

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)
- ΔA 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



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

Non-stationary

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

Semi-stationary

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

Stationary

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

Contributions

- Assessing one framework on 5 different variables: While only T in [4], ΔA in [2], L in [1], [3] and [5] (and none for A, B)
- A balance between frugality and complexity: While linear models are too frugal in [4] or too complex in [2]

Results

Models		Number of coefs	Railway operations		Passenger flow		
Name	L-Shape		T [s]	ΔA [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
Semi-stationary	P = Q = 1	403	9,2	16,1	10	18	23
	P = Q = 2	440	9,2	15,8	9	18	23
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

[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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