Data-driven modelling and validation of the inbound flow at some major European airports

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Summary

Problem

Estimating the daily demand at major European airports

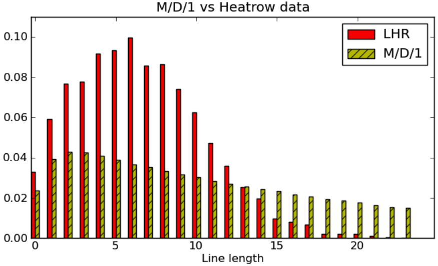
Data and Methods

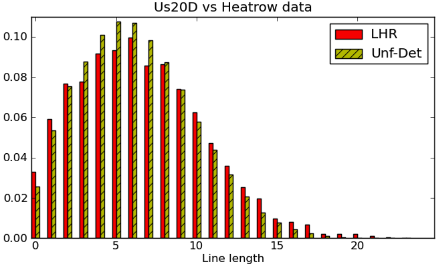
- Entrance time in a cylinder of radius 40 NM around airport
- Data-driven definition of Poisson process and Pre-scheduled Random Arrivals
- Comparison of the two processes

Conclusions

PSRA outperforms Poisson arrivals in estimating the daily demand

Motovation: inbound queue at Heathrow

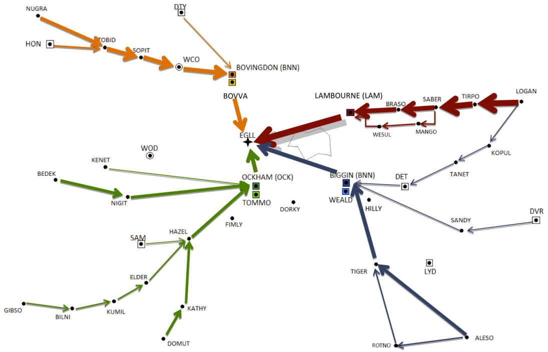




From Caccavale, Iovanella, **Lancia**, **Lulli**, Scoppola (2014) A model of inbound air traffic: The application to Heathrow airport.

Journal of Air Transport Management, 34, 116–122

Motivation: inbound queue at Heathrow



From Caccavale et al. (2014) *J Air Transp Manag*, 34, 116–122

- Indirect comparison through a $\cdot$/D/1 queue model
- Analysis overlooks action of TC on inbound stream
- *This leads to overestimating PSRA parameter* σ
- Deterministic schedule of PSRA is equally spaced in time (OK for Heathrow, though)

Airport selection and Arrival areas

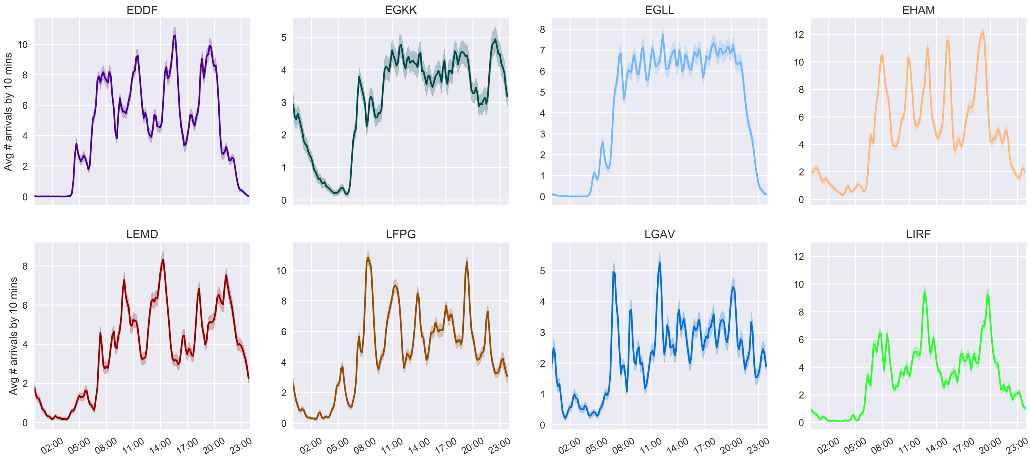
Dataset overview

airport name	ICAO code	sample size
Frankfurt am Main International Airport	EDDF	58167
London Gatwick Airport	EGKK	39746
London Heathrow Airport	EGLL	56716
Amsterdam Airport Schiphol	EHAM	63279
Madrid Barajas International Airport	LEMD	48162
Charles de Gaulle International Airport	LFPG	60122
Athens International Airport	LGAV	29503
Rome Fiumicino International Airport	LIRF	43333

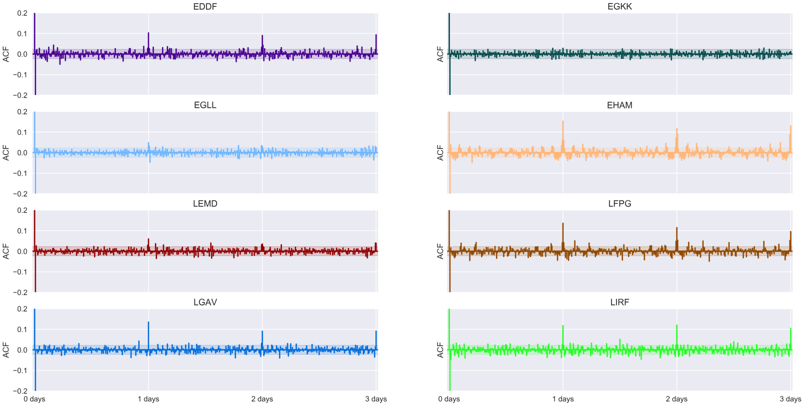
Study period goes from June 15 to September 15, 2016

We model the demand using first time within 40 NM from airport

Average daily demand



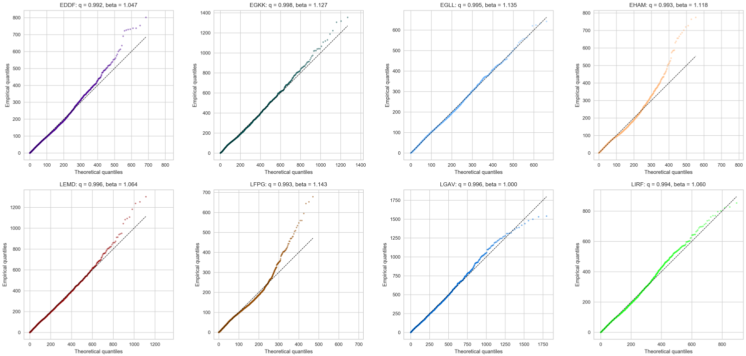
Significant autocorrelations at lag 10 mins and 1-2 days



We expect batch arrivals *(typically Weibull interarrivals)* and a daily-periodic demand

Interarrival times are (nearly) exponential

Fitted Weibull: $P_W(X = x; q, \beta) = q^{x^\beta} - q^{(x+1)^\beta}$



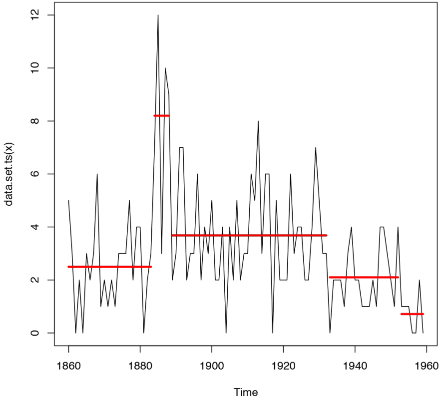
Poisson process explains shape $\simeq 1.0$ *but clashes with negative lag-1 autocorrelation*

Data-driven Poisson process

1. Aggregate arrivals TS, e.g. by intervals of 10 minutes
2. Run a changepoint-detection algorithm, e.g. PELT, under the null hypothesis of Poissonian arrivals to obtain
   - changepoint time $\hat{t}_k$
   - $\hat{\lambda}_k$, estimated intensity in $[\hat{t}_k, \hat{t}_{k+1})$
3. Cluster couples $\{(\hat{t}_k, \hat{\lambda}_k)\}_k$, e.g. via DBSCAN
4. Compute the centroid $(\bar{t}_i, \bar{\lambda}_i)$ of each cluster
5. Define a step-wise, periodic intensity function that takes on $\bar{\lambda}_i$ for $t \in [\bar{t}_i, \bar{t}_{i+1})$

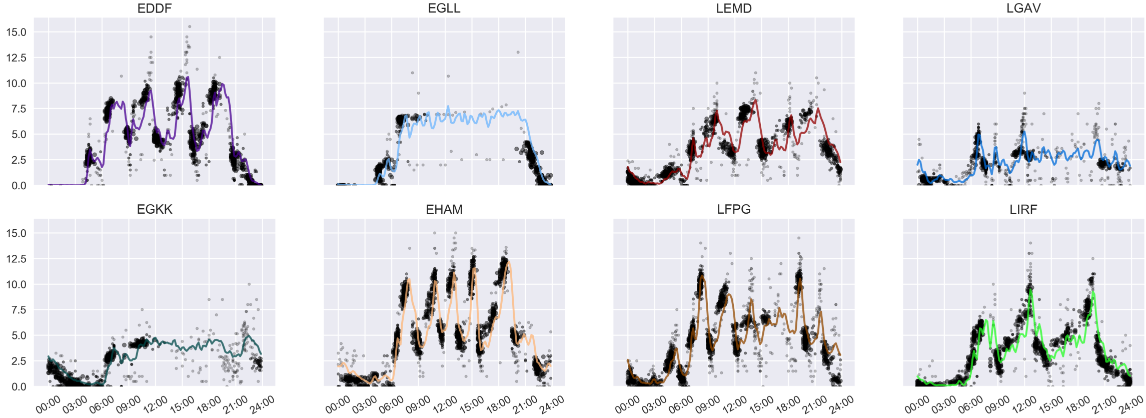
Changepoint detection via PELT

- PELT is an algorithm for multiple changepoint detection in a time series
- It can detect changes in mean, variance, or both
- Software available via R package `changepoint`
- We work under the null hypothesis of Poisson arrivals



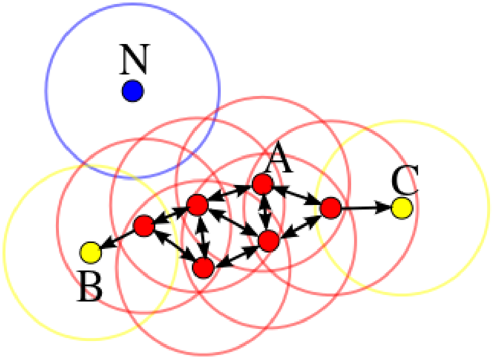
Killick, Eckley (2014) *J Stat Soft* 58(3)

Result of PELT



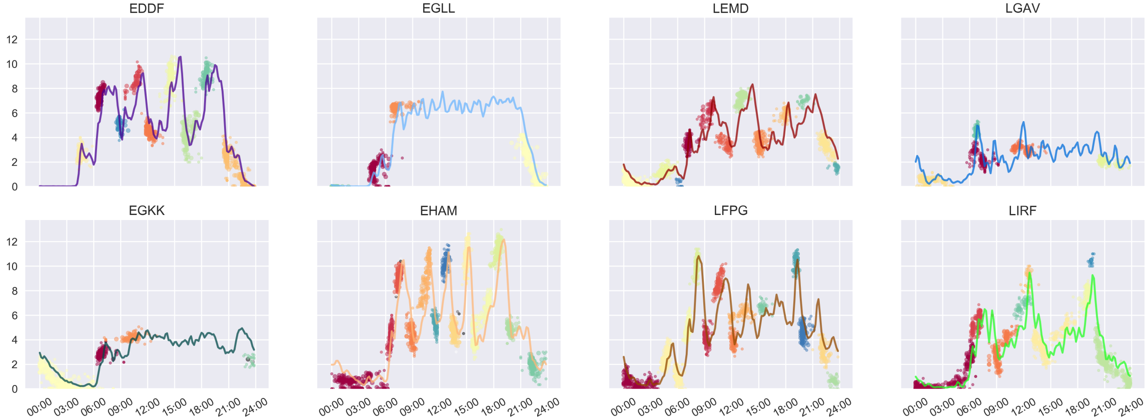
Clustering via DBSCAN

- Density-based spatial clustering of applications with noise (DBSCAN)
- Two hyperparameters, ε and n_{pts}
- Core points (red) have at least n_{pts} other points within distance ε
- Non-core (yellow) lie within ε from a core point
- The remainders are outliers (blue)

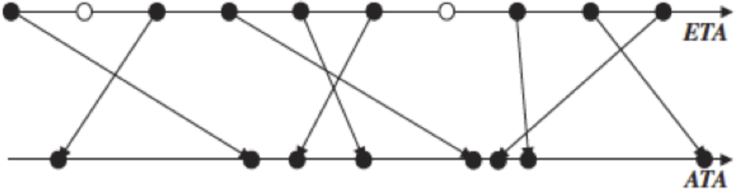


Source: Wikimedia Commons

Implementation of data-driven Poisson process



Pre-scheduled random arrivals (PSRA)



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Idea

Fixed, deterministic schedule perturbed by IID random variables

$$t_i = \frac{i}{\mu} + \xi_i$$

Note. It weakly converges to Poisson process when delays's standard deviation $\sigma_\xi \to \infty$

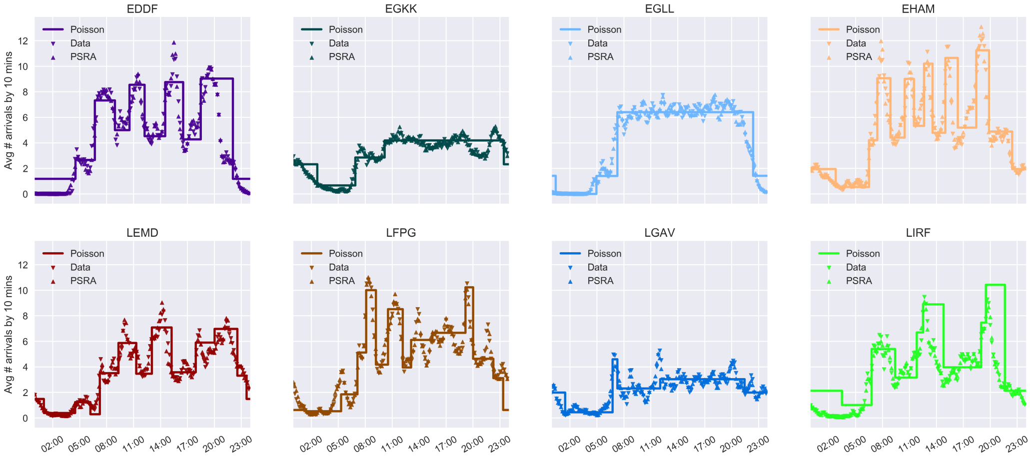
Data-driven PSRA

1. Let t_i^{M3} the *actual* arrival time at 40 NM
2. Let t_i^{M1} the *anticipated* arrival time at 40 NM (from the last flight plan agreed with Eurocontrol)
3. Compute the *delays* $\delta_i = t_i^{\mathrm{M3}} - t_i^{\mathrm{M1}}$
4. Define

$$t_i = t_i^{\mathrm{M1}} + \xi_i$$

   where $\{\xi_i\}_i$ are IID rvs drawn from the empirical distribution of the delays $\{\delta_i\}_i$

Data-driven Poisson vs PSRA

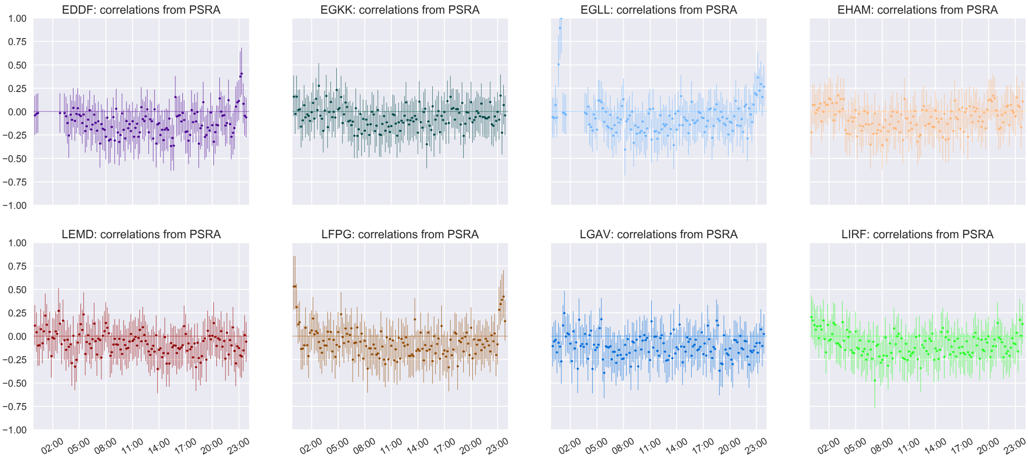


Data-driven Poisson vs PSRA

- PSRA outperform Poisson arrivals in reproducing the average daily demand
- Average demand reproduced with Poisson model by forcing intensity to vary over a finer time scale, e.g. every 10 minutes
  - Caveat number of parameters required increases in a sensible manner (144)
  - Caveat system mostly out of equilibrium
  - Caveat mathematical tractability is greatly reduced
- PSRA is non-parametric
- A semi-parametric model is possible by defining $\xi_i = \xi_i(Z)$
- PSRA inherits arrivals correlation-structure from the M1 schedule
- In contrast, Poissonian arrivals have independent increments by definition

Arrivals correlation

Correlations from simulation of PSRA



Conclusions

- PSRA describes better the inbound flow than Poisson arrivals
- Poisson arrivals lead to overestimation of the queue
- Only advantage of Poisson is mathematical tractability
- If time scale is small, only the transient matters, *i.e. no benefit*
- PSRA are difficult to tackle, but efficient approximation schemes are possible, see Lancia et al (2017) `https://arxiv.org/abs/1302.1999`

Acknowlegments

Lorenzo Capanna and Luigi De Giovanni for their help with querying the DDR database

Preprint

Lancia, Lulli (2017) Data-driven modelling and validation of aircraft inbound-stream at some major European airports `https://arxiv.org/abs/1708.02486`