June 11, 2026.
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Etienne **CÔME**
Latifa **OUKHELLOU**

Mitigating the Temporal Deterioration of Synthetic Populations: A Projected Bayesian Network Approach

Journées Populations Synthétiques.

Université Gustave Eiffel
LABORATOIRE GRETTIA
GÉNIE DES RÉSEAUX
DE TRANSPORT TERRESTRES
ET INFORMATIQUE AVANCÉE

Menu

Publications

Need for Forecasted Synthetic Populations → WCTR 2026[1]

Projective Bayesian Network for Future Populations → hEART + article in preparation

[1] Darsel, Côme, Rich, et al., 2026.

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Need for Forecasted Synthetic Populations

Temporality of Synthetic Populations

Agent-based simulation models

Synthetic Population

[a]W. Axhausen, Horni, and Nagel, 2016.

Agent-based simulation models

Synthetic Population with activity chains →

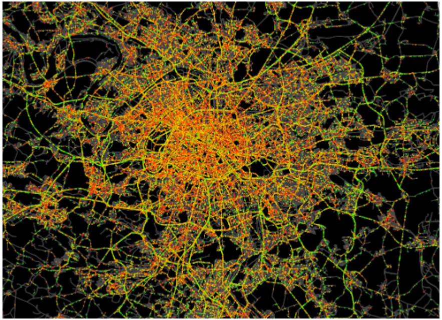

Figure: Agent-based transport simulation (credit: Île-de-France scenario, MatSIM[a])

[a] W. Axhausen, Horni, and Nagel, 2016.

Agent-based simulation models

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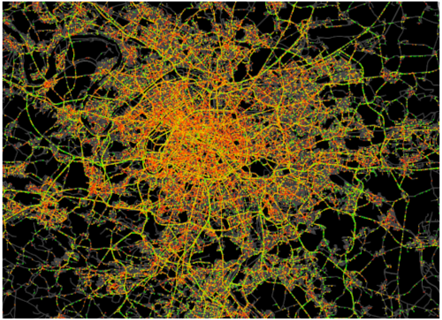

Figure: Agent-based transport simulation (credit: Île-de-France scenario, MatSIM[a])

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- Mobility analysis
- Traffic estimation
- Demand-Responsive Transport simulation
- PT project evaluation
- Policy evaluation
- Greenhouse Gas Emissions forecasts
- ...

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Agent-based simulation models

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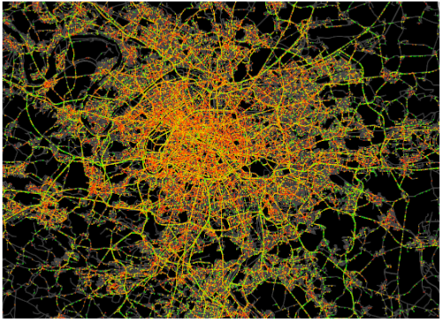

Figure: Agent-based transport simulation (credit: Île-de-France scenario, MatSIM[a])

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- Mobility analysis
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Agent-based simulation models in the Future

Synthetic Population with activity chains →

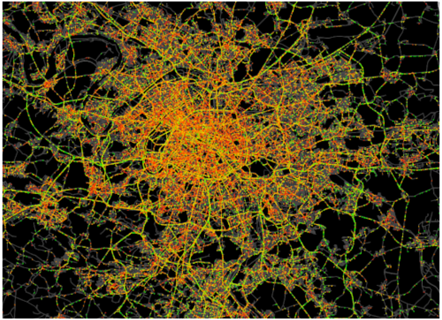

Figure: Agent-based transport simulation in the Future (credit: Île-de-France scenario, MatSIM[a])

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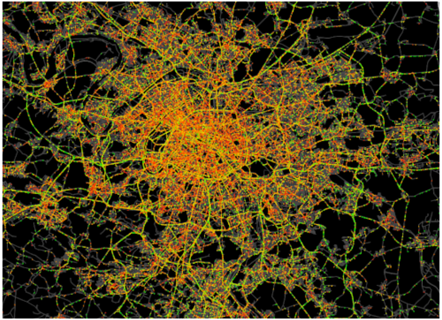
Agent-based simulation models in the Future

Future(?) Synthetic Population with activity chains →



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Initial Problematic

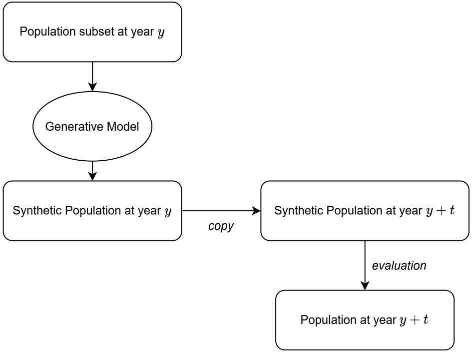
Is a static synthetic population adequate for future scenarios simulations ?

Need for Forecasted Synthetic Populations

Experiments

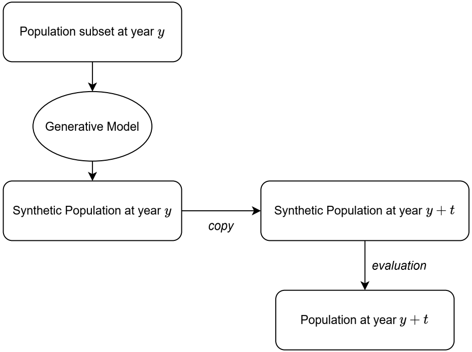
Comparing static model with evolving model

Static model

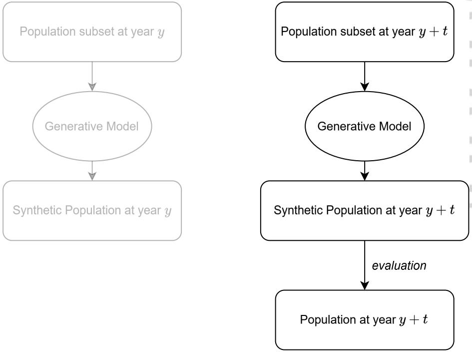


Comparing static model with evolving model

Static model



Time-consistent model



Experimental framework

- **Data:** French Census data from 2016 to 2021, with individuals described by 5 to 13 variables
  - **Training:** Subset composed of 0.03% or 1% of the total population
  - **Evaluation:** Total population
- **Model:** Bayesian Network (best model for this level of complexity[2])
- **Evaluation Design:**
  - **Distribution:** statistical matching between the generated population and the true population evaluated on **marginals**, but also on the **multivariate** distributions (bivariate and trivariate distributions) $\rightarrow$ *Metric:* $\overline{\text{SRMSE}}$
  - **Realism:** ensure that all individuals are plausible $\rightarrow$ *Metric:* SSCIOD

[2] Darsel, Côme, and Oukhellou, 2025.

Results

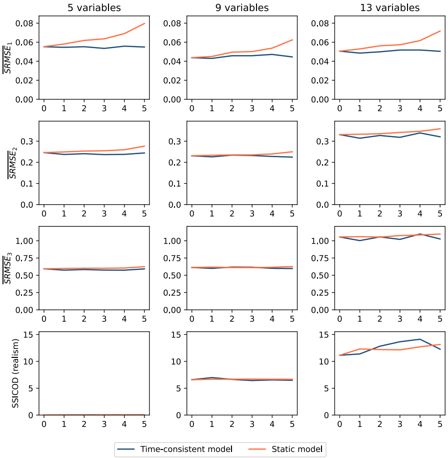


Figure: Model performances with 0.03% training set

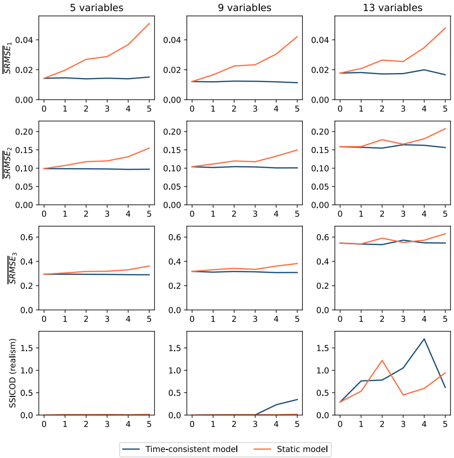


Figure: Model performances with 1% training set

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Deterioration of a static synthetic population over time

The synthetic population needs to be adapted to still be representative of the population

Projective Bayesian Network for Future Populations

Projective Bayesian Network for Future Populations

Literature Review on Synthetic Population Projection

4 different approaches to project population

- Static Projection
- Dynamic Projection
- Resampling
- Hybrid Method

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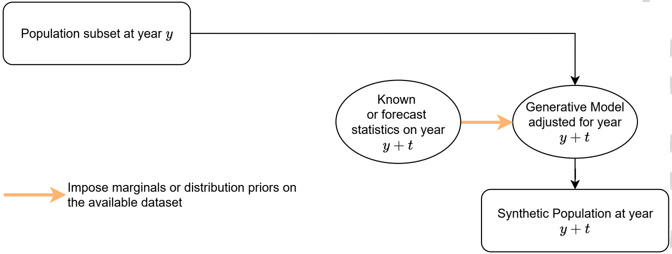
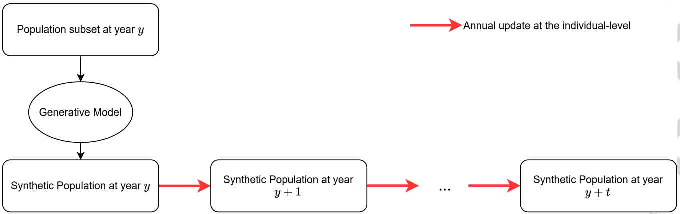


Notable work: Lomax and Smith (2017)

4 different approaches to project population

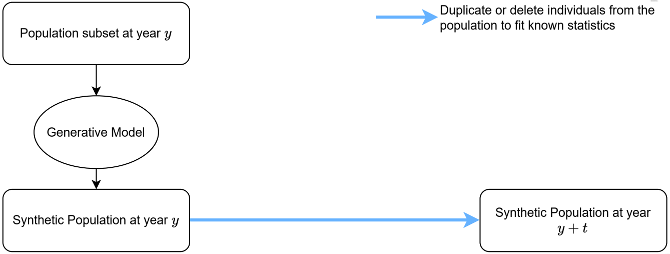
- Static Projection
- Dynamic Projection
- Resampling
- Hybrid Method



Notable work: Fatmi and Habib (2017)

4 different approaches to project population

- Static Projection
- Dynamic Projection
- **Resampling**
- Hybrid Method



Notable work: Prédhumeau and Manley (2023)

4 different approaches to project population

- Static Projection
- Dynamic Projection
- Resampling
- Hybrid Method

Mixture between different projections methods depending on data availability (usually Dynamic Projection and Resampling)

Notable work: Kukic, Benchelabi, and Bierlaire (2023)

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Literature Limitations & Proposed Shifts

1. Temporal Dimension

Current State:

Single year data

Static snapshot, misses macro/micro evolutions.

2. Model Independence

Current State:

Expert-knowledge or unknown data dependency

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Our Approach: Multi-year dataset

Catch statistical evolutions at different levels:

→ *Explore trends on marginals*

→ *Explore trends on attribute correlations*

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2. Model Independence

Current State:

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Our Approach: Data-driven model

Self-sufficient architecture:

- → ***Universal model*** *(no expert priors required)*
- → *Eliminates manual calibration bias*

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Projective Bayesian Network for Future Populations

Model presentation

New Architecture

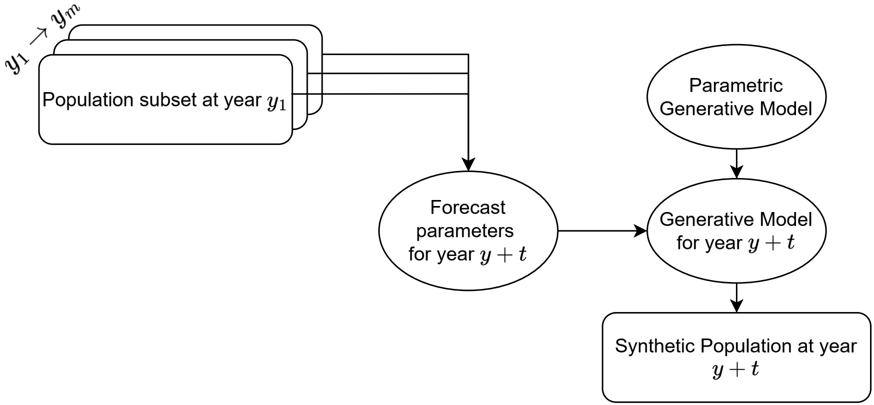


Figure: Data-driven Static Projection

Projective Bayesian Network (principle)

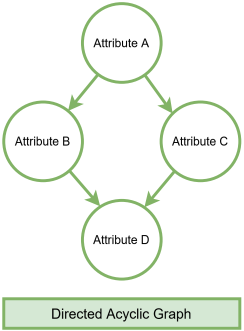
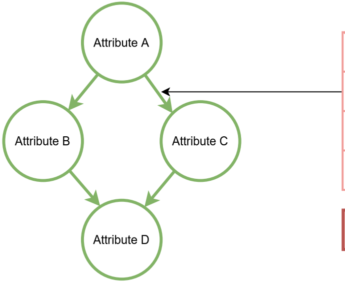


Figure: Classic Bayesian Network

Projective Bayesian Network (principle)



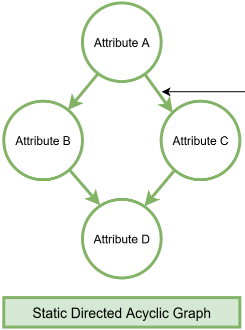
Directed Acyclic Graph

	A_1	A_2	A_3
C_1	$AC_{1,1,t}$	$AC_{2,1,t}$	$AC_{3,1,t}$
C_2	$AC_{1,2,t}$	$AC_{2,2,t}$	$AC_{3,2,t}$
C_3	$AC_{1,3,t}$	$AC_{2,3,t}$	$AC_{3,3,t}$

Conditional Probabilistic Tables

Figure: Classic Bayesian Network

Projective Bayesian Network (principle)



	A_1	A_2	A_3
C_1	$AC_{1,1,t}$	$AC_{2,1,t}$	$AC_{3,1,t}$
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Time Dependant Conditional Probabilistic Tables

Figure: Our model (Projective Bayesian Network)

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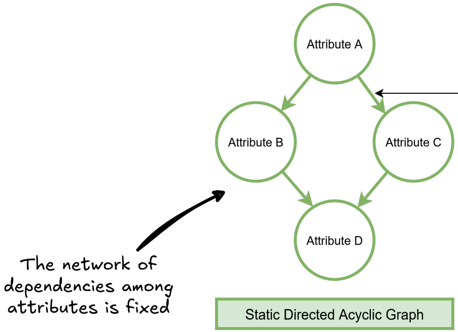

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Time Dependant Conditional Probabilistic Tables

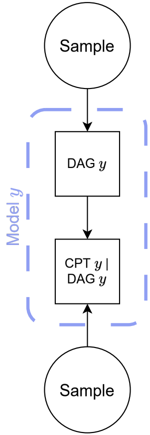
How attributes affect one another changes over time

Figure: Our model (Projective Bayesian Network)

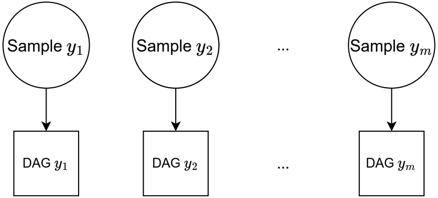
Projective Bayesian Network for Future Populations

Model training

Training a Bayesian Network



Training Projective Bayesian Network



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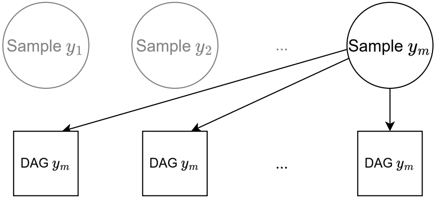

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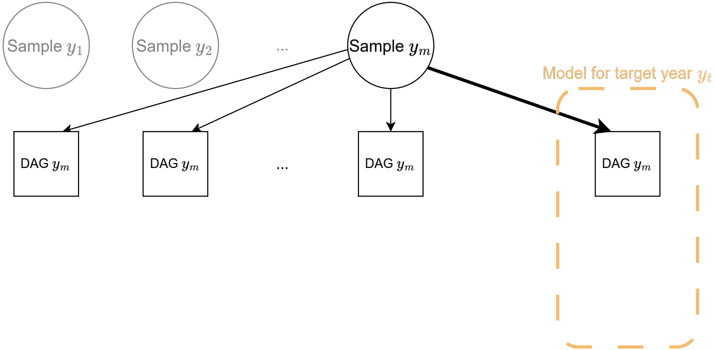

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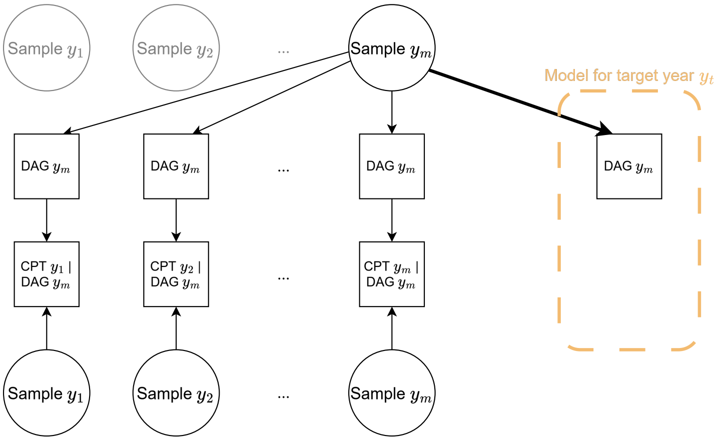
Training Projective Bayesian Network



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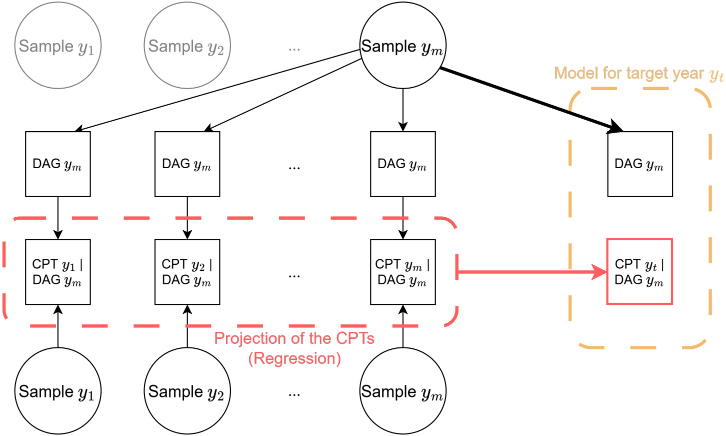
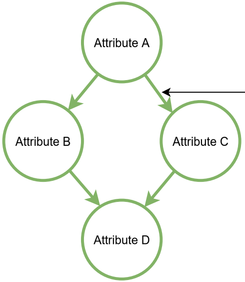


Regression for one Conditional Probabilistic Table



Static Directed Acyclic Graph

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Time Dependant Conditional Probabilistic Tables

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Regression for one Conditional Probabilistic Table

For each table, we need to determine the accurate trend and temporal effect to avoid overfitting.

Regression for one Conditional Probabilistic Table

For each table, we need to determine the accurate trend and temporal effect to avoid overfitting.

Two hyperparameters to fit for each table:

- Select the degree of the polynomial degree $n \in \{0,1\}$
- Select the discount factor $\alpha \in [0,1]$

$$\mathscr{L}_{\alpha,n}(r_i) = \sum_{t=1}^{m} (1-\alpha)^{y_t - t} (r_i(t) - \tilde{c}_{i,t})^2 ; r_i \in \mathbb{R}_n[X] \tag{2}$$

where $\tilde{c}_{i,t}$ is the i-th coefficient for year t

Hyperparameter selection

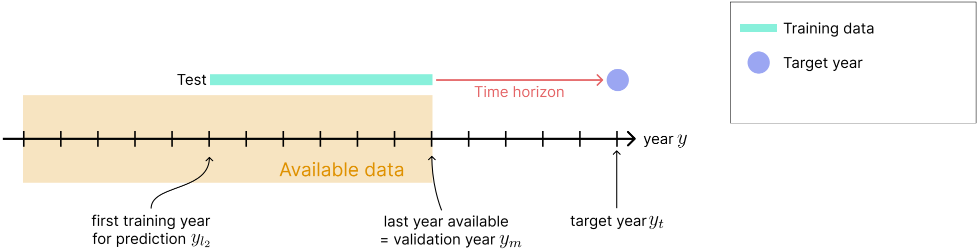
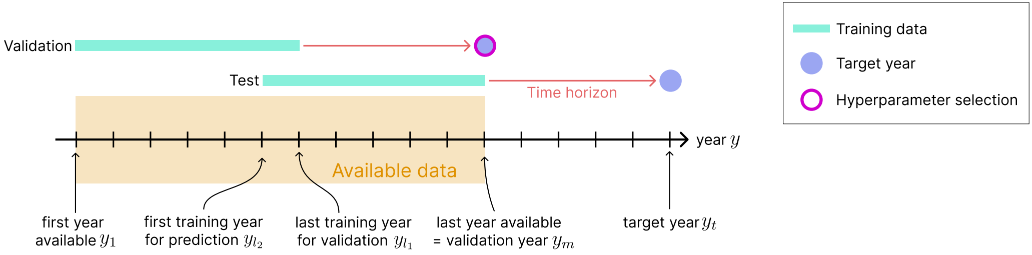


Figure: Walk-Forward Sliding Window validation for hyperparameters selection

$\rightarrow$ Evaluation via the joint distribution

Hyperparameter selection



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Model tuning for better alignment

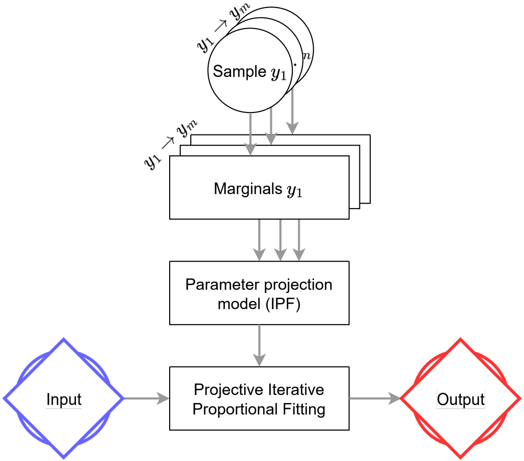

Figure: Temporal Marginal Alignment Model

Model tuning for better alignment

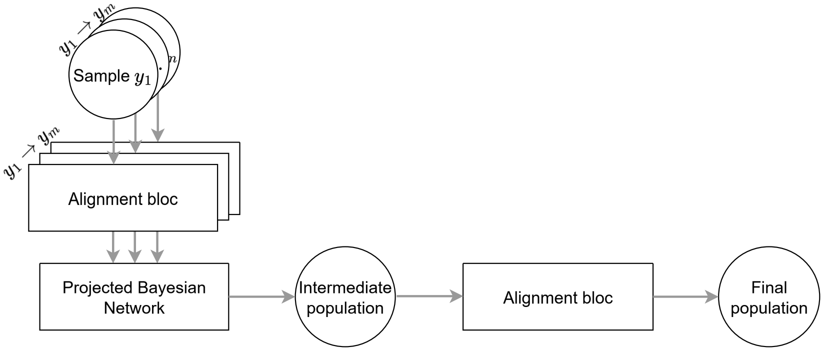

Figure: Final model combining alignment blocs and Projective Bayesian Network

Model tuning for better alignment

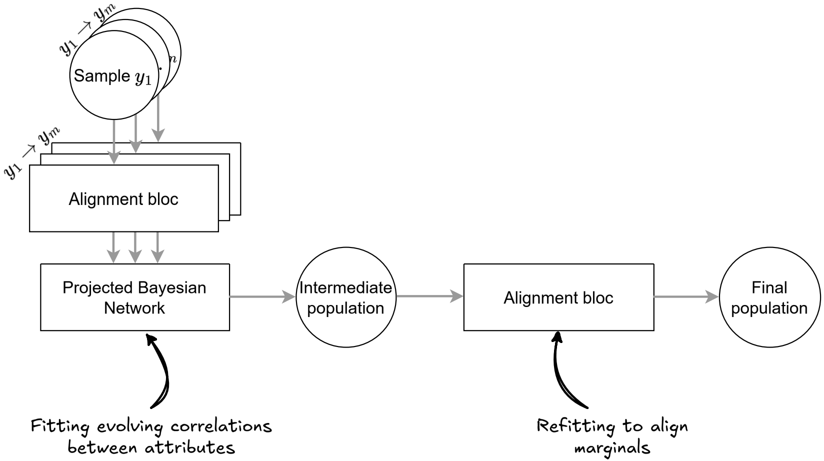

Figure: Final model combining alignment blocs and Projective Bayesian Network

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Projective Bayesian Network for Future Populations

Experiments

Experimental framework

- **Data:** French Census data from 2007 to 2021, with individuals described by 5 to 13 variables
  - **Training:** Subset composed of 0.03% or 1% of the total population from 2007 to 2020 (different time horizons)
  - **Evaluation:** Total population from 2021
- **Evaluation Design:**
  - **Distribution:** statistical matching between the generated population and the true population evaluated on **marginals**, but also on the **multivariate** distributions (bivariate and trivariate distributions) $\rightarrow$ *Metric:* $\overline{\text{SRMSE}}$
  - **Realism:** ensure that all individuals are plausible $\rightarrow$ *Metric:* SSCIOD
- **References:** Methods from the literature

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Preliminary Results

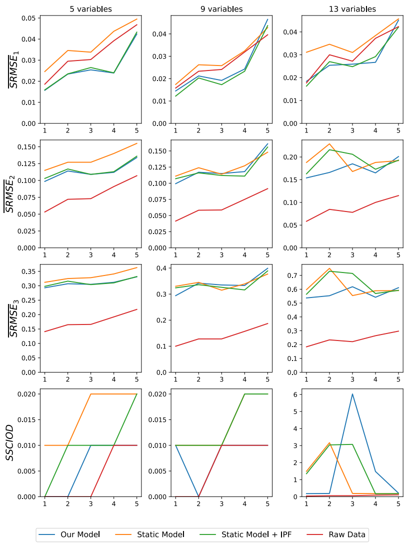

Figure: Results at 0.03%

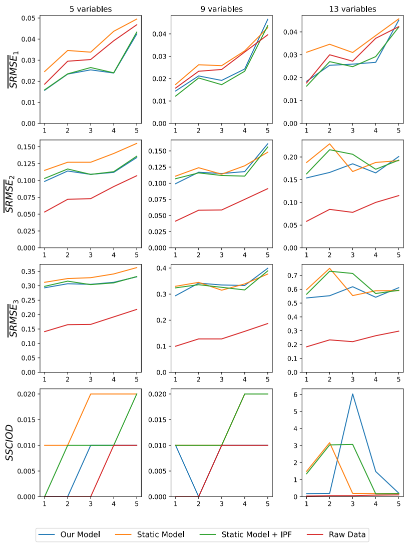

Figure: Results at 1%

Conclusions

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Conclusions

- A synthetic population becomes quickly outdated
- We provide a model that learns multi-year of data to grab trends on this evolving population, and provide a more accurate population
- Specially, our model performs well in low data cases

Limitations & Perspectives

- Limited to short-term prediction

Limitations & Perspectives

- Limited to short-term prediction
- Attributes limitation of Bayesian Networks

Limitations & Perspectives

- Limited to short-term prediction
- Attributes limitation of Bayesian Networks
- Analysis evolving relationships

Darsel, Vianey, Etienne Côme, and Latifa Oukhellou (June 2025). "Population Synthesis with Deep Generative Models -is it worth it? Exploring new models and metrics". In: **13th Symposium of the European Association for Research in Transportation**. Munich, Germany: Technische Universität München. URL: https://hal.science/hal-05130079 (visited on 07/03/2025).

Darsel, Vianey, Etienne Côme, Jeppe Rich, et al. (July 2026). "The Fragility Of Synthetic Populations Over Time: An Evaluation Of Forecasting Strategies For Agent-Based Models". en. In: **World Conference on Transport Research 2026 [Accepted]**. Toulouse, France: Transportation Research Procedia.

Fatmi, Mahmudur Rahman and Muhammad Ahsanul Habib (Jan. 2017). “Baseline Synthesis and Microsimulation of Life-stage Transitions within an Agent-based Integrated Urban Model”. In: **Procedia Computer Science**. 8th International Conference on Ambient Systems, Networks and Technologies, ANT-2017 and the 7th International Conference on Sustainable Energy Information Technology, SEIT 2017, 16-19 May 2017, Madeira, Portugal 109, pp. 608–615. **ISSN**: 1877-0509. **DOI**: 10.1016/j.procs.2017.05.366. **URL**: https://www.sciencedirect.com/science/article/pii/S1877050917310359 (visited on 05/01/2025).

Kukic, Marija, Salim Benchelabi, and Michel Bierlaire (Sept. 2023). “Hybrid Simulator for Capturing Dynamics of Synthetic Populations”. In: **2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)**, pp. 2646–2651. **DOI**: 10.1109/ITSC57777.2023.10422198. **URL**: https://ieeexplore.ieee.org/abstract/document/10422198 (visited on 04/29/2025).

- Lomax, Nik and Andrew P. Smith (May 2017). "An introduction to microsimulation for demography". In: **Australian Population Studies** 1.1, pp. 73–85. **DOI**: 10.3316/informit.999839569685668. **URL**: https://search.informit.org/doi/abs/10.3316/informit.999839569685668 (visited on 07/01/2025).
- Prédhumeau, Manon and Ed Manley (Mar. 2023). "A synthetic population for agent-based modelling in Canada". en. In: **Scientific Data** 10.1, p. 148. **ISSN**: 2052-4463. **DOI**: 10.1038/s41597-023-02030-4. **URL**: https://www.nature.com/articles/s41597-023-02030-4 (visited on 04/28/2025).
- W. Axhausen, Kay, Andreas Horni, and Kai Nagel, eds. (2016). **The Multi-Agent Transport Simulation MATSim**. English. Accepted: 2016-12-31 23:55:55. Ubiquity Press. **DOI**: 10.5334/baw. **URL**: https://library.oapen.org/handle/20.500.12657/32162 (visited on 12/01/2024).

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Thank you for your attention.

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Supplementary material

Complementary experiments

Impact of the alignment bloc before the Bayesian Network

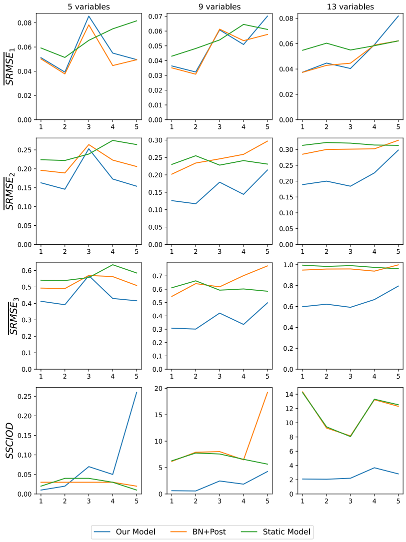

Figure: Results at 0.03%

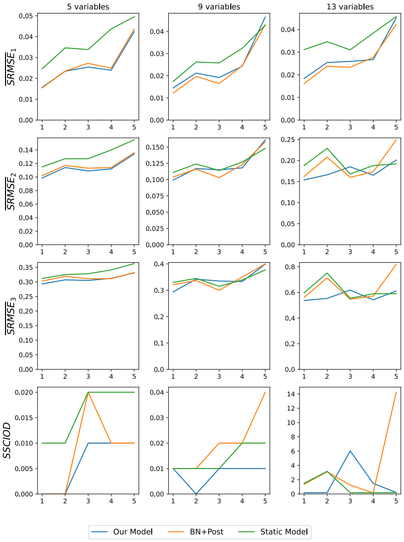

Figure: Results at 1%

Impact of the alignment bloc after the Bayesian Network

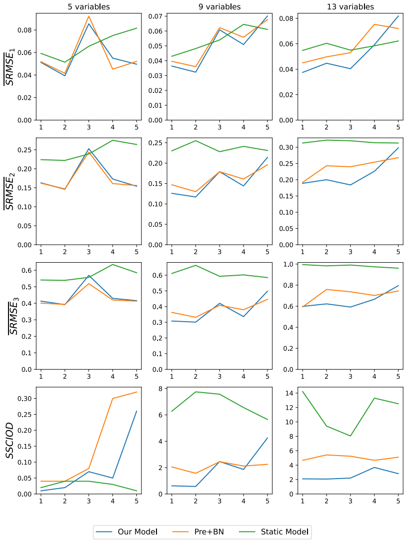

Figure: Results at 0.03%

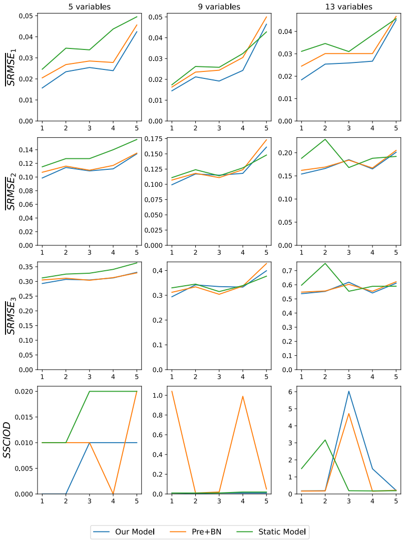

Figure: Results at 1%

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Impact of the Projective Bayesian Network (vs Static Bayesian Network)

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