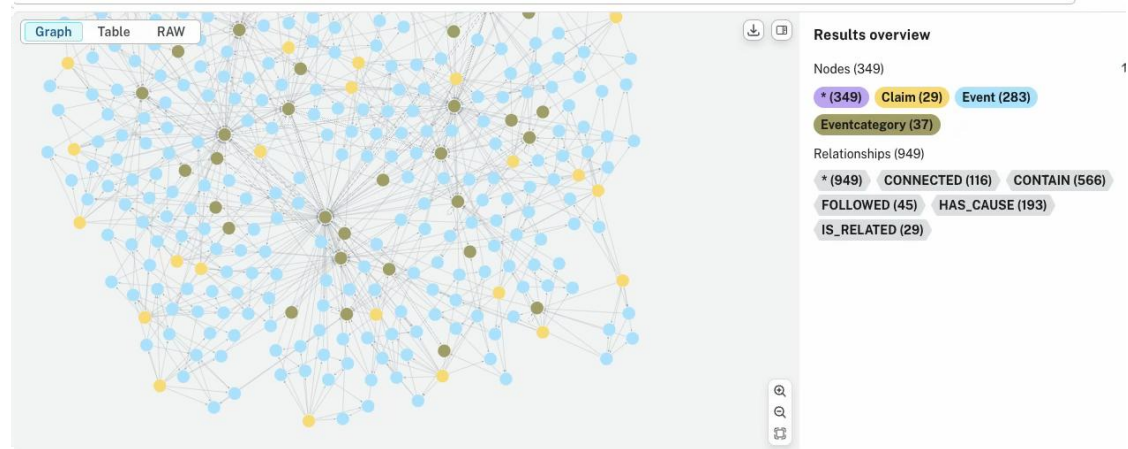
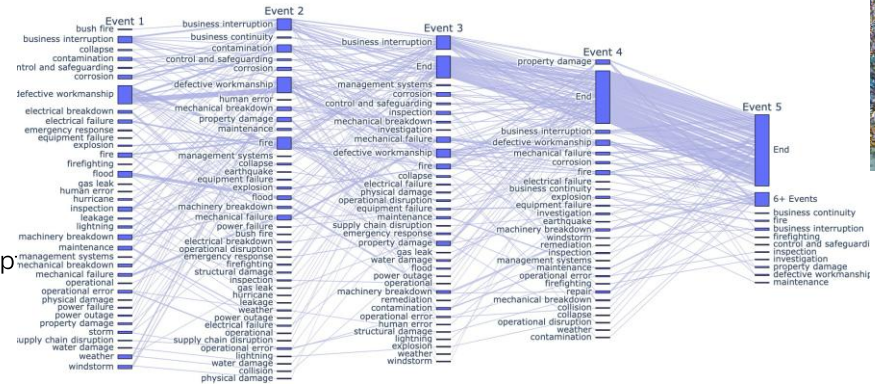
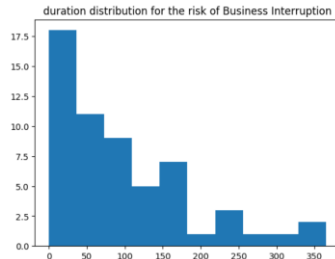
+ Graphes jumeaux contenant les metadata

+ 30 à 90 évènements type

+ Distribution d'attributs via le graph agrégé

ID: 33  
EVENT: FIRE

```
"duration": [
  "85",
  "48",
  "68",
  "2",
  "219",
  "123",
  "162",
  "240"
],
```





# 2.4 Usages

## Consultation & visualisations

+ App pour trier les UCR et rendre disponible les graphes

CLAIM ID	SCORE	STATUS	PRIORITY	DATE RECEIVED	LOB	TOTAL LOSS	COMPANY	REGION	DOCUMENTS
PER20WPO0222	87%	Processing	High	2024-02-15	Property	\$2.5M	Tech Industries Ltd	North America	2 documents
PER20WPO0223	76%	Accepted	Medium	2024-02-18	Liability	\$1.8M	Global Manufacturing Co	Europe	1 documents
PER20WPO0224	92%	Received	High	2024-02-20	Marine	\$3.2M	Ocean Shipping Inc	Asia Pacific	0 documents
PER20WPO0225	45%	Rejected	Low	2024-02-21	Property	\$1.2M	Retail Solutions Corp	North America	0 documents
PER20WPO0226	88%	Processing	High	2024-02-22	Cyber	\$4.5M	Digital Systems Ltd	Europe	0 documents
PER20WPO0227	78%	Accepted	Medium	2024-02-23	Energy	\$5.8M	Power Generation Co	Middle East	0 documents
PER20WPO0228	82%	Received	High	2024-02-24	Construction	\$2.9M	Build Right Inc	South America	0 documents
PER20WPO0229	95%	Processing	High	2024-02-25	Aviation	\$7.2M	Sky Fleet Airlines	Global	0 documents

Figure: application de consultation des sinistres



## Requêtes et agents

+ Requête en langage naturel vers cypher query vers LLM

### Incident Reports Chatbot

Chat with our agent to easily explore incident reports stored in a graph database.

Chatbot

What types of incidents are most frequently reported?

Based on the data analysis, there are two main types of incidents that are reported with equal frequency:

1. **Explosion incidents** - These represent one type of reported incident
2. **Pressure Rupture incidents** - These also represent one type of reported incident

Both types of incidents appear to occur with the same frequency in the dataset, with each type accounting for one reported case. This suggests that explosion events and pressure rupture events are equally common among the incidents that have been documented.

## Référentiels

+ Création de classes à partir d'attributs libres

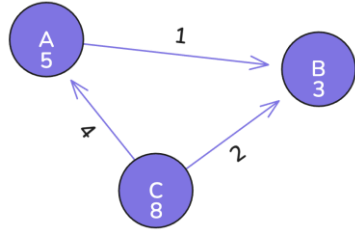
```
{  
  "node_properties_eventCategory": {  
    "Abnormal or Unplanned": "Abnormal or Unplanned",  
    "Anchor Drag": "Anchor Drag",  
    "Assessment": "Assessment",  
    "Assignment": "Assignment",  
    "Authorization": "Authorization",  
    "Blowout; no fire": "Blowout; no fire",  
    "Bodily Injury": "Bodily Injury",  
    "Burglary": "Burglary",  
    "Bush Fire": "Bush Fire",  
    ...  
  }  
}
```

# 2.5 Applications actuarielles



## Tarification

- + Estimer un cout/une occurrence moyenne via techniques markoviennes
- + Si non applicable, poser un système de rapprochement par clustering

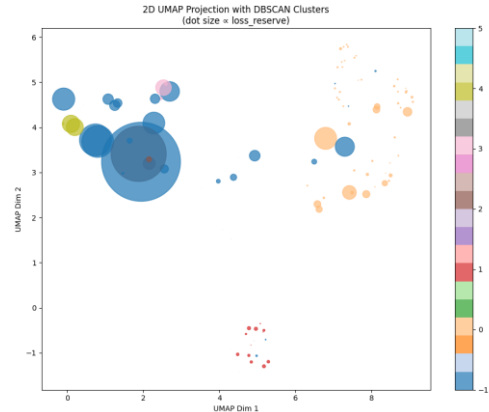


$$M_{i \rightarrow j} = \begin{pmatrix} & A & B & C & \emptyset \\ A & 0 & \frac{1}{5} & 0 & \frac{4}{5} \\ B & 0 & 0 & 0 & 1 \\ C & \frac{4}{8} = \frac{1}{2} & \frac{2}{8} = \frac{1}{4} & 0 & \frac{2}{8} = \frac{1}{4} \\ \emptyset & \frac{1}{9} & 0 & \frac{8}{9} & 0 \end{pmatrix}$$

Figure: exemple de matrice de proba de passage

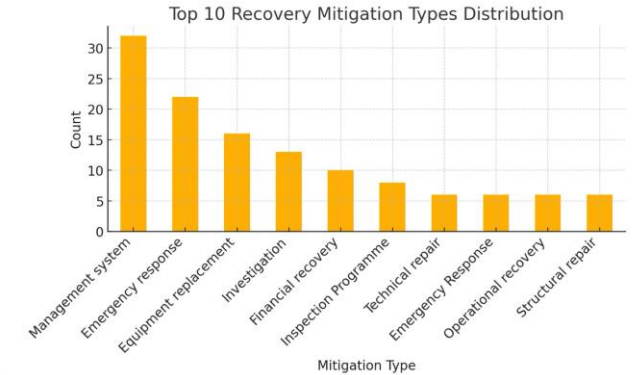
## Provisionnement

- + Suggérer d'autres segmentations
- + Identifier les pertes en cours/ à l'issue des développements
- + Evaluer l'impact des changements de DAG sur les pertes estimées
- + Identifier les causes primaires aboutissant à des couts nul



## Prévention

- + Observer les causes primaires fréquentes, en déduire des actions de prévention
- + Identifier les causes secondaires ou conséquences pour limiter les transmissions
- + Suggérer des méthodes de limitation des couts à l'ultime



# 2.6 Perspectives



## Limites

- + Le chunking des documents n'est pas contextuel
- + Le modèle de données pourrait être par concept
- + La déduplication des nœuds est restrictive
- + Il manque de gold standard (notamment pour les causes)

## Prochaines étapes

- + Eprouver le procédé sur un jeu de données plus important
- + Etendre le cadre agentique des outils de tarification, provisionnement et prévention (notamment via des tools)

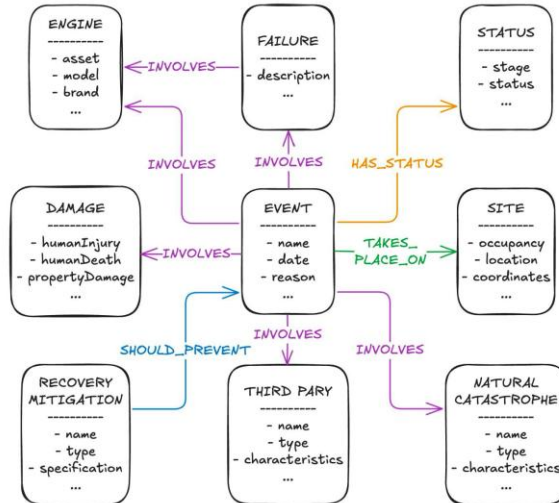


Figure: exemple de concepts / ontologies

Chatbot

What are the top primary causes of claims ?

Based on the data analysis, here are the top primary causes of claims:

- Inspection Programme - 4 claims**  
This is the most common primary cause, accounting for 4 out of 10 total claims. This suggests that issues with inspection programs are a significant factor in insurance claims.
- Management of Change (MoC) - 3 claims**  
The second most frequent cause, with 3 claims related to problems in managing operational changes within facilities or processes.
- Operations Practices & Procedures - 2 claims**  
Two claims were attributed to issues with operational practices and procedures.
- Control of Work (CoW) - 1 claim**  
One claim was linked to problems with work control systems.

The data shows that inspection-related issues are the leading cause of claims, followed closely by change management problems. Together, inspection programs and management of change account for 70% of all claims, indicating these are critical areas that require attention to reduce future incidents.

# 3. Discussions



Opportunités et limites de l'approche causale