

# One-station-ahead forecasting of dwell time, arrival delay and passenger flows on trains equipped with automatic passenger counting (APC) device

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## Background

- Real time arrival delays and crowding information are becoming the norm in the public transport network
- Two “time” series: along stations (for the same train ride) or along trains (for the same station) --- hence the wish of bi-auto regressive models exploiting both simultaneously



## Data source

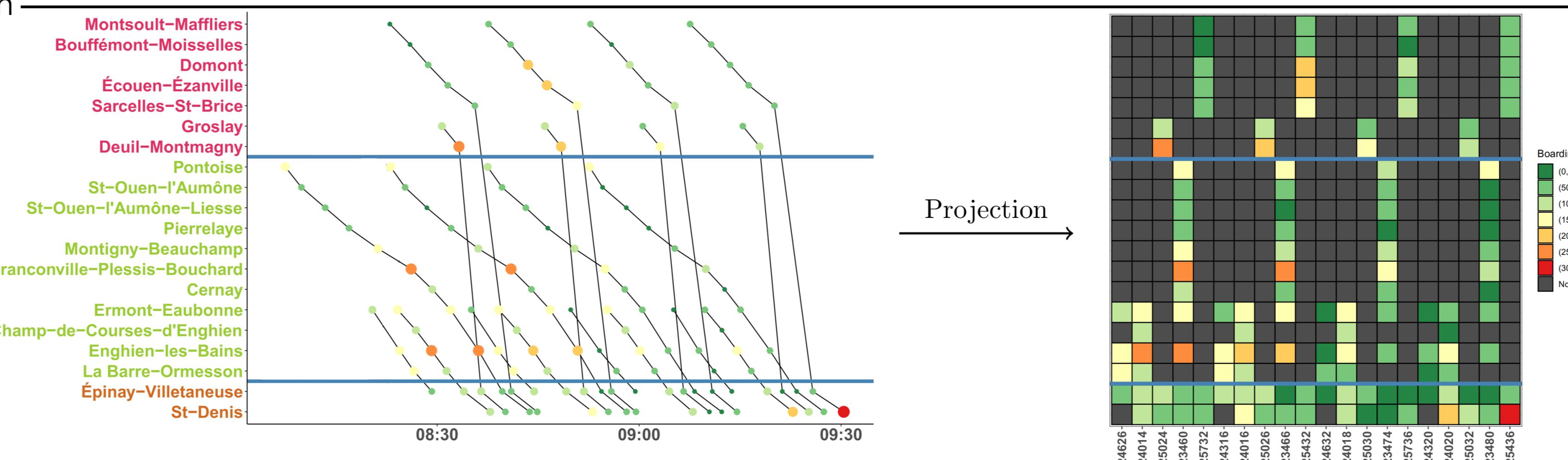
- Railway operations (AVL) + Passenger flow (APC)
- $\Delta A$  arrival delay
  - $T$  dwell time
  - $A$  alighting passengers
  - $B$  boarding passengers
  - $L$  load

## Perimeter

- 34,000 observed stops on 20 stations during 6 months
  - 55 trains on rush hours toward Paris
  - Train (70%) - Test (30%) split for evaluation
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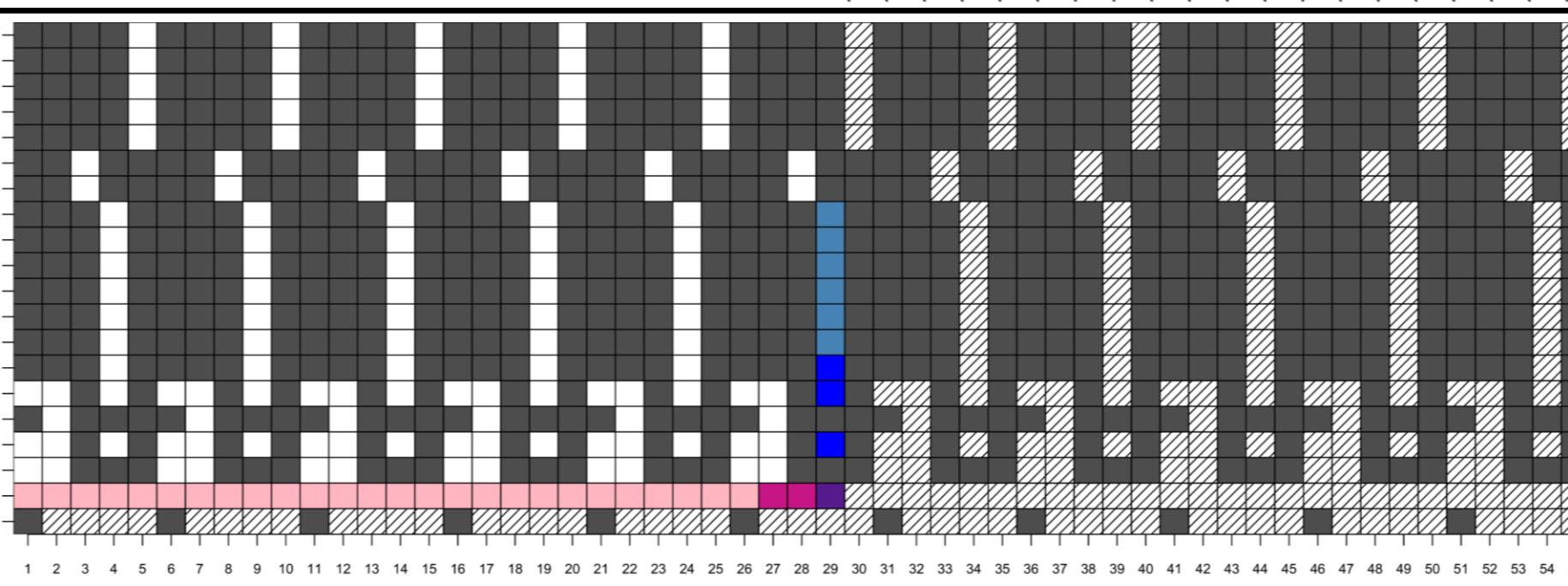
## Method

### Projection



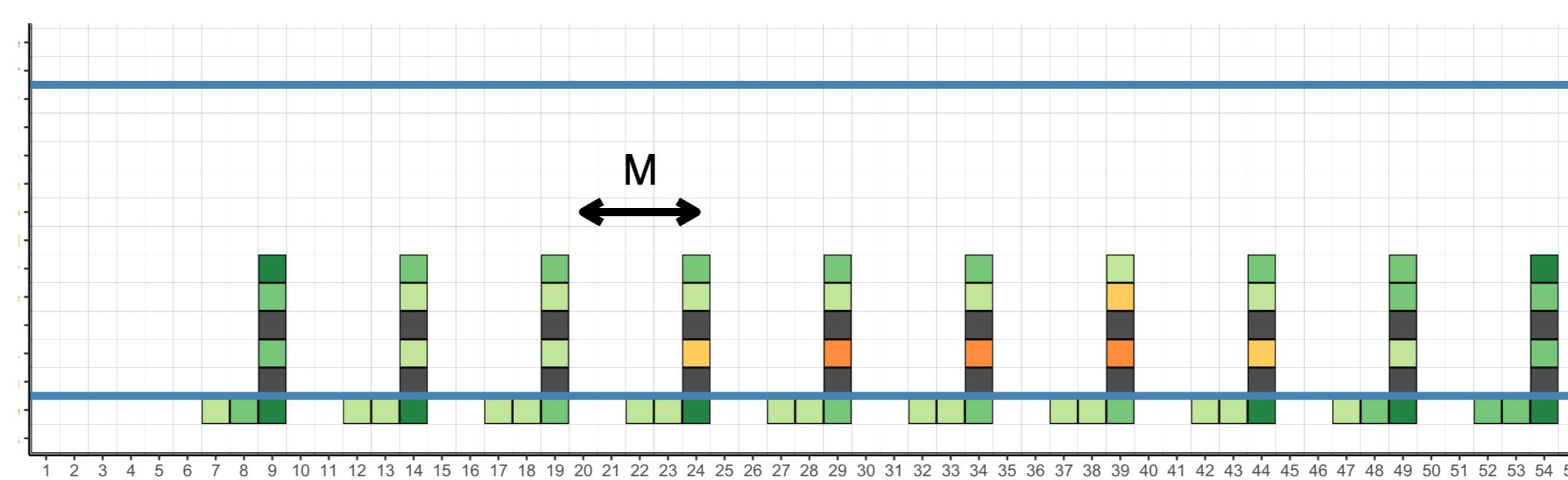
### L-Shape

- Only [3] and [2] use neighborhood along train rides (pink) or along stations (blue)
- Symmetric L-shape with neighborhoods  $P = Q \leq 3$



### Pattern

- Railway timetable consists of repeated patterns, which we identify
- Repetition of patterns during a given day and also along days



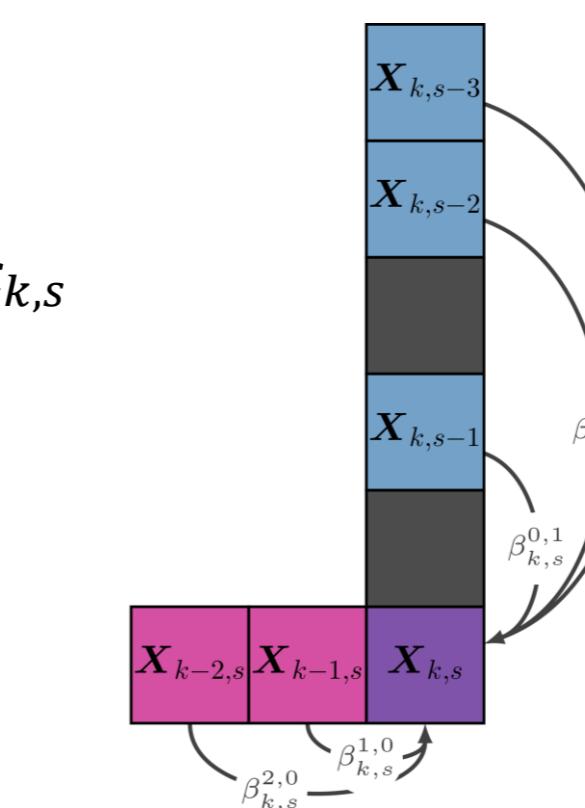
### Bi-auto-regressive modeling

- Linear Gaussian models at each pair (station  $s$ , train ride  $k$ ), with three degrees of complexity
- $k[M]$  indicates that the coefficient only depends on the position of the train ride within the pattern

$$\text{Non-stationary } X_{k,s} = \beta_{k,s}^{0,0} + \sum_{p=1}^P \beta_{k,s}^{p,0} X_{k-p,s} + \sum_{q=1}^Q \beta_{k,s}^{0,q} X_{k,s-q} + \varepsilon_{k,s}$$

$$\beta_{k,s}^{p,0} \Rightarrow \beta_{k[M],s}^{p,0}$$

$$\beta_{k,s}^{p,0} \Rightarrow \beta_{k[M],s}^{p,0} \text{ and } \beta_{k,s}^{0,0} \Rightarrow \beta_{k[M],s}^{0,0}$$



## Contributions

1. Assessing one framework on 5 different variables:

While only  $T$  in [4],  $\Delta A$  in [2],  $L$  in [1], [3] and [5] (and none for  $A, B$ ) While linear models are too frugal in [4] or too complex in [2]

2. A balance between frugality and complexity:

## Results

Models	Railway operations		Passenger flow					
	Name	L-Shape	Number of coefs	T [s]	$\Delta A$ [s]	A [count]	B [count]	L [count]
Non-stationary	$P = Q = 0$	327	9,7	35,8	10	21	70	
	$P = Q = 1$	915	9,5	16,1	9	18	22	
	$P = Q = 1$	403	9,2	16,1	10	18	23	
	$P = Q = 2$	440	9,2	15,8	9	18	23	
Semi-stationary	$P = Q = 3$	466	9,1	15,8	9	18	23	
	$P = Q = 1$	76	9,3	16,2	10	21	30	
	$P = Q = 2$	113	9,2	15,8	9	20	29	
	$P = Q = 3$	139	9,2	15,9	9	20	29	
Stationary								

[Semi]-stationary models obtain a performance similar to the non-stationary model for passenger flow and railway operations variables with fewer parameters (twice fewer or 8 times fewer)

## Next steps

- Are bi-auto-regressive models suitable for several-step-ahead forecasts?
- Extension to multivariate bi-auto-regressive models: e.g., how to leverage past values of  $A$  and  $B$  to help forecasting  $L$

## References

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