Motivation

Formal Background

Causal Generative Neural Nets

Structure Agnostic Model

Application to Human Resources
  General Causal Relations
  Category 1 (low-tech industry)
  Category 2 (medium-low-tech industry)
  Category 3 (medium-high-tech industry)
  Category 4 (high-tech industry)

Discussion
**Goal:** A generative model

- Does not require CPDAG as input
- Avoids combinatorial search for structure
- Less computationally demanding
The $i$-th neural net

- Learns conditional distribution $P(X_i|X_{\backslash i})$ as $\hat{f}_i(X_{\backslash i}, E_i)$
- Filter variables $a_{i,j}$ are used to enforce sparsity (Lasso-like, next slide)
- 1st non-linear layer builds features $\phi_{i,k}$, 2nd layer builds linear combination of features:

$$f_i(X_{\backslash i}, E_i) = \sum \beta_{i,k} \phi_{i,k}(a_{i,1}X_1, \ldots, a_{i,d}X_d, E_i)$$

In the large sample limit, $a_{i,j} = 1$ iff $X_j \in MB(X_j)$

(MB: Markov Blanket)
Generative Adversarial Networks

**Goal:** Find a generative model

- Classical: learn a distribution
- Idea: replace a distribution evaluation by a 2-sample test

**Principle**

- Find a good generative model, s.t. generated samples **cannot be discriminated** from real samples (not easy)

LeCun: a revolution within the Deep revolution
Principle

Elements

▶ True samples $x$ (real)
▶ A generator $G$ generates fake samples:
▶ A discriminator $D$: discriminates fake from real (like an internal Turing test)

- Generator $G_{\theta} : \mathcal{L} \rightarrow \mathcal{D}$
- Discriminator $D_{\phi} : \mathcal{D} \rightarrow [0, 1]$

$z \sim \mathcal{N}(0, 1)$

Dataset $\xrightarrow{} \hat{x} \xrightarrow{} P(x \sim p_D)$

Goodfellow, 2017
Principle, 2

Mechanism

- Alternate minimization
- Optimize $D$ to tell fake from rest
- Optimize $G$ to deceive $D$

$$
\text{Min}_G \text{ Max}_D \mathbb{E}_{x \in \text{data}}[\log(D(x))] + \mathbb{E}_{z \sim p_x(z)}[\log(1 - D(z))]
$$

Caveat

- The above loss has a vanishing gradient problem because of the terms in $\log(1 - D(z))$.
- We can replace it with $-\log((1 - D(z)/D(z))$, which has the same fixed point (the true distribution) but doesn't saturate.
Generative adversarial networks

Goodfellow, 2017
Generative adversarial networks, 2

Goodfellow, 2017
Limitations

Training instable
co-evolution of Generator / Discriminator

Mode collapse
Limitations, 2

Generating monsters
Given observational data \( \{x_1, \ldots, x_n\} \sim P(X_1, \ldots, X_d) \) where \( x_i \) is in \( \mathbb{R}^d \)

**Adversarial learning**

- Generate \( \{\tilde{x}_i^{(j)}\} \) with \( j \)-th component of \( \tilde{x}_i^{(j)} \) set to \( \hat{f}_i(x_i, \epsilon), \epsilon \sim \mathcal{N}(0, 1) \)
- Discriminator \( D \) among observational data \( \{x_i\} \) and generated data \( \{\tilde{x}_i^{(j)}, i = [1, n], j = [1, d]\} \)
- Learning criterion (adversarial + sparsity)

\[
\min \left( \text{Accuracy} (D) + \lambda \sum_{i,j} |a_{i,j}| \right)
\]
**Learning criterion**  \[ \min \left( \text{Accuracy} (D) + \lambda \sum_{i,j} |a_{i,j}| \right) \]

**Competition** between discriminator and sparsity term \( \sum \|a\|_1 \)
- Avoids combinatorial search for structure
- Cycles are possible
- DAGness achieved by enforcing constraints on trace of \( A = (a_{i,j}) \) and \( A^k \)
Quantitative benchmark - artificial DAG

Directed **acyclic** artificial graphs (DAG) of 20 variables

<table>
<thead>
<tr>
<th></th>
<th>PC Gauss</th>
<th>PC HSIC</th>
<th>GES</th>
<th>MMHC</th>
<th>DAGL1</th>
<th>LINGAM</th>
<th>CAM</th>
<th>SAM</th>
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<tr>
<td>Linear</td>
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<td>0.29</td>
<td>0.40</td>
<td>0.36</td>
<td>0.30</td>
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<td>0.29</td>
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<td>Sigmoid AM</td>
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<td>0.12</td>
<td>0.15</td>
<td><strong>0.52</strong></td>
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<tr>
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<td>0.17</td>
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<td>0.32</td>
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<tr>
<td>NN</td>
<td>0.40</td>
<td>0.38</td>
<td>0.42</td>
<td>0.11</td>
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<td>10h</td>
<td>&lt;1s</td>
<td>&lt;1s</td>
<td>2s</td>
<td>2s</td>
<td>2.5h</td>
<td>1.2h</td>
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Execution time: 1s 10h
**Quantitative benchmark - artificial DG (with cycles)**

Directed **cyclic** artificial graphs of 20 variables

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  Category 4 (high-tech industry)

Discussion
Causal Modeling and Human Resources

Position of the problem

A Quality of life at work employee’s perspective
B Economic performance firm’s perspective

▶ ... are correlated

Question: Are there causal relationships ?

A → B ; or B → A; or ∃ C / C → A and C → B

▶ Answering the question is key to evolve management strategies.

Data

▶ Gathered by Group Alpha Secafi (trade union advisor)
▶ Tax files + social audits for 408 firms
Firms

Category 1
- Chocolatier, Lesieur, Dassault, Compagnie des fromages, ...

Category 2
- ArcelorMittal, St Gobain, Lafarge, Vallourec, Michelin,...

Category 3
- Air Liquide, Thalès, Mersen, Filtrauto, Fenwick,...

Category 4
- Hispano-Suiza, TurboMéca, Sanofi, Snecma,...
Variables

Economics

- Total number of employees
- Capitalistic intensity, Total payroll, Gini index
- Average salary (of workers, technicians, managers)
- Productivity, Operating profits, Investment rate

People

- Average age, Average seniority, Physical effort,
- Permanent contract rate, Manager rate, Fixed-term contract rate,
  Temporary job rate, Shift and night work, Turn-over
- Vocational education effort, duration of stints, Average stint rate (for
  workers, technicians, managers);
Variables, cont’d

Quality of life at work

▶ Frequency & Gravity of work injuries, Safety expenses, Safety training expenses
▶ Absenteism (diseases), Occupational-related diseases
▶ Resignation rate, Termination rate, Participation rate
▶ Subsidy to the works council

Men/Women

▶ Percentage of women (employees, managers)
▶ Wage gap between women and men (average, for workers, technicians, managers)
General Causal Relations
General Causal Relations

Access to training ↑
- ↓ Gravity of work injuries
- ↓ Occupational-related diseases

Termination rate ↑
- ↑ Absenteism (diseases)

Percentage of managers ↑
- ↑ Access to training
- ↓ Shift or night working hours

Age ↑
- ↓ Fixed-term contract rate
- ↓ Productivity (weak impact)

? ↑
- ↑ Productivity → Participation rate ↑
Global relations between QLW and performance?

**Failure**
- Nothing conclusive

**Interpretation**
- Exist confounders (controlling QLW and performance) \( C \rightarrow A \) and \( C \rightarrow B \)
- One such confounder is the activity sector
- In different activity sectors, causal relations are different (hampering their identification)
- \( \Rightarrow \) Condition on confounders (independently handle the activity sectors)
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Discussion
Low-tech industry
Category 1 (low-tech industry)

- Resignation rate \( \uparrow \), Productivity \( \downarrow \)

- Average salary \( \uparrow \), Productivity \( \uparrow \) very significant

- Occupational-related diseases \( \uparrow \), Productivity \( \downarrow \)

- Temporary job rate \( \uparrow \), Gravity of work injuries \( \uparrow \)

- Permanent contract rate \( \uparrow \), Safety training \( \downarrow \)

- Duration training stints \( \uparrow \), Termination rate \( \downarrow \)
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Discussion
Medium-low-tech industry
Category 2 (medium-low-tech industry)

- Permanent contract rate ↗, Productivity ↗
- Average salary ↗, rate of occupational related diseases ↘
- Frequency of work injuries ↗, Termination rate ↗
- Percentage of women ↗, operating profitability ↗
- Temporary job rate ↗, Permanent contract rate ↗
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Application to Human Resources
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  **Category 3 (medium-high-tech industry)**
  Category 4 (high-tech industry)

Discussion
Medium-high-tech industry
Category 3 (medium-high-tech industry)

- Occupational-related diseases ↑, Productivity ↓
- Temporary job rate ↑,
  - Frequency of work injuries ↑
  - Average salary ↓
- Average training effort ↑, Permanent contract rate ↑
- Average salary workers ↑, Turn-over Permanent contract rate ↓
- Average age ↑, Absenteism (diseases) ↑
- Average seniority ↑, Occupational-related diseases ↑
- Training of workers ↑, Productivity ↑
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Discussion
High-tech industry

Part des rémunérations les plus élevées dans la masse salariale

Productivité

Taux d'investissement

Durée moyenne des stages de formation

Taux d'interim

Rémunération annuelle moyenne

Taux de démissions

Turn-over CDI
Category 4 (high-tech industry)

- Manager rate ↑, Termination rate ↓
- Total number of employees ↑, Training of managers ↑
- Occupational-related diseases ↑, Productivity ↓
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Discussion
Outcomes & Limitations

Causal modeling and exploratory analysis

▶ Efficient filtering of plausible relations (several orders of magnitude);
▶ Complementary w.r.t. visual inspection (experts can be fooled and make sense of correlations & hazards);
▶ Multi-factorial relations? yes; but even harder to interpret.

Not a ready-made analysis

▶ Causal relations must be
  ▶ interpreted
  ▶ confirmed by field experiments; polls; interviews.
Perspectives

Spurious relations due to redundant variables

- E.g., in analytical accounting
- Variable selection
- Feature construction
dimensionality reduction

Handling confounders

- Based on prior knowledge (e.g. using industry sectors)
- But many confounders are plausible (age and size of firm; company ownership and shareholdings; capitalistic intensity);
- Based on posterior analysis: finding latent dependency structures

Webb et al., 18
Thanks!

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Olivier Goudet

Philippe Caillou

Isabelle Guyon

Paola Tubaro