LABORATOIRE
AMÉNAGEMENT
ÉCONOMIE
TRANSPORTS

Detection of Subway Service Disruptions and Contribution of Alternative Stops to Public Transport Resilience

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AI seminar – April 1st, 2025

Research Question

- **Disruption** is defined as an event that causes substantial deviation from the usual performance levels of a system.

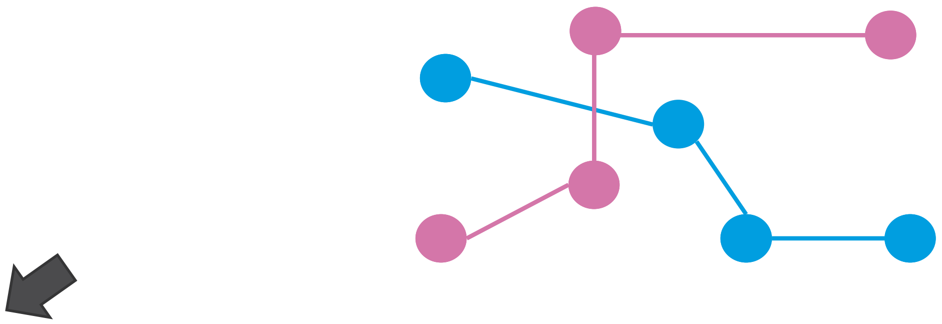
  1. Disruptions reduce satisfaction and undermine the resilience of public transport network by causing unplanned reallocation and crowding. It must be managed in short periods of time.

  2. Very granular data are available to finely and rapidly assess the performance levels of public transport systems.

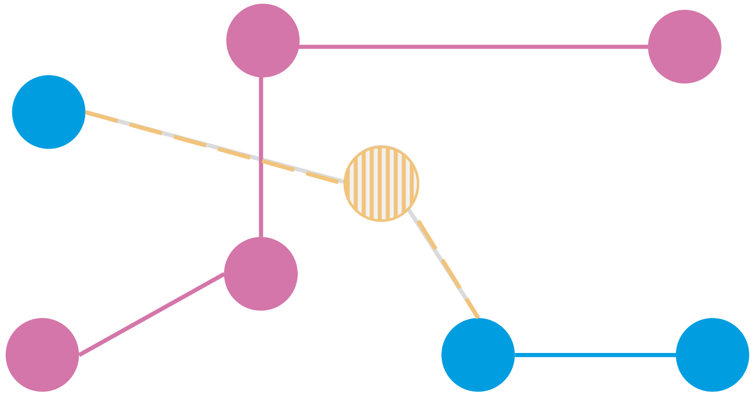
- *To what extent can data-driven methods be implemented to detect Public Transit disruptions? How can we measure the contribution of existing alternative options to the resilience of Public Transit systems?*

Objectives

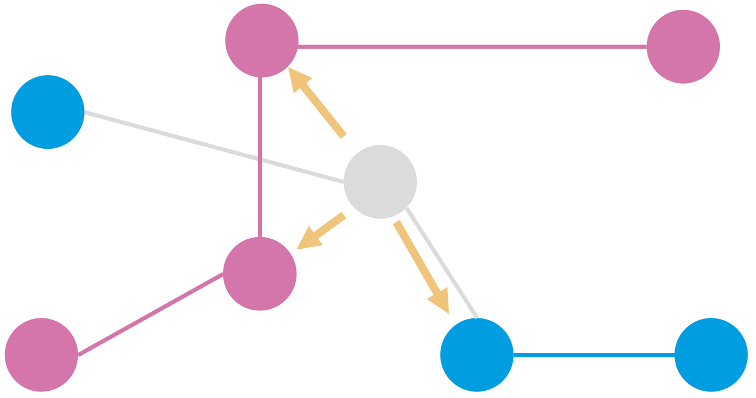
- Considering the following network, partly disrupted such as :



Service-based management plans
(Adaptive resilience)



Demand-based management plans
(Inherent resilience)



Objectives

- **Three objectives:**
  1. Detect most significant disruptions
  2. Identify where demand reallocation is done
  3. Take rapid actions to mitigate the effects of disruptions

- **Data used in literature:**
  a. Supply through vehicle locations and delays *(Marra et Corman, 2019; Yap et Cats, 2021)*
  b. Supply though network topology *(Cats, 2016; Ge et al. 2022)*
  c. Demand through Origin-Destination matrices *(Yap et al. 2018; Mo et al. 2023)*
  d. Demand through time series *(Sun et al. 2016; Briand et al. 2017)*
  e. Other data sources, such as social media *(Tonnelier et al., 2018; Ji et al., 2018)*

	a	b	c	d	e
1	x	x	x	x	x
2		x	x	x	
3	x			x	x

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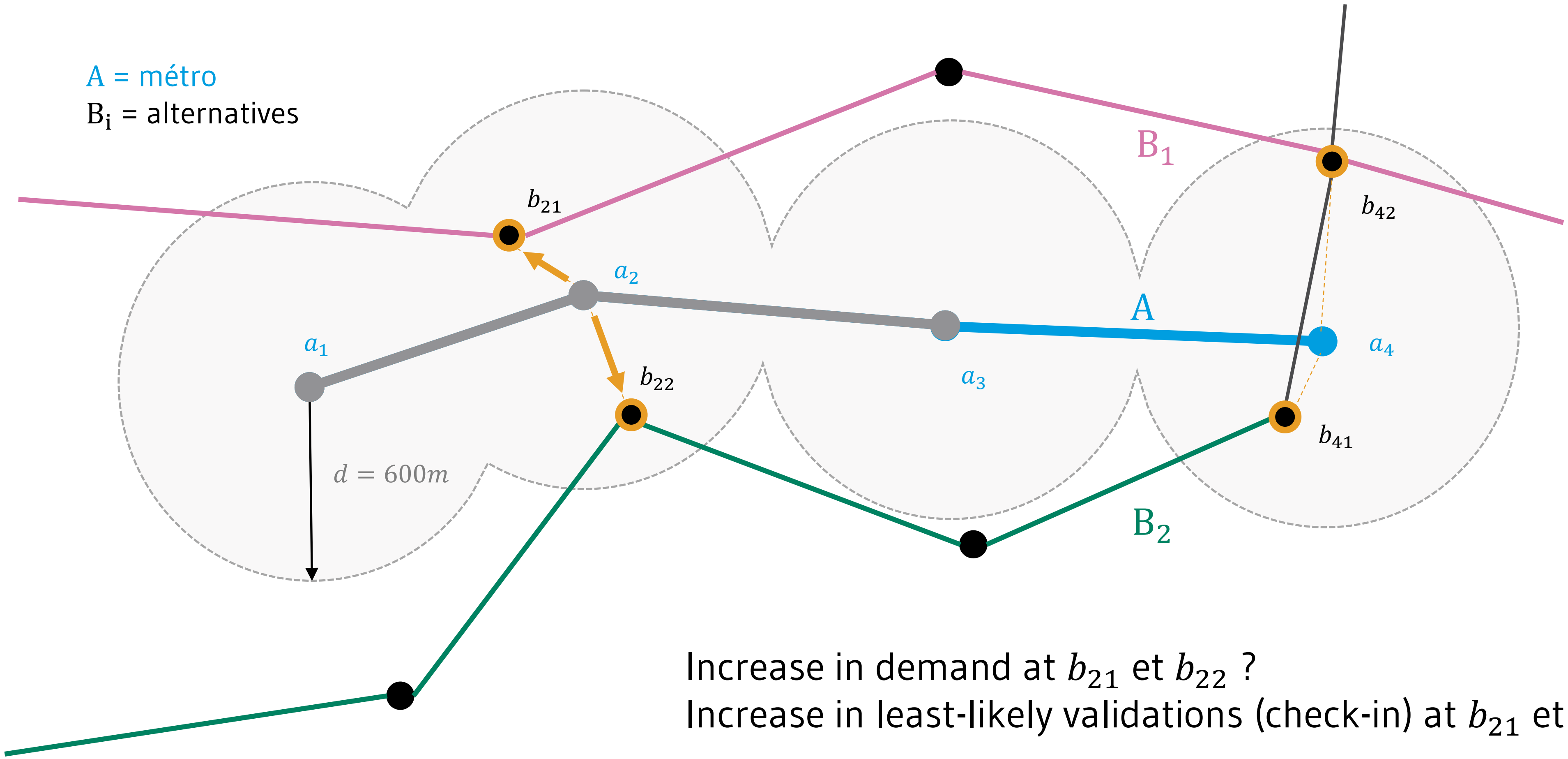
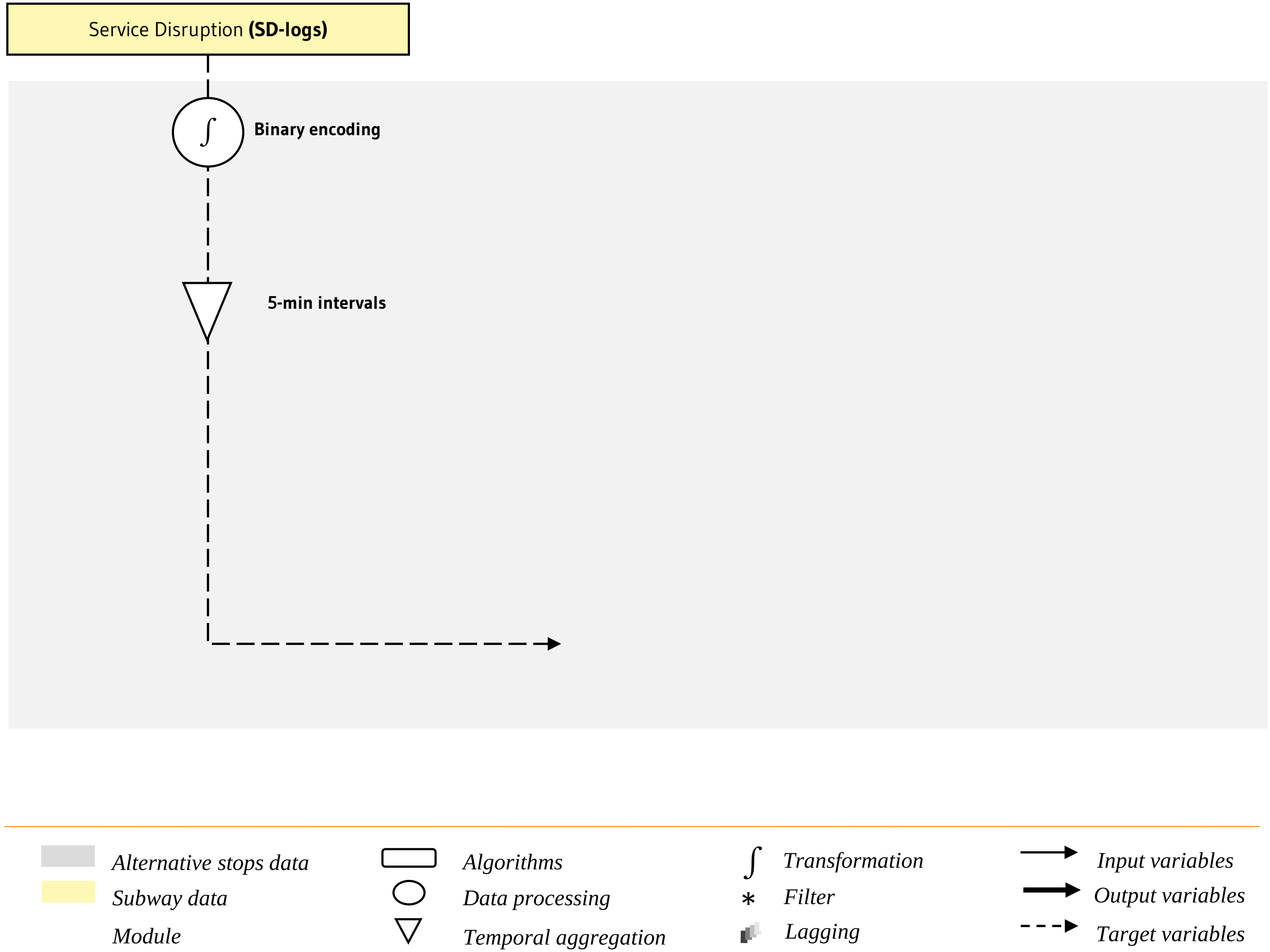
	a	b	c	**d**	e
1	x	x	x	**x**	x
2		x	x	**x**	
3	x			**x**	x

Intuition

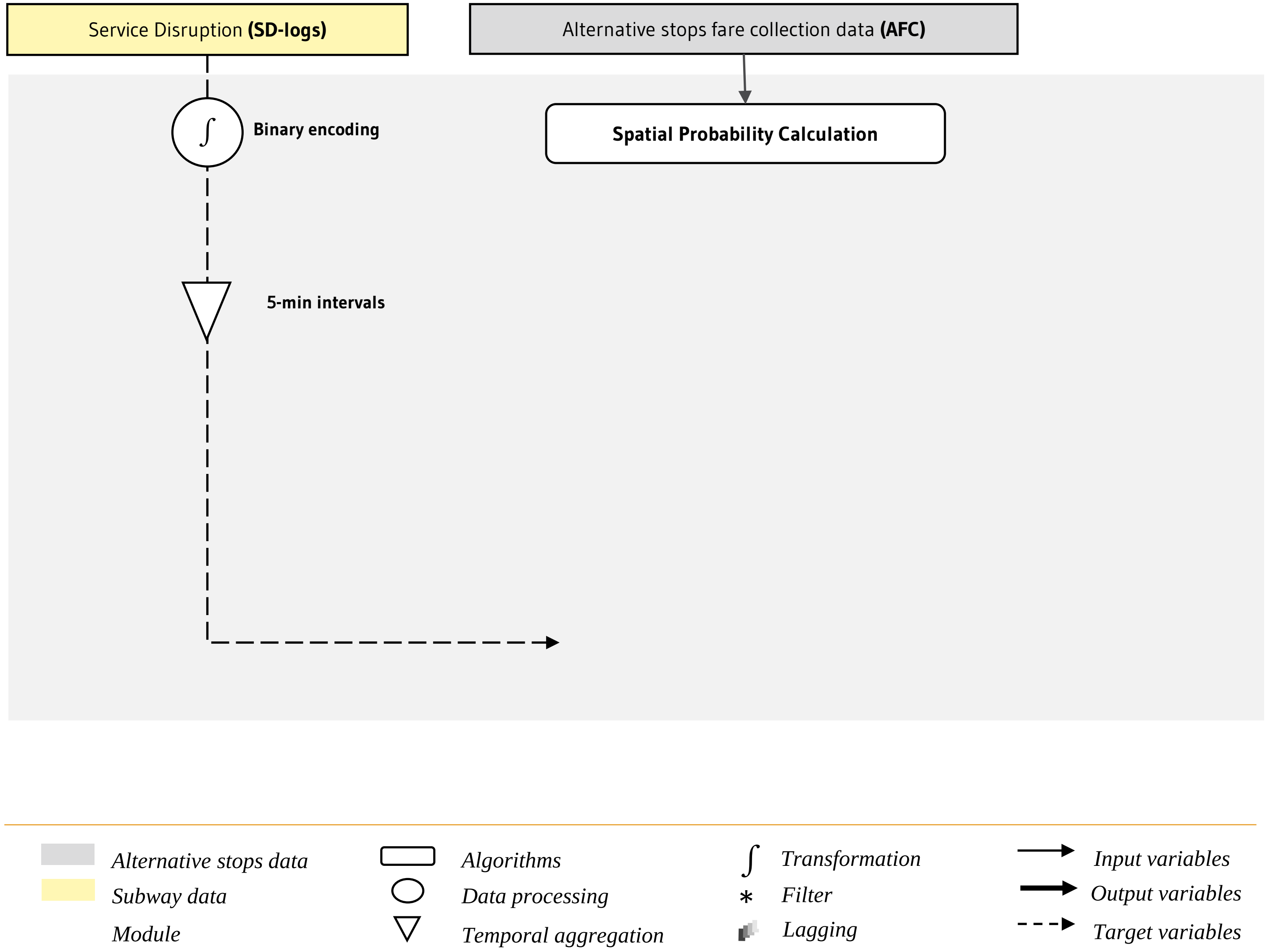


Increase in demand at b_{21} et b_{22} ?
Increase in least-likely validations (check-in) at b_{21} et b_{22} ?

Supervised binary classification settings



Supervised binary classification settings



Spatial Probability

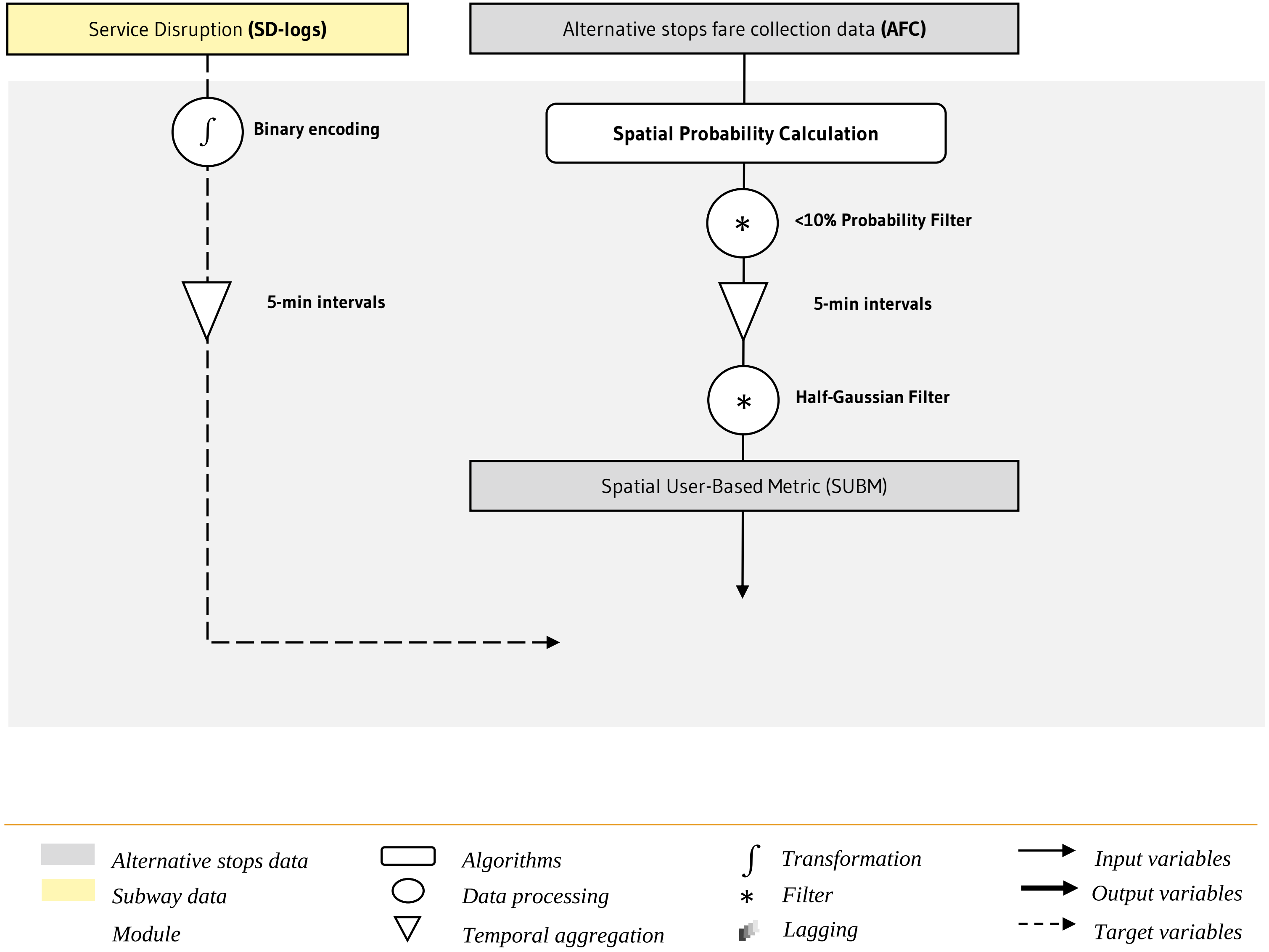
Let us denote each validation $v = (u, s, t)$:

- u is the user
- s is the stop
- t is the check-in time

For each validation v and each user u', the user probability to check-in at station s' is :

$$P(s'|u') = \frac{|\{v \mid (u = u',\ \ s = s',\ \ t)\}|}{|\{v \mid (u = u',\ \ s\ ,\ \ t)\}|}$$

Supervised binary classification settings



<10% Probability Filter

- The 10% least-likely validation are selected for each alternative stop

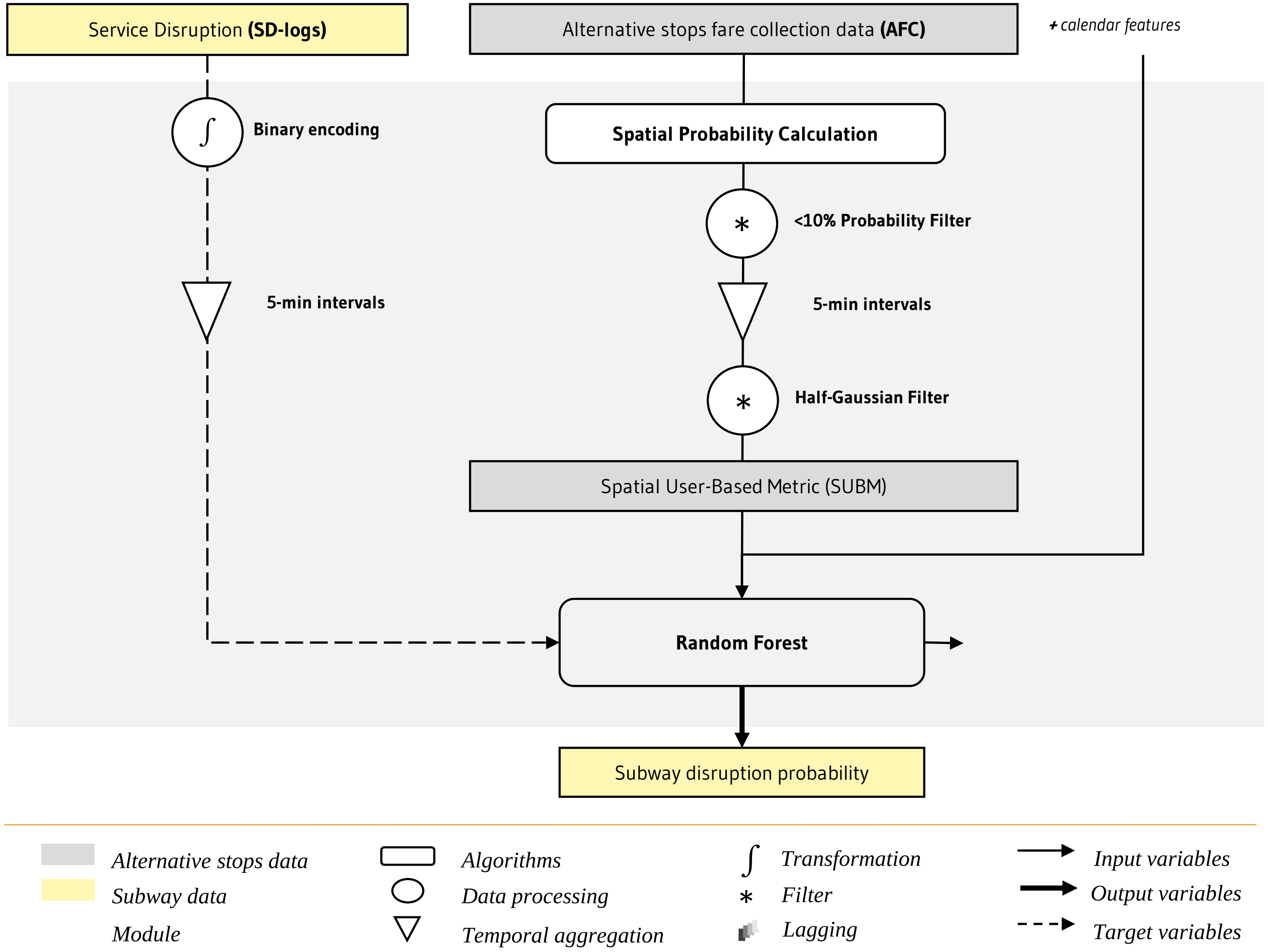
5-min intervals

- Temporal aggregation

Half Gaussian Filter

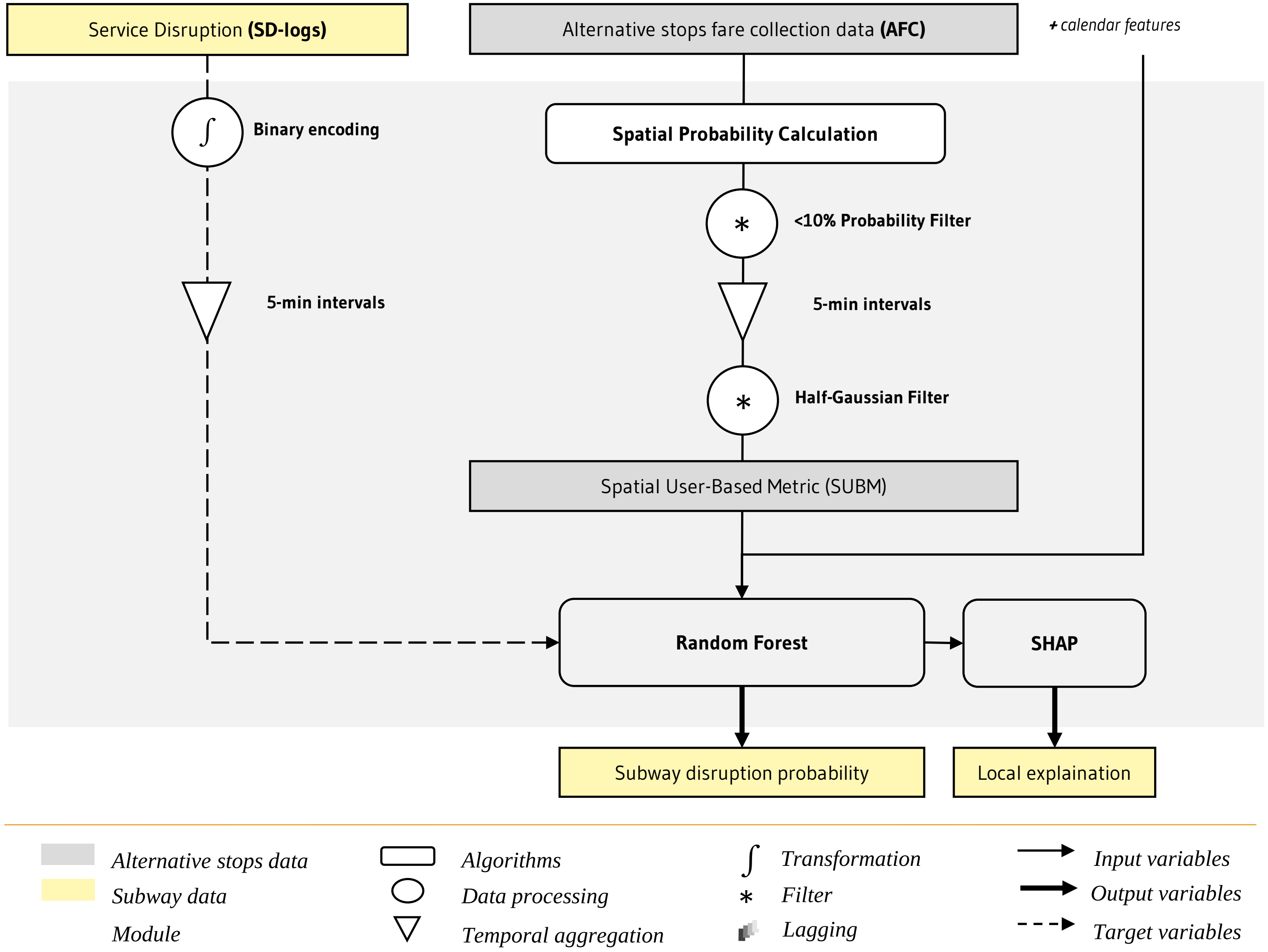
- The Half-Gaussian Filter is used for denoising without using data points *« in the future »*

Supervised binary classification settings



Random Forest
- Works fine with imbalanced data;
- Computes probabilities (*soft-labeling*) ;
- Has low computing time compared to other tree-based model such as Gradient Boosting.

Supervised binary classification settings



SHAP

- Post-hoc evaluation of local variable importance

SHapley Additive exPlaination (SHAP) (Lundberg et Lee, 2017)

The SHAP theory is based on game theory, where *"a prediction can be viewed as a coalitional game by considering each [variable] value of an instance as a player in a game"* (Molnar, 2023)

- <u>Example of game:</u> *How to share the treasure?*

Max and Alice are treasure hunters. Together, they find **100 gold coins** with the following distribution :

- Alice finds **60** gold coins alone
- Max finds **30** gold coins alone
- When hunting together, they find **10** gold coins

1 – We compute the following *value functions* :

- $v(\{\}) = 0$ (no treasure hunters, no gold coins)
- $v(\{Alice\}) = 60$ (Alice alone finds 60 gold coins)
- $v(\{Max\}) = 30$ (Max alone finds 30 gold coins)
- $v(\{Alice, Max\}) = 100$ (together, they find 100 gold coins)

SHapley Additive exPlaination (SHAP) (Lundberg et Lee, 2017)

2 – We compute *marginal contributions* of each player

- **Alice's Marginal Contribution**:
  When she joins Max: $v(\{Alice, Max\}) - v(\{Max\}) = 100 - 30 = 70$
  When she is alone: $v(\{Alice\}) = 60$

- **Max's Marginal Contribution**:
  When he joins Alice: $v(\{Alice, Max\}) - v(\{Alice\}) = 100 - 60 = 40$
  When he is alone: $v(\{Max\}) = 30$

3 - Shapley values are the **average of the marginal contributions of each player to all possible coalitions**.

Shapley value for Alice:

$$S(Alice) = \frac{70 + 60}{2} = 65$$

Shapley value for Max:

$$S(Max) = \frac{40 + 60}{2} = 35$$

SHapley Additive exPlaination (SHAP) (Lundberg et Lee, 2017)

- **Advantages** :
  - SHAP is a post-hoc and model-agnostic method
  - Tree-SHAP computes exact values when used in combination with tree-based models
  - Also deals with interactions between variables
  - Additive property

- **Drawbacks**:
  - Computationally expensive
  - Calculates approximated values for other machine learning models

Data

Fare collection data (AFC)

- 40 metro stations (39 modèles)
- All alternative stops (~ 520) in the service area of each metro station (600m buffer zone)
- Data collected from January 1st 2021 to December 31st, 2023
- Transformed in 5-minute time series

Service Disruptions (SD-logs)

- 3 916 disruptions
- Data collected from January 1st, 2021 to December 31st, 2023

Classification :

- Contamination rate : ≤ 1%
- The efforts to correct imbalance (SMOTE, Balanced Random Forest) did not significantly affect the model's performance
- Model's performance is measured with Average Precison score ($\mathrm{AP} \in [0,1]$).

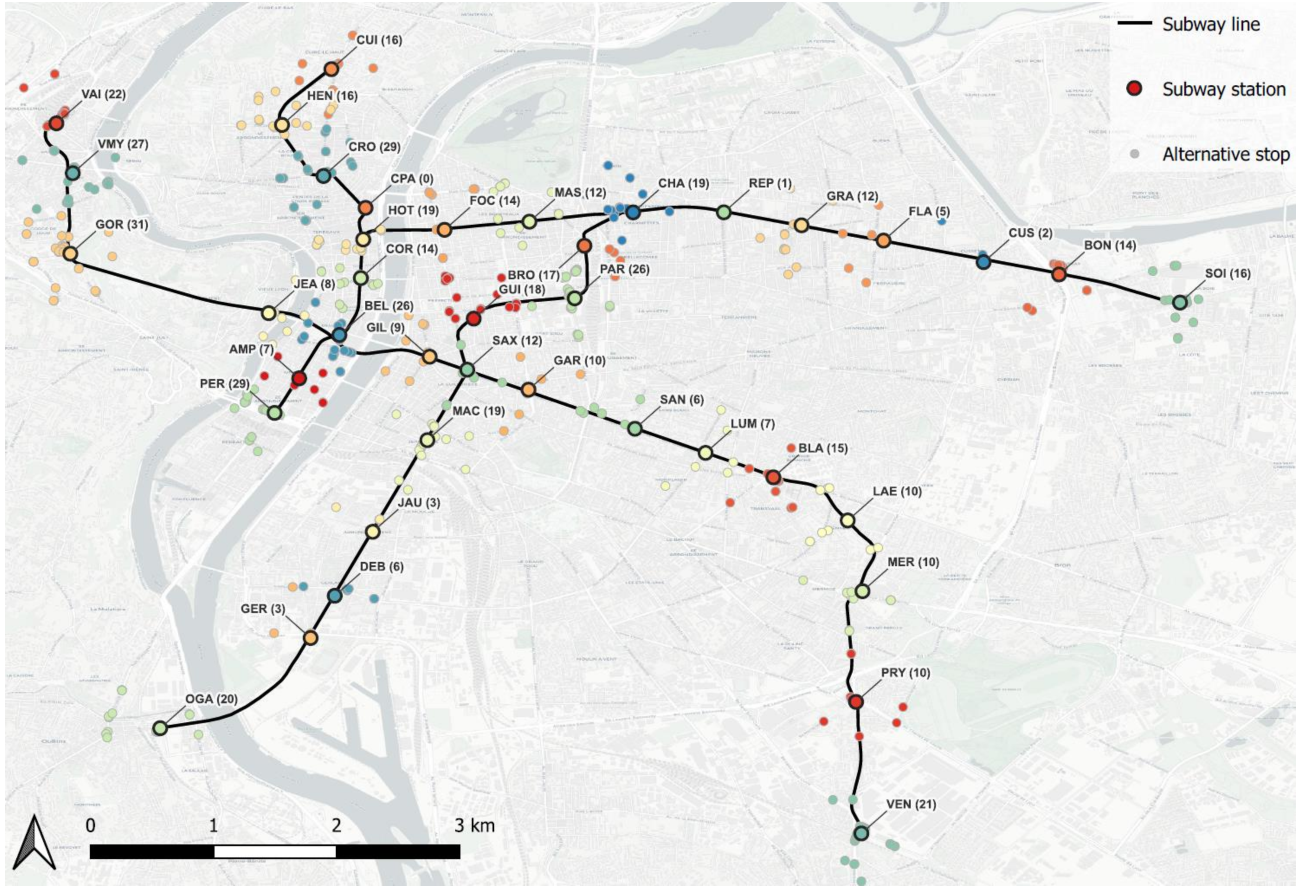


Fig1. Spatial distribution of disruptions on Lyon's metro network
(source: OSM, auteurs)

Performance

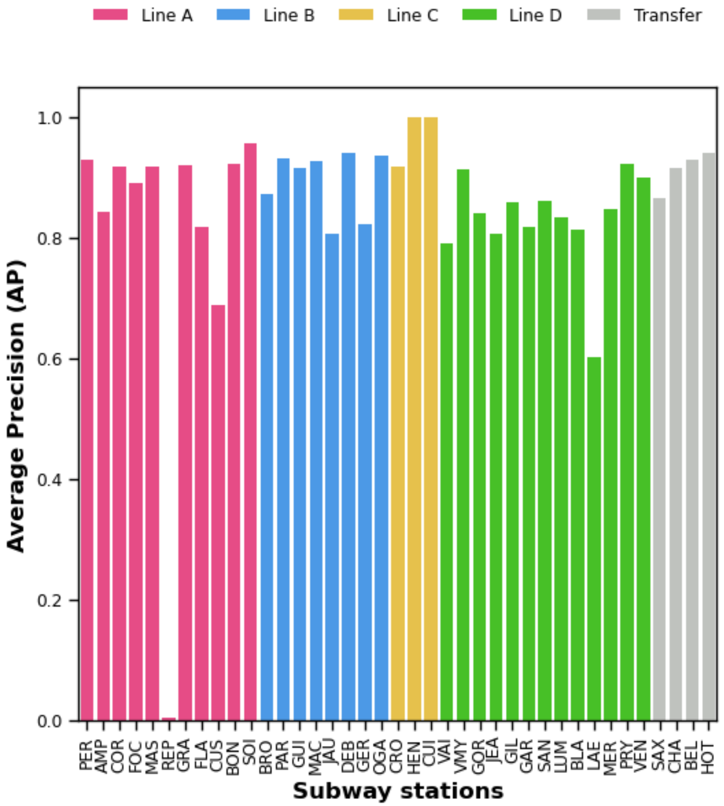


Fig2. Model's performance for each station and each line *(source : auteurs)*

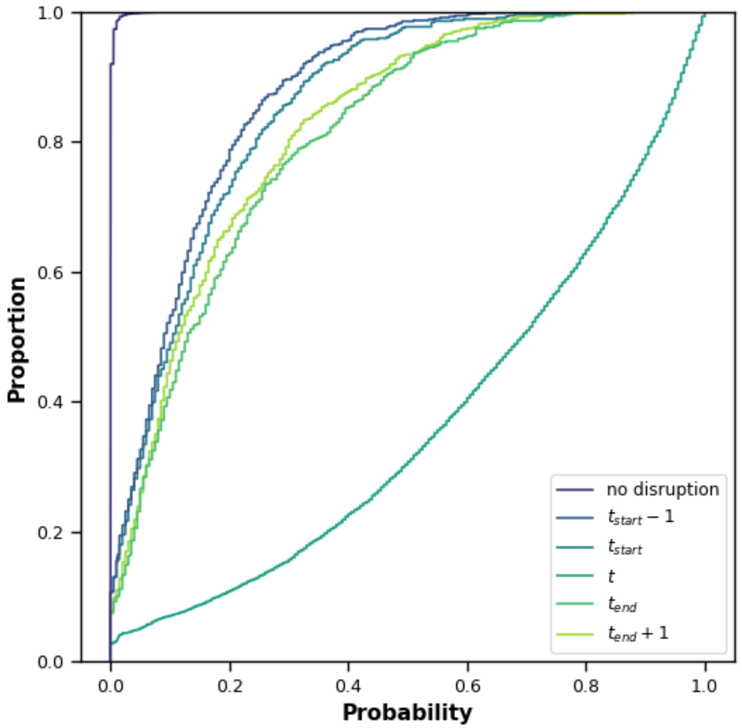
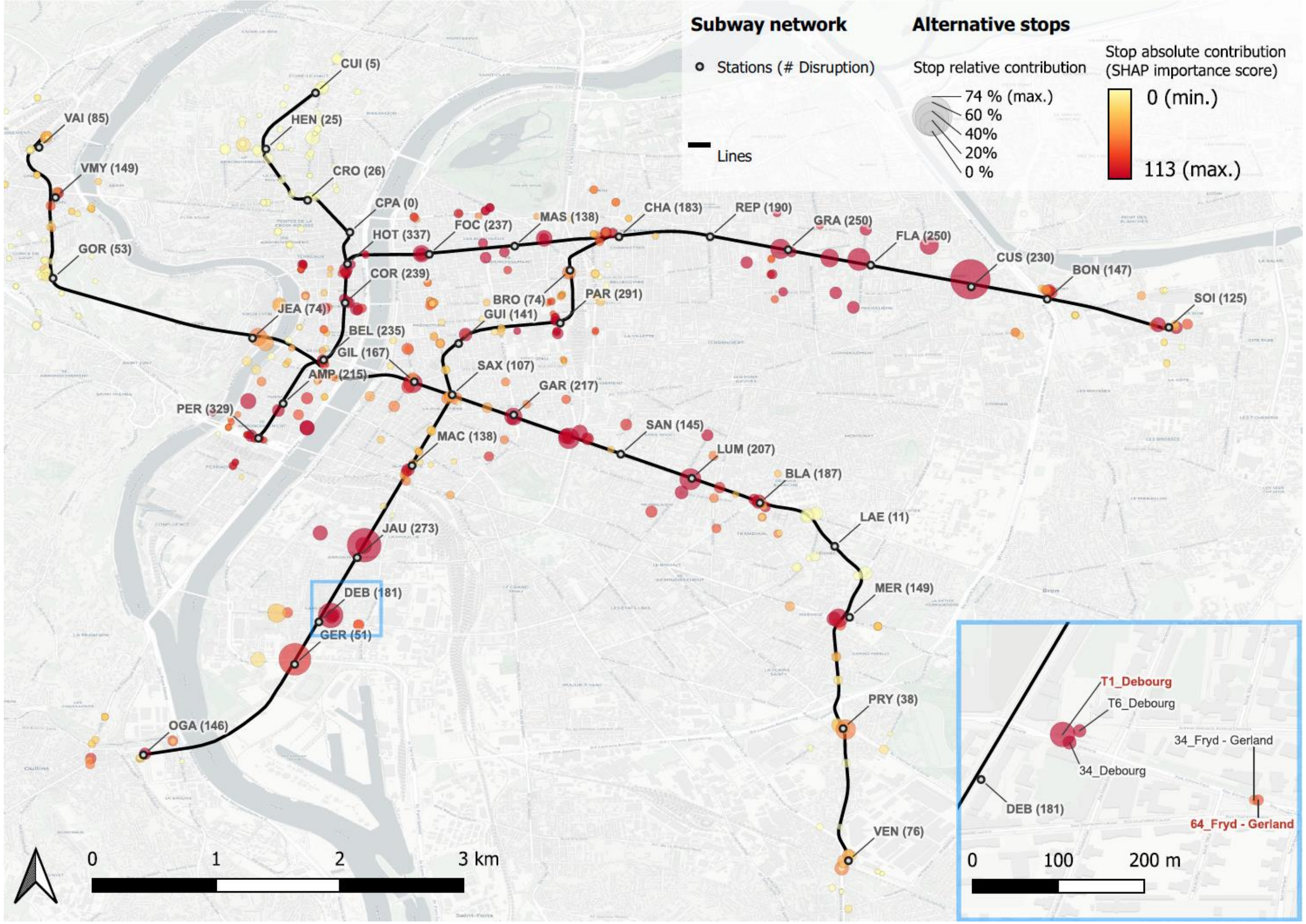


Fig3. Cumulative probability to face a disruption according to disruption's timeline *(source : auteurs)*

Contribution of alternative stops to the detection task

Fig5. SHAP importance score for each alternative stops *(source : auteurs)*



Contribution of alternative stops to the detection task

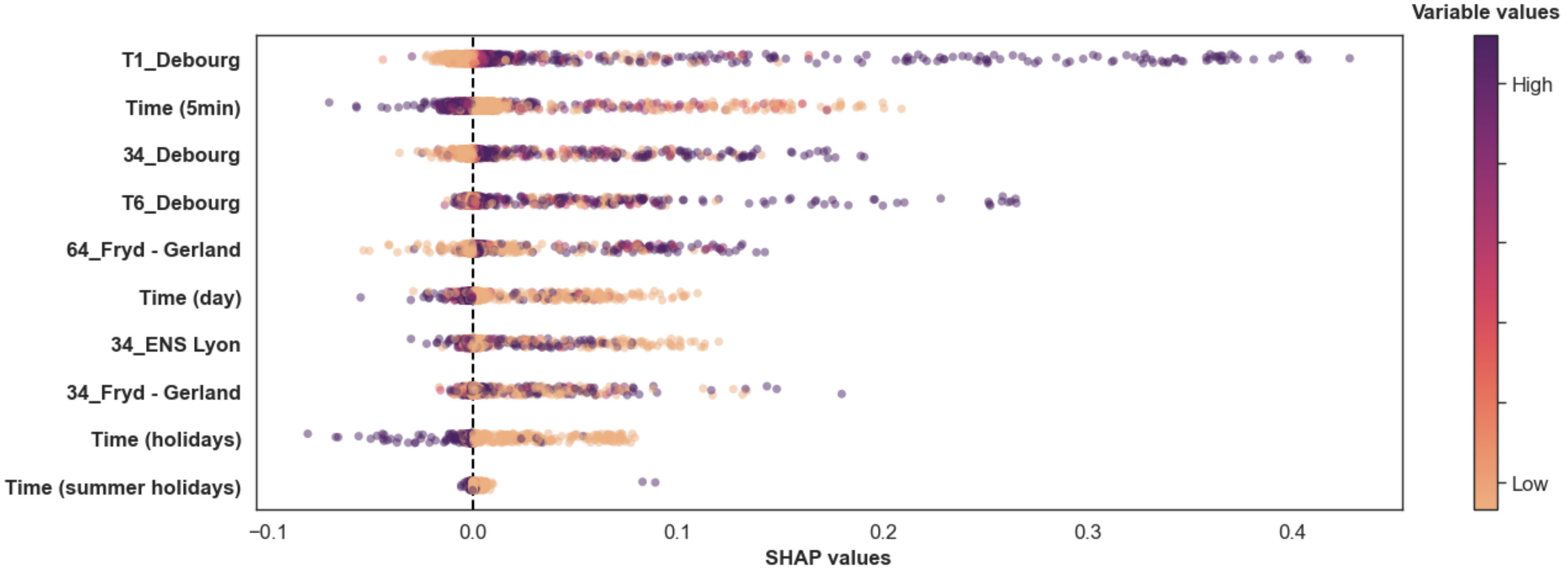


Fig5. SHAP values for the detection model at metro station Debourg *(source : auteurs)*.

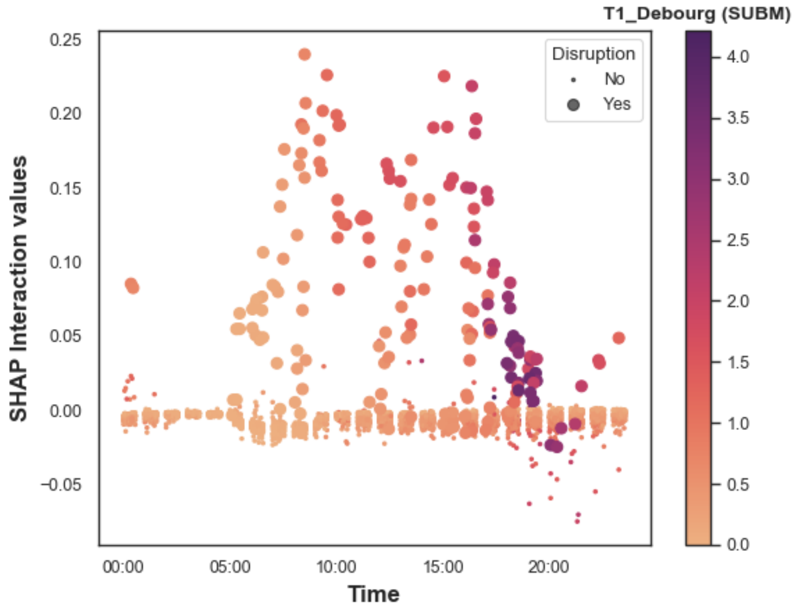


Fig6. SHAP interaction values between time variable (5min time step) and SUBM for alternative stop T1 at metro station Debourg *(source : auteurs)*.

Conclusions

- The proposed model shows high prediction perfomances
  - 90% of metro stations have a AP score higher than 0,8 ;
  - The model can foresee the occurrence of disruptions 5 minutes before their registered beginning in SD-logs;
  - The model minimizes false alarm rates
- SHAP allows to target the most-used alternative stops
  - Which is relevant insight to improve the flow reallocation process;
  - And to develop service-based managment plans in most vulnerable areas.
- Space-time interactions strengthen model's performance :
  - For each metro station, different alternative profiles are combined and complement each other;
  - Other calendar variables could improve the model's performance (e.g. soccer games at La Soie).
- Further works
  - Integrate the detection task to forecasting algorithms
  - Adapt the model to real-time operations;
  - Balance incident distributions for better comparability between stations.