

## Nov 21 Update Report

2022-11-19

# Outline

- ▶ Recap
- ▶ Show results
- ▶ Discussion
- ▶ Adding in outlier term

## Recap 1

- ▶ Setup:
  - ▶ Let  $y_t$  be the daily case count at day  $t$
  - ▶ Then  $y_t \sim \text{Pois}(r_t * w_t)$ , where  $w_t = \sum_a y_{t-a} w_a$
- ▶ Objective function:
  - ▶  $\text{argmin}_r \frac{1}{n} (\sum_{i=1} w_i r_i - y_i \log(w_i r_i)) + \lambda \|Dr\|_1$
- ▶ Scaled Augmented Lagrangian:
  - ▶ Let  $Dr = z$ , adding penalty for being not equal
  - ▶  $L(r, u, z) = \frac{1}{n} (\sum_{i=1} w_i r_i - y_i \log(w_i r_i)) + \lambda \|z\|_1 + \frac{\rho}{2} \|Dr - z + u\|_2^2 + \frac{\rho}{2} \|u\|_2^2$
- ▶ Update step for  $r$ 
  - ▶  $r \leftarrow \text{argmin}_r \frac{1}{n} (\sum_{i=1} w_i r_i - y_i \log(w_i r_i)) + \frac{\rho}{2} \|Dr - z + u\|_2^2$

## Recap 2

- ▶ Linearize the update step of  $r$
- ▶ If penalizing  $Dr$ :  $r \leftarrow \operatorname{argmin}_r \frac{1}{n} (\sum_{i=1} -w_i r_i + y_i \log(w_i r_i)) + \rho r^T (D^T D r^o - D^T z + D^T u) + \frac{\mu}{2} \|r - r^o\|_2^2$
- ▶ If penalizing  $D \log(r)$ :  $r \leftarrow \operatorname{argmin}_r \frac{1}{n} (\sum_{i=1} -w_i r_i + y_i \log(w_i r_i)) + \rho r^T (D^T D r^o - D^T z + D^T u) (\mathbf{r}^o)^{-1} + \frac{\mu}{2} \|r - r^o\|_2^2$

## Pseudocode for summary

Initialize  $r^o, u^o, z^o$  Until converge

- Find  $r$  that solves

$$\frac{d}{dr} \frac{1}{n} (\sum_{i=1} -w_i r_i + y_i \log(w_i r_i)) + \rho r^T (D^T D r^o - D^T z + D^T u) + \frac{\mu}{2} \|r - r^o\|_2^2$$

- $z = \text{sign}(z^o) * (|z^o| - (D * r - u))$
- $u = u^o + Dr - z$

## Finalizing $r$ update

- ▶ KKT stationarity condition:

$$\frac{d}{dr} \frac{1}{n} (\sum_{i=1} -w_i r_i + y_i \log(w_i r_i)) + \rho r^T (D^T D r^o - D^T z + D^T u) + \frac{\mu}{2} \|r - r^o\|_2^2$$

$$\implies -\frac{y_i}{n} \frac{1}{r_i} + \mu r_i + \rho (D^T D r^o - D^T z + D^T u)_i - \mu r_i^o + \frac{w_i}{n} = 0$$

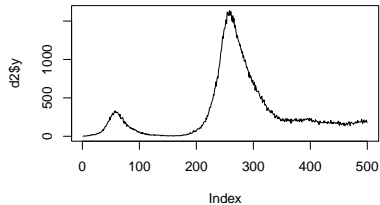
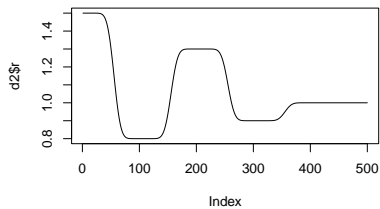
- ▶ Multiply both side by  $r_i$ , because  $r_i$  non-zero, and solve using quadratic equation
- ▶ Similarly, if penalize  $\log(r)$ , then

$$\implies -\frac{y_i}{n} \frac{1}{r_i} + \mu r_i + \rho (D^T D r^o - D^T z + D^T u)_i (r_i^o)^{-1} - \mu r_i^o + \frac{w_i}{n} = 0$$

- ▶ Question: Quadratic equation has two solutions
- ▶ "If this is satisfied uniquely (i.e., above problem has a unique minimizer), then the corresponding point must be the primal solution" - Geoff Gordon & Ryan Tibshirani's lecture slide

# Synthetic dataset

Reference synthetic dataset

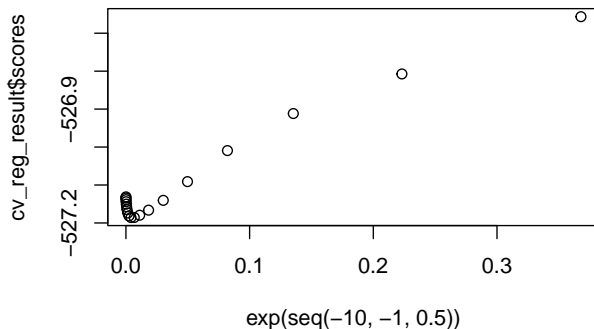


## Trend Filter CV

- ▶ Optimal  $\rho$  chosen by cv (same as last time).

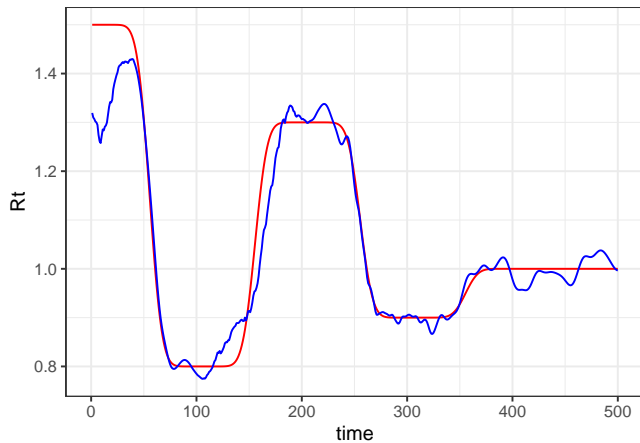
```
## [1] 0.004086771
```

- ▶ Notice the scores are very similar



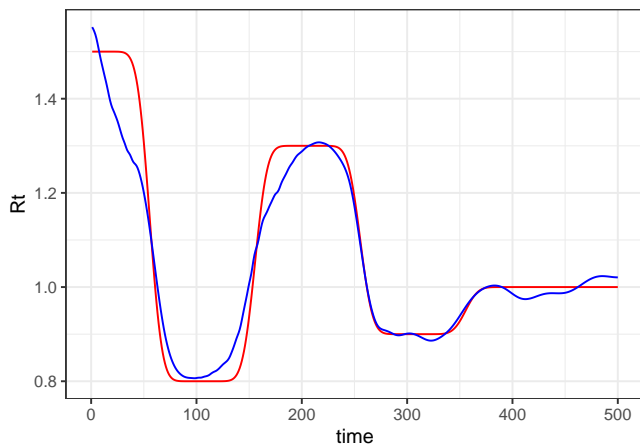


## Trend Filter Fit

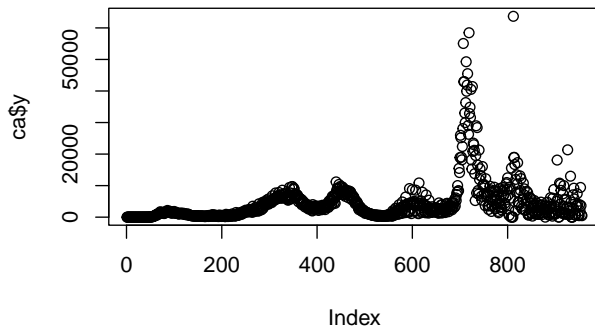


## Trend Filter Fit, pick $\rho$ myself

- Since scores are similar, pick a  $\rho$  that looks better

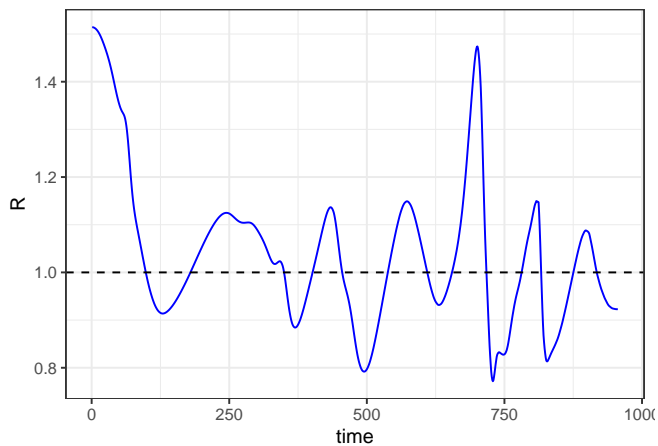


## Canadian case

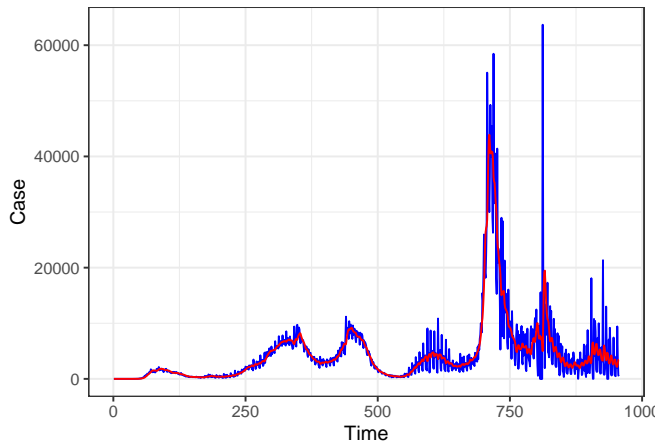


## CA Trend Filter fit

►  $\rho = 0.1$

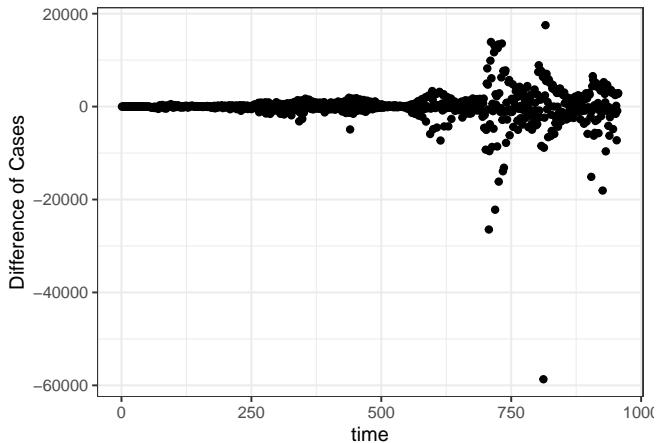


## One day ahead prediction



## Diagnostics plot

- Is residual plots appropriate for non-parametric regression?



## Check for additions

- ▶ Model outlier (Done)
- ▶ Maximizing log likelihood of Poisson or Normal of true case count given predicted.
  - ▶ Is it reasonable to use a negative binomial distribution?
- ▶ Difference matrix  $D$  here is assumed to be of lag 1 and order 1
  - ▶ Higher order  $D$  makes sense? Or should we make it so that the degree can be chosen via CV.

## Justifying outlier term

Is modeling an outlier term necessary?

- ▶ Pascal et al. “Nonsmooth convex optimization . . . against low quality data”
- ▶  $y_t \sim \text{Pois}(r_t * w_t + o_t)$
- ▶ Then add L1 penalty  $\sum |o_t|_1$
- ▶ Modeling outliers gives better residuals. Differences between predicted and true case count complemented by the outlier term.



## Adding outlier term

- ▶  $y_t \sim \text{Pois}(r_t * w_t + \mathbf{o}_t)$
- ▶ For simplicity, use L2 penalty on  $\mathbf{o}_t$ .

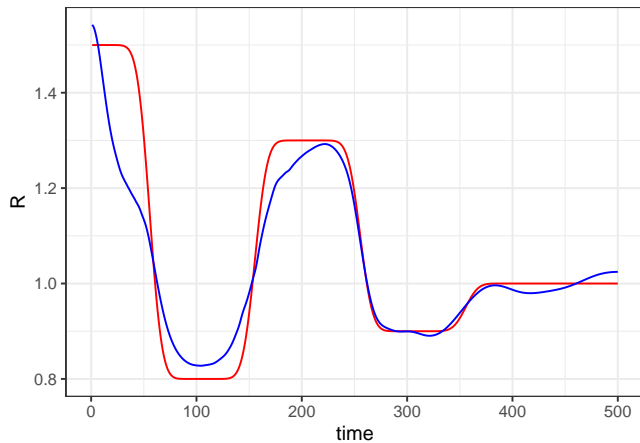
$$L(r, \mathbf{o}, \mathbf{u}, \mathbf{z}) =$$

$$\frac{1}{n} \left( \sum_{i=1} w_i r_i + o_i - y_i \log(w_i r_i + o_i) \right) + \gamma \|\mathbf{o}\|_2^2 + \lambda \|\mathbf{z}\|_1 + \frac{\rho}{2} \|D\mathbf{r} - \mathbf{z} + \mathbf{u}\|_2^2 + \frac{\rho}{2} \|\mathbf{u}\|_2^2$$

- ▶  $r$  update step is changed slightly
- ▶  $\mathbf{o}$  step: Find  $\mathbf{o}$  that solves  $\frac{1}{n} \left( \sum_{i=1} w_i r_i + o_i - y_i \log(w_i r_i + o_i) \right) + \gamma \|\mathbf{o}\|_2^2$

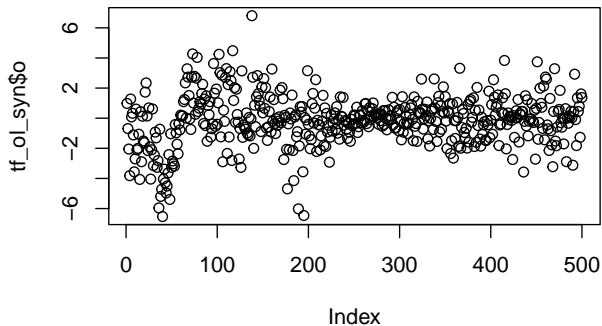
## Synthetic dataset

- Here,  $\rho = 5e - 2$ , and  $\gamma = 1e - 4$  are chosen randomly, CV for this with outlier term is under construction.

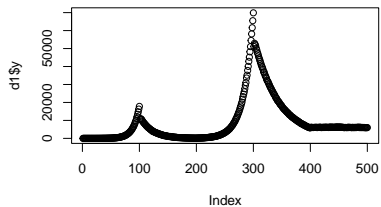
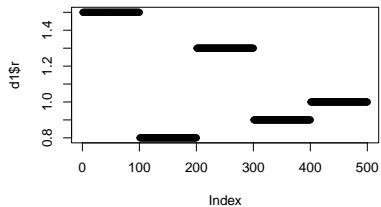


# Outliers

- Modeling outliers not very significant

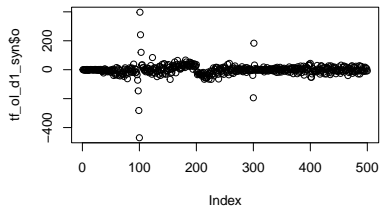
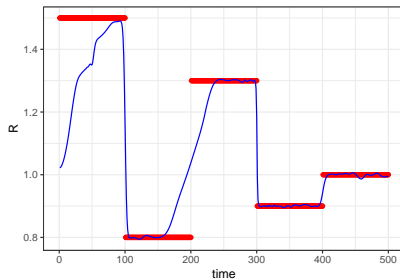


## Synthetic dataset, sudden changes

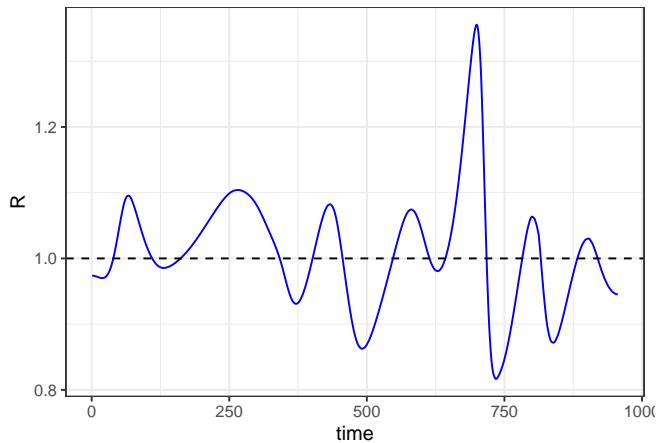


# Fit and outlier

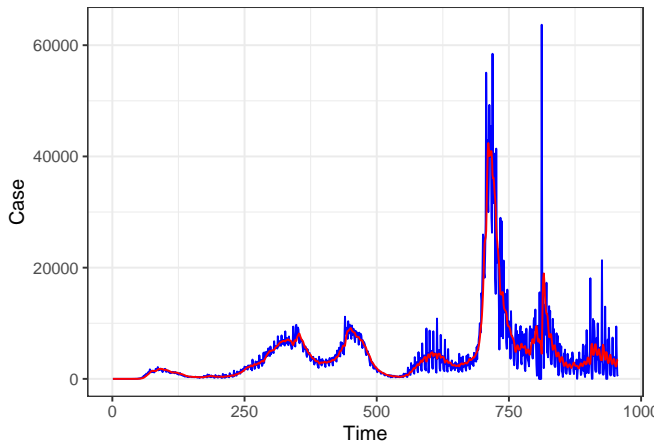
► Red is truth, blue is predicted



## Result

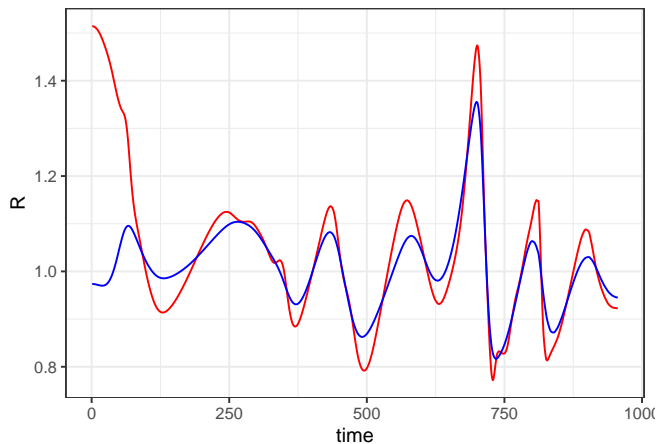


## One day



## Compare

- Then compare two methods. Blue, with outlier term modeled





## Next step

- ▶ OOP of trend filter class