Forecasting Products with Intermittent Demand

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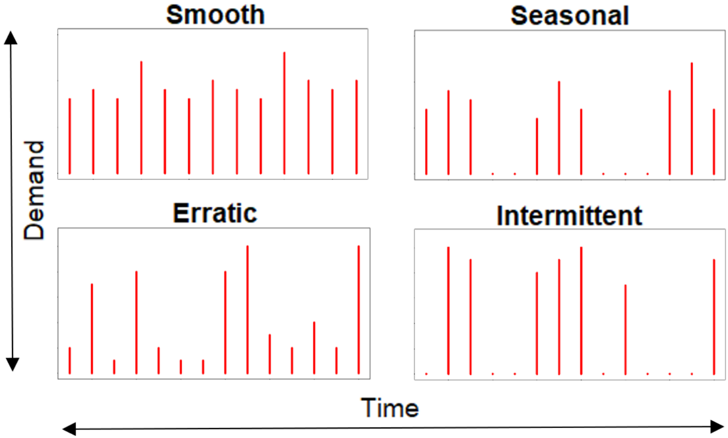
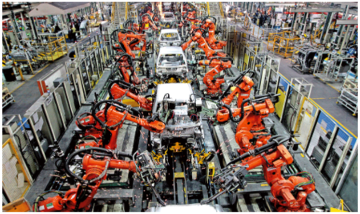
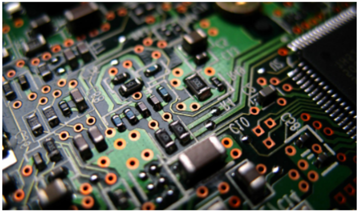
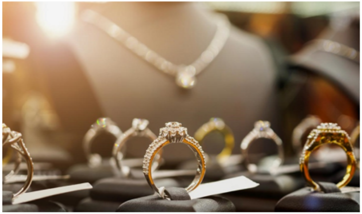
Outline

What is Intermittent Demand?

- Intermittent demand is a classification of sales data characterised by having several, sporadic and sometimes highly varying periods of demand.



Product Examples

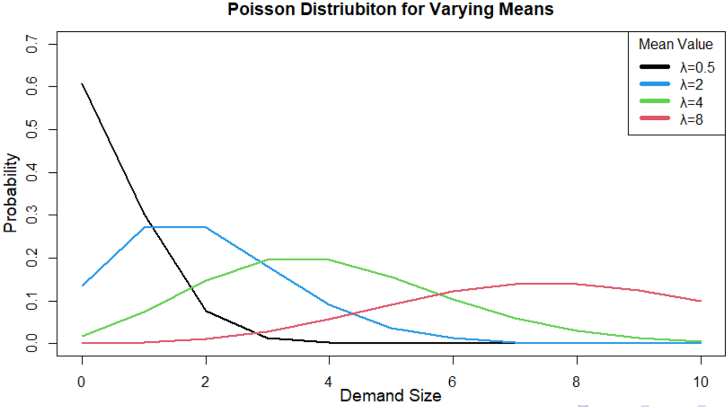





Distributing our Data

- With the aim of deciding stock levels we need to be able to find the probability of demand sizes
- Therefore we need to find a distribution that best describes our data

Poisson Distribution

- For slower moving items with less variability Poisson is a fairly optimum fit
- However for data with higher variance Poisson does not capture larger demand size as accurately

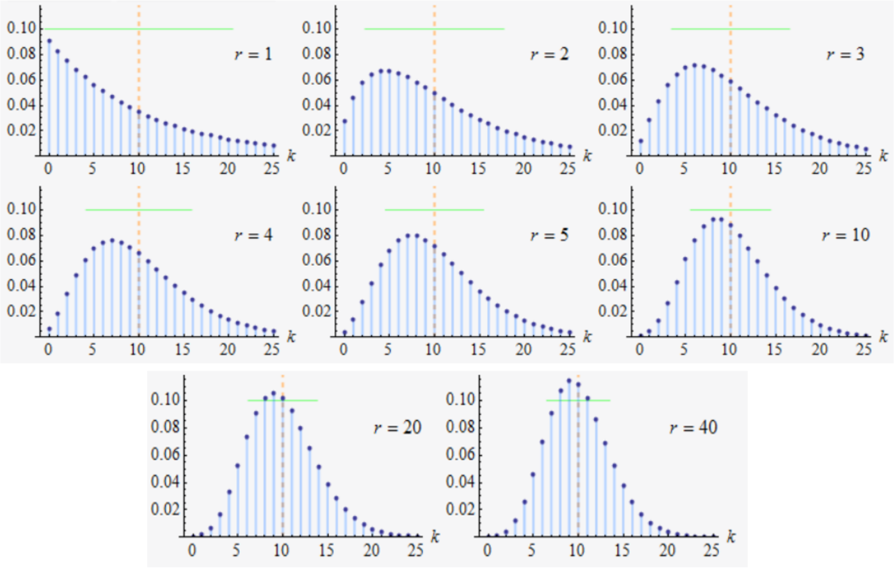


Negative Binomial

- To combat the pitfalls of Poisson we look to use the negative binomial distribution
- Unlike Poisson, negative binomial isn't restricted to equality between the mean and variance allowing us more flexibility
- Interpretable as the number of failures "r", before "k" successes with probability of success "p".

$$\mathbb{P}(k) = \frac{(k+r-1)!}{k!(r-1)!)} p^r (1-p)^k$$

Negative binomial Distributions



Simple Exponential Smoothing (SES)

- SES is a primitive method for forecasting the mean of intermittent demand,

  Given by ;

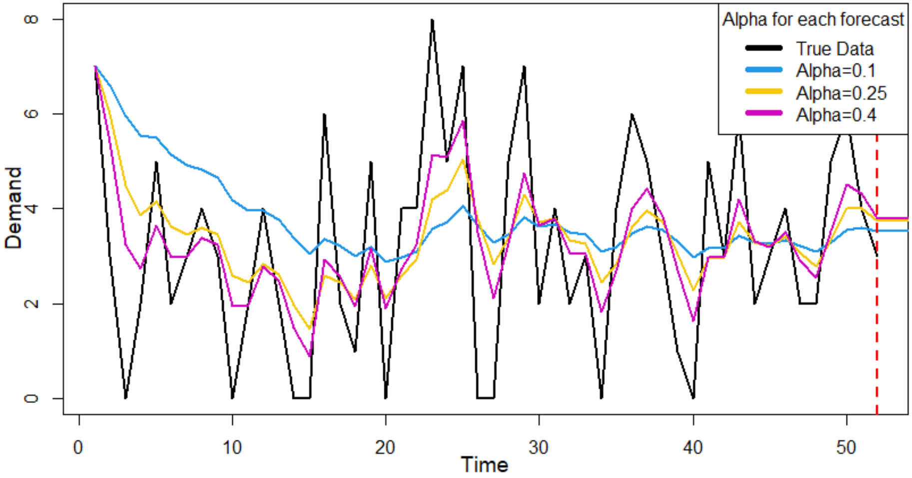
$$\hat{d}_{t+1} = \hat{d}_t + a(d_t - \hat{d}_t),$$

- Being a recursive formula we can expand it to be,

$$\hat{d}_{t+1} = ad_t + (1-a)(ad_{t-1} + (1-a)\hat{d}_{t-1}),$$

- "a" is a constant to our error term between 0 and 1 varying how much we let our previous forecasts impact our future ones. In practice it is usually between 0.1 and 0.3 [1].

Simple Exponential Smoothing



Croston's Method [2]

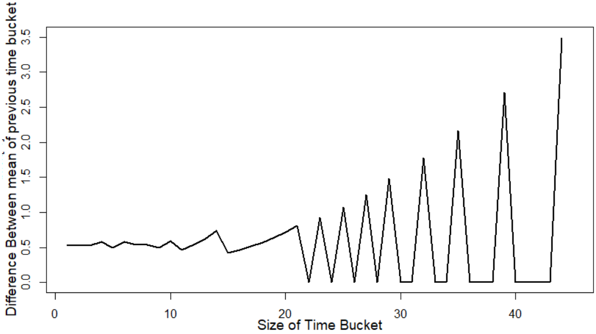
- Developed to improve upon the upwards bias of SES,
- It uses SES to forecast both the mean interval between non-zero demand periods and the mean size of the non-zero demands,

$$\hat{R}_{t+1} = \hat{R}_t + a(R_t - \hat{R}_t), \qquad \hat{I}_{t+1} = \hat{I}_t + a(I_t - \hat{I}_t), \qquad \hat{D}_{t+1} = \frac{\hat{R}_{t+1}}{\hat{I}_{t+1}}$$

- Croston's Method still has an upwards bias however it is far more reasonable than SES.

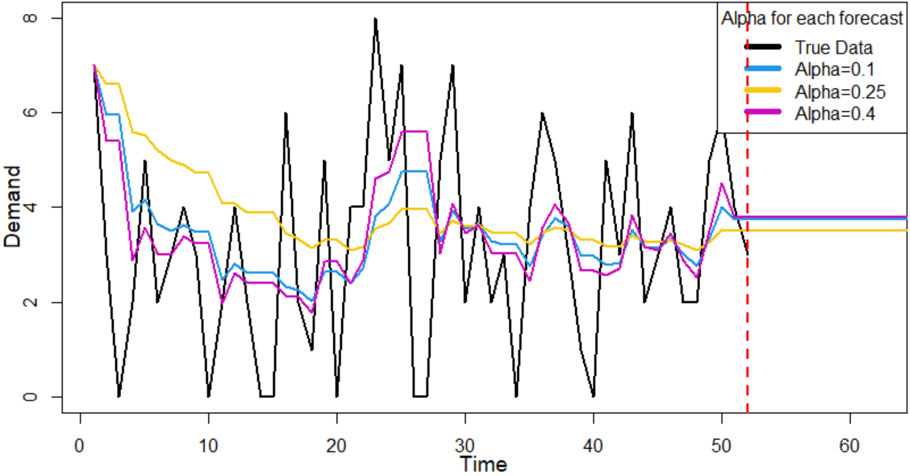
Optimising the error constant

- Using different error metrics to calculate our forecasts performance with varying error constant we can optimise it fairly easily,
  - For simplicity we look purely at mean squared error, which for different alpha values gives;



- Here we find the optimum alpha to near 0.25

Croston's method



The Problem of upwards Bias

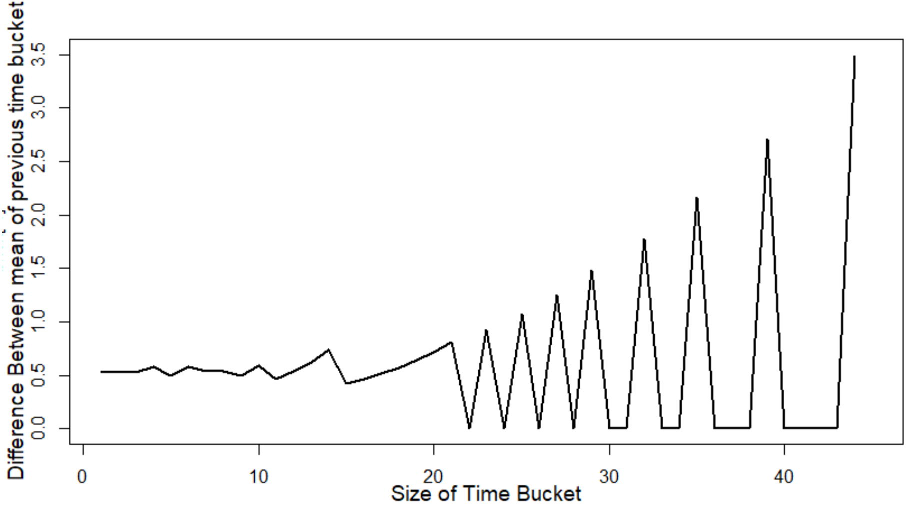
- The methods we have shown have an upward bias and depending upon where a product is in its life-cycle may overpredict the mean demand.
- Particularly when products are tending towards obsoletion the discussed methods perform poorly
- The method SBA or Syntetos-Boylan Approximation however induces a negative bias with the addition of another term [1];

$$\hat{D}_{t+1} = \frac{\hat{R}_{t+1}}{\hat{I}_{t+1}} \implies \hat{D}_{t+1} = (1 - \frac{a}{2})\frac{\hat{R}_{t+1}}{\hat{I}_{t+1}}$$

Temporal Aggregation

- The time period we choose to record our data over can have a large impact on the forecasting methods we use. Measuring over a longer time period, lets to a higher average demand across the time periods hence making the data look less intermittent
- Doing this "reduces" the amount of data or forecasting techniques have to use and can be less informative in the real world when quarterly long predictions don't negate cost benefit

Temporal Aggregation



Further Research

- Explore variance forecasting and put the negative binomial to further use
- Detail stock policies and methodology in how we optimise stock from our results
- Using Chi-Squared finalise my work on temporal aggregation manipulating data into distributions more suited to standard forecasting techniques

List of References

[1] J.E. Boylan and Aris A Syntetos. “Intermittent Demand Forecasting: Context, Methods and Applications”. In: (2021).

[2] J. D. Croston. “Forecasting and Stock Control for Intermittent Demands”. In: *The Journal of the Operational Research Society* (1972).

[3] H.L. Hinton Jr. “Defense Inventory: Continuing Challenges in Managing Inventories and Avoiding Adverse Operational Effects.”. In: (1999).

[4] F. R. et.al Johnston. “Forecasting for Items with Intermittent Demand”. In: *JORS* (1996).

Thank You for Listening!