Intermittent or not? How to tell the difference

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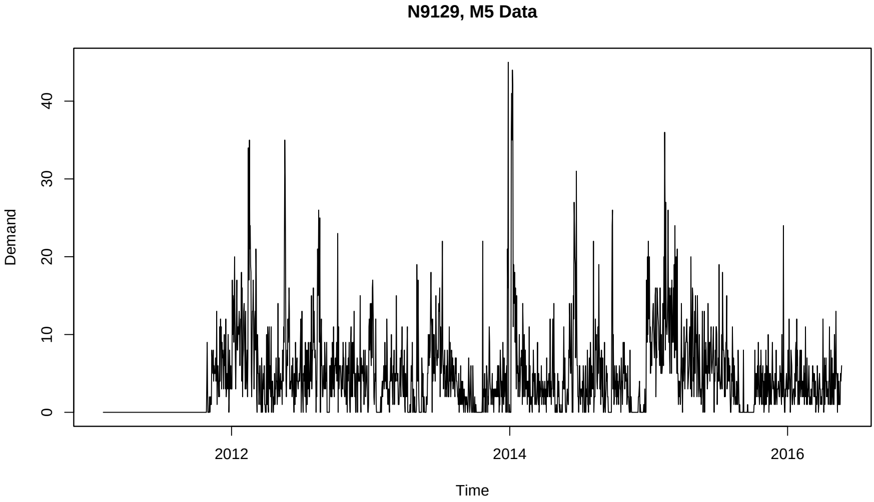
Why do zeroes happen?



Why do zeroes happen?

Several possible reasons:

- Recording started later;
- We stopped selling the product;
- We do not sell the product this time of year;
- Stockouts;
- Technical issues;
- Other reasons?

What we know: definitions

Intermittent demand

Demand that happens at **irregular frequency** (Svetunkov and Boylan, 2023).

- zeroes are present
- can be fractional or count

Regular/fast demand

Demand that happens with **some regularity**.

- can be fractional or count
- might observe some occasional non-random zeroes (stockouts?)

Count demand

Demand that takes **integer** values.

- might observe zeroes

Intermittent demand components

Intermittent demand consists of:

- Demand sizes, z_t,
- Demand occurrence, o_t (or intervals between demands, q_t).

$$y_t = o_t z_t,$$

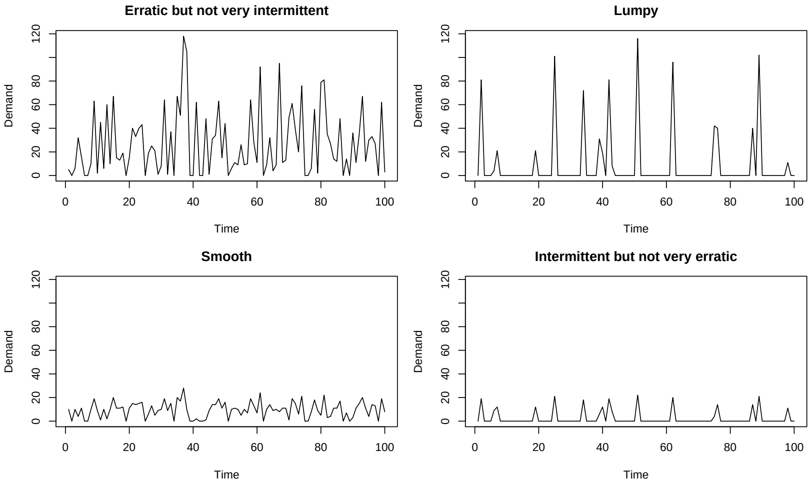
$$o_t \sim \text{Bernoulli}(p_t),$$

$$q_t - 1 \sim \text{Geometric}(p_t).$$

p_t is the probability of occurrence.

Intermittent demand types

Syntetos et al. (2005) developed intermittent demand classification based on coefficient of variation and average demand intervals:



Why do zeroes happen?

The context is important.

- "Smooth":
  - Zeroes happen because not many people buy the product;
- "Erratic but not very intermittent":
  - Why would you have zeroes there?
  - Are they really random?
  - Stockouts maybe?
- "Intermittent but not very erratic":
  - the product is not very popular;
  - people buy less frequently than in case of the "smooth";
- "Lumpy":
  - A wholesaler?
  - Sales could be due to external events.
  - Seasonal lumpy demand?

There are also Kostenko and Hyndman (2006) and Petropoulos and Kourentzes (2015).

How do you know that the demand is intermittent?

Just set a threshold like 30% and if the number of "zeroes" exceeds this threshold then declare it to be an intermittent demand series. For guidelines to deal with "unusual demands" rather than believing them and Level Shifts (n.b. A level Shift is not a time trend) . Also since intermittent demand can yield rates that are auto-regressive (i.e autocorrelated) models like the Poisson Model or the Croston approach are of limited value. Please see the discussion Please see my comments in How to forecast based on aggregated data over irregular intervals? regarding this.

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30% could be just stockouts.

No good universal rule.

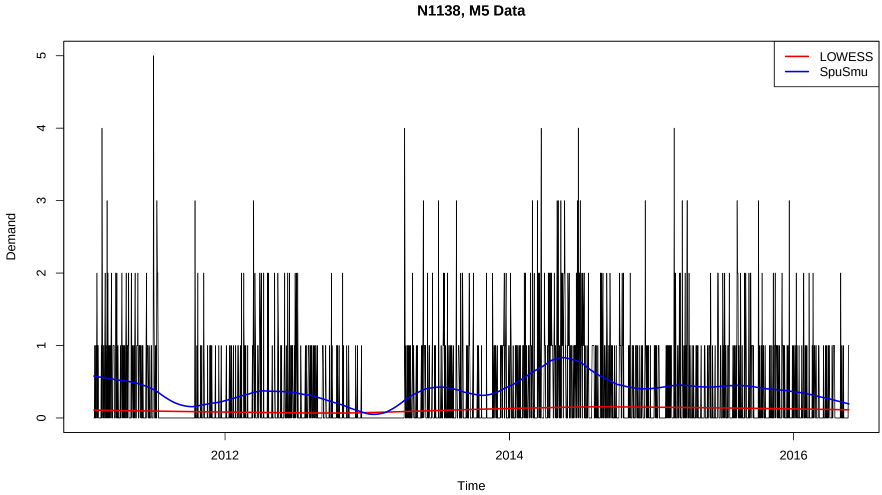
Why should we care?

- We need to forecast demand, not sales (where possible).
- Intermittent demand should be treated differently than the regular one (if aggregation does not align with the decisions).
- If you model the demand occurrence separately, you might gain in accuracy.
  - e.g. in Svetunkov and Boylan (2023) the intermittent demand ETS performed better than the conventional ETS, Poisson and Negative Binomial models.

Capturing structure

- Typically, we need to capture dynamics of demand (sizes/occurrence).
- We do that using some model/method that allows forecasting.
- For the purposes of identification, we do not care about the model/method.
- We just need to capture the dynamics.
- One of ways of doing that – smoothing the series.
    - Options: Friedman's Super Smoother (SupSmu, Friedman, 1984) or LOWESS (Cleveland, 1979).

Smoothing examples

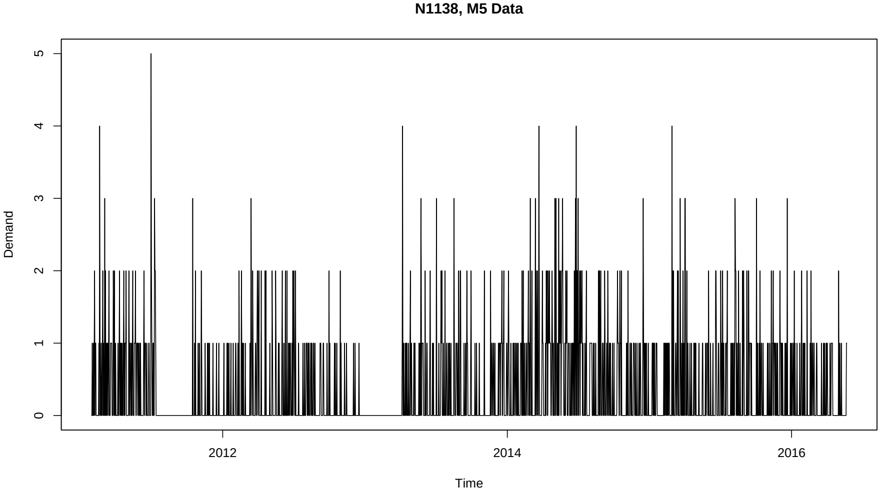


Do you think all zeroes are random? Potential stockouts?
If so, how can we identify those?

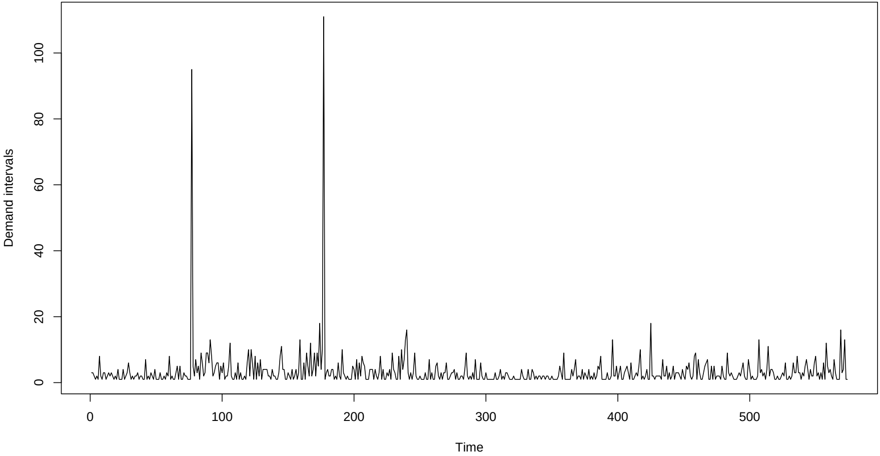
Stockout identification using smoothing

1. Stockout identification
   1.1 Extract inter-demand intervals q_t;
   1.2 Smooth them using SupSmu to get a series $\tilde{q}_t$. This way we capture the potential structure changes (e.g., probability of occurrence increases);
   1.3 Build a regression with Geometric distribution of $q_t - 1$ from $\tilde{q}_t$;
      - Croston (1972) argues that demand intervals follow Geometric distribution with some time-varying probability $p_t = \frac{1}{q_t - 1}$;
   1.4 Extract the residuals and flag those that are above a threshold (confidence level, e.g., 0.99);
      - These residuals are potential stockouts;
      - If they happen on the first or the last observation, the product was introduced later or is not sold anymore respectively.

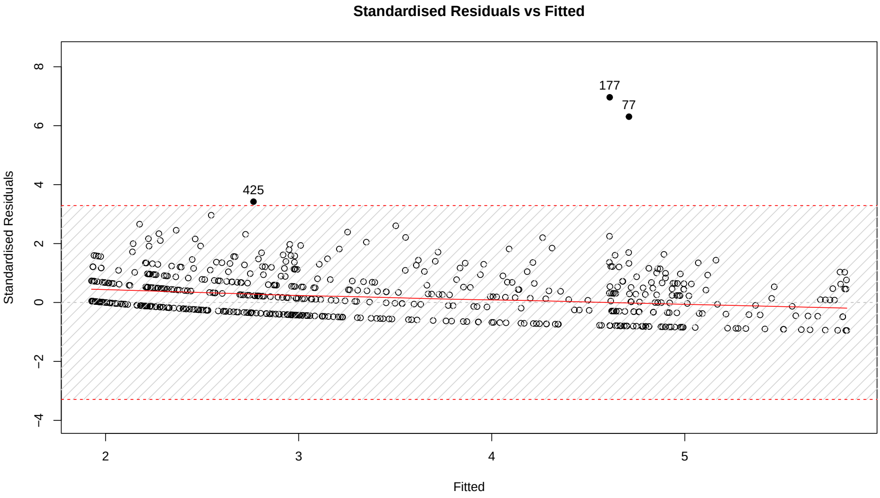
Stockouts identification: example



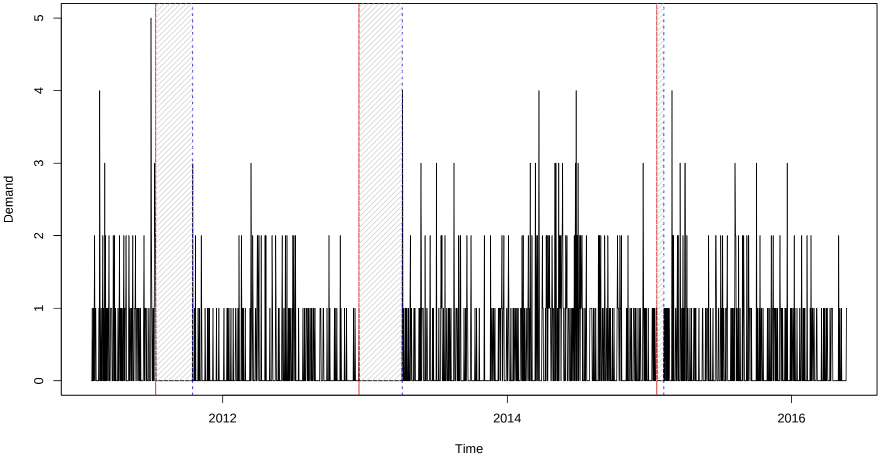
Stockouts identification: demand intervals



Stockouts identification: Outliers



Stockouts identification: Result



What do we do with these? Open question - any ideas are welcome!

Demand identification

2. Demand identification
    - 2.1 Smooth the original series with SupSmu to get $\tilde{y}_t$;
    - 2.2 Extract demand sizes z_t and demand occurrence o_t;
    - 2.3 Apply SupSmu to both of them to get $\tilde{z}_t$ and $\tilde{p}_t$;
    - 2.4 Build several models:
        - 2.4.1 For the original data from $\tilde{y}_t$, assume Normal distribution;
        - 2.4.2 For the demand sizes from $\tilde{z}_t$, assume Normal distribution;
        - 2.4.3 For the demand occurrence from $\tilde{p}_t$ via Logistic regression;
    - 2.5 Create a mixture distribution model from 2.4.2 and 2.4.3;
    - 2.6 Calculate information criteria for models 2.4.1 and 2.5. Select the one that has the lowest one:
        - If the model 2.4.1 has the lowest IC, the demand is regular;
        - Otherwise the demand is intermittent;
    - 2.7 Check whether the original data is count. If it is, the demand is in addition a count one.

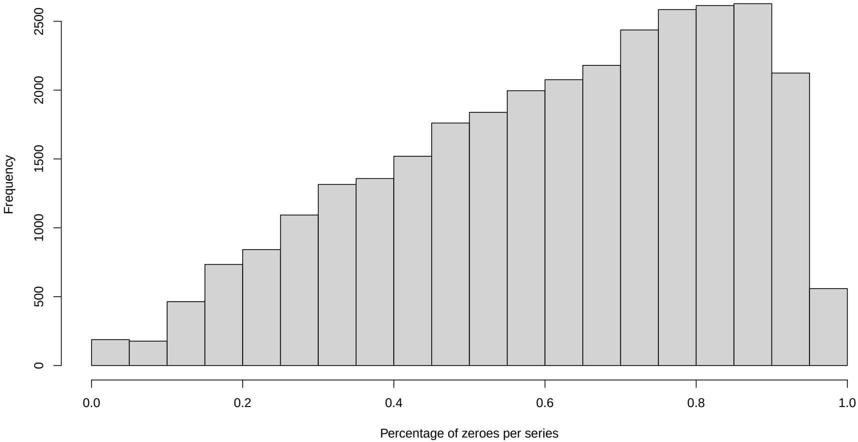
M5 dataset: the setting

30490 daily SKU level time series

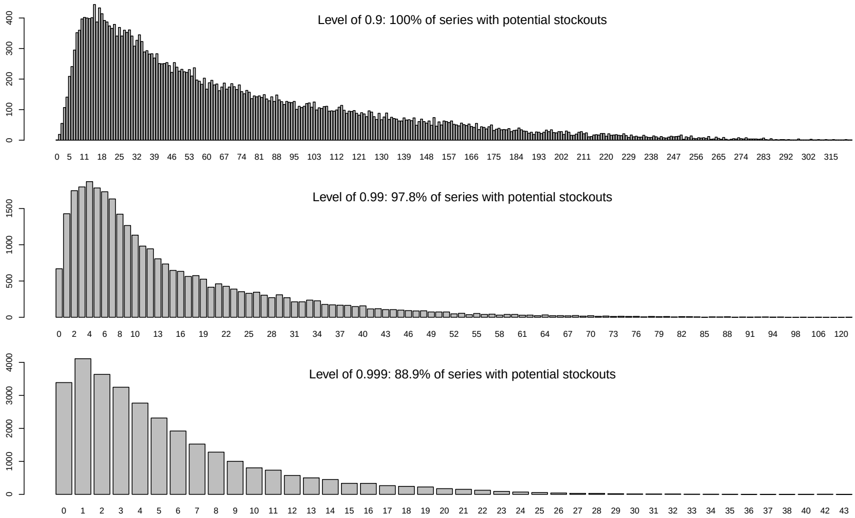
Makridakis et al. (2022).

Applied the approach with levels of 0.9, 0.99 and 0.999

M5: Percentage of Zeroes (without heads and tails)



M5: Number of stockouts



M5: Type of demand

	Level of 0.9	Level of 0.99	Level of 0.999
New	66.3%	57.9%	53.3%
Obsolete	17.1%	4.0%	2.1%

Roughly 8.1% of regular vs 91.9% of intermittent.

Note that we haven't dealt with stockouts.

Royal Airforce dataset: the setting

Data from Eaves and Kingsman (2004).

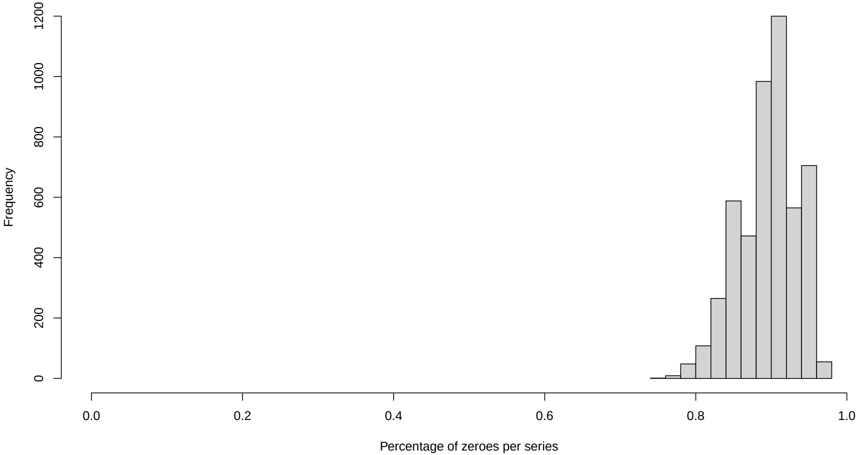
5000 products

Classical intermittent data

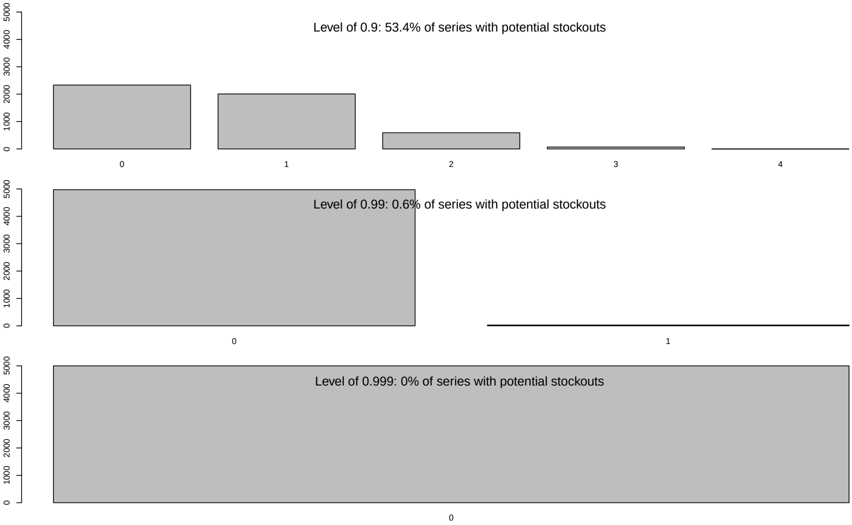
Slow moving product, should not expect stockouts

Same idea as with M5 in terms of automatic identification

RAF: Percentage of Zeroes (without heads and tails)



RAF: Number of stockouts



RAF: Type of demand

	Level of 0.9	Level of 0.99	Level of 0.999
New	4.7%	0.0%	0.0%
Obsolete	6.8%	0.0%	0.0%

Roughly 7% of regular vs 93% of intermittent demand.

Results and conclusions

We aimed

- to understand why zeroes happen (fundamental question!);
- to identify automatically regular and intermittent demand, so a better model selection could be used;

We observed a huge problem with stockouts (unusual periods of zero demand), and proposed a way to identify those

Works well on M5 data and Royal Airforce datasets

Next steps

- We need to deal with stockouts;
- We should measure the impact of classification on accuracy/inventory performance;
- Which of smoothers works better: SupSmu or LOWESS?

Thank you for your attention!

Any questions?

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