An introduction to time series approaches in biosurveillance

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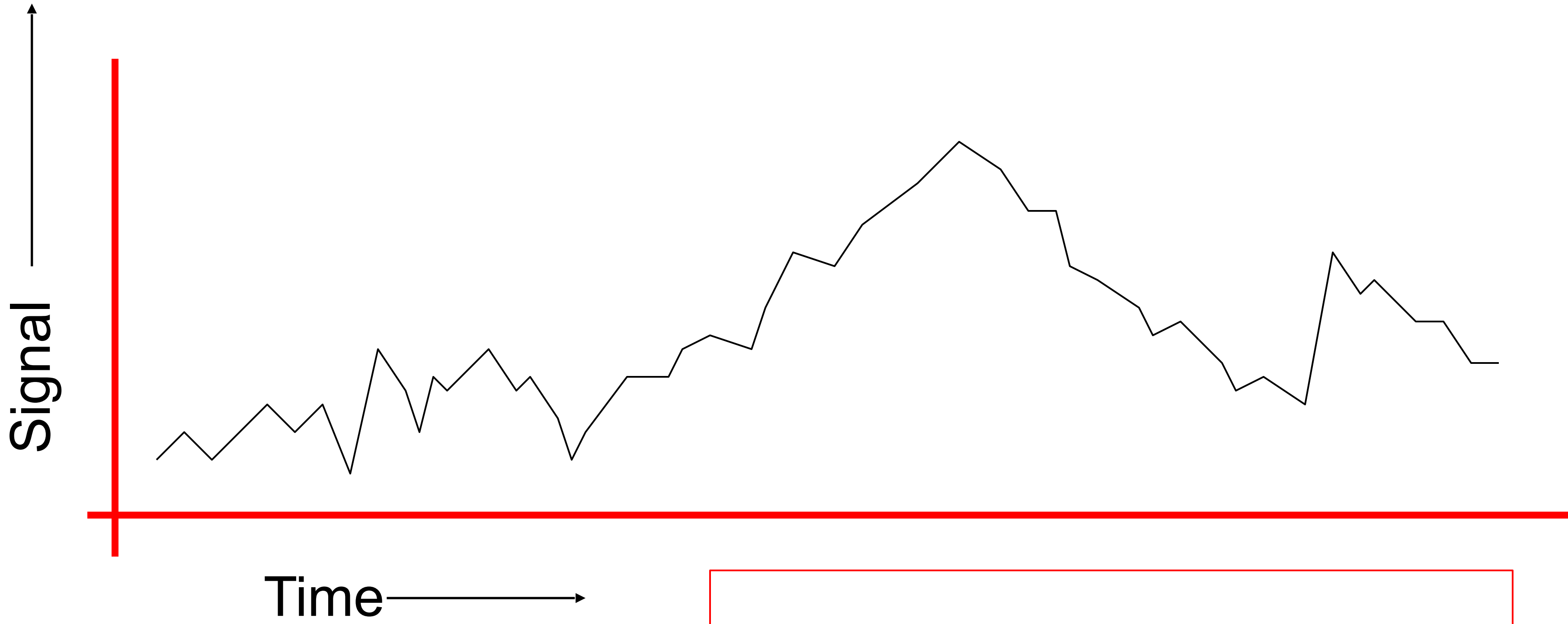
Univariate Time Series



Example Signals:

- Number of ED visits today
- Number of ED visits this hour
- Number of Respiratory Cases Today
- School absenteeism today
- Nyquil Sales today

(When) is there an anomaly?

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This is a time series of counts of primary-physician visits in data from Norfolk in December 2001. I added a fake outbreak, starting at a certain date. Can you guess when?

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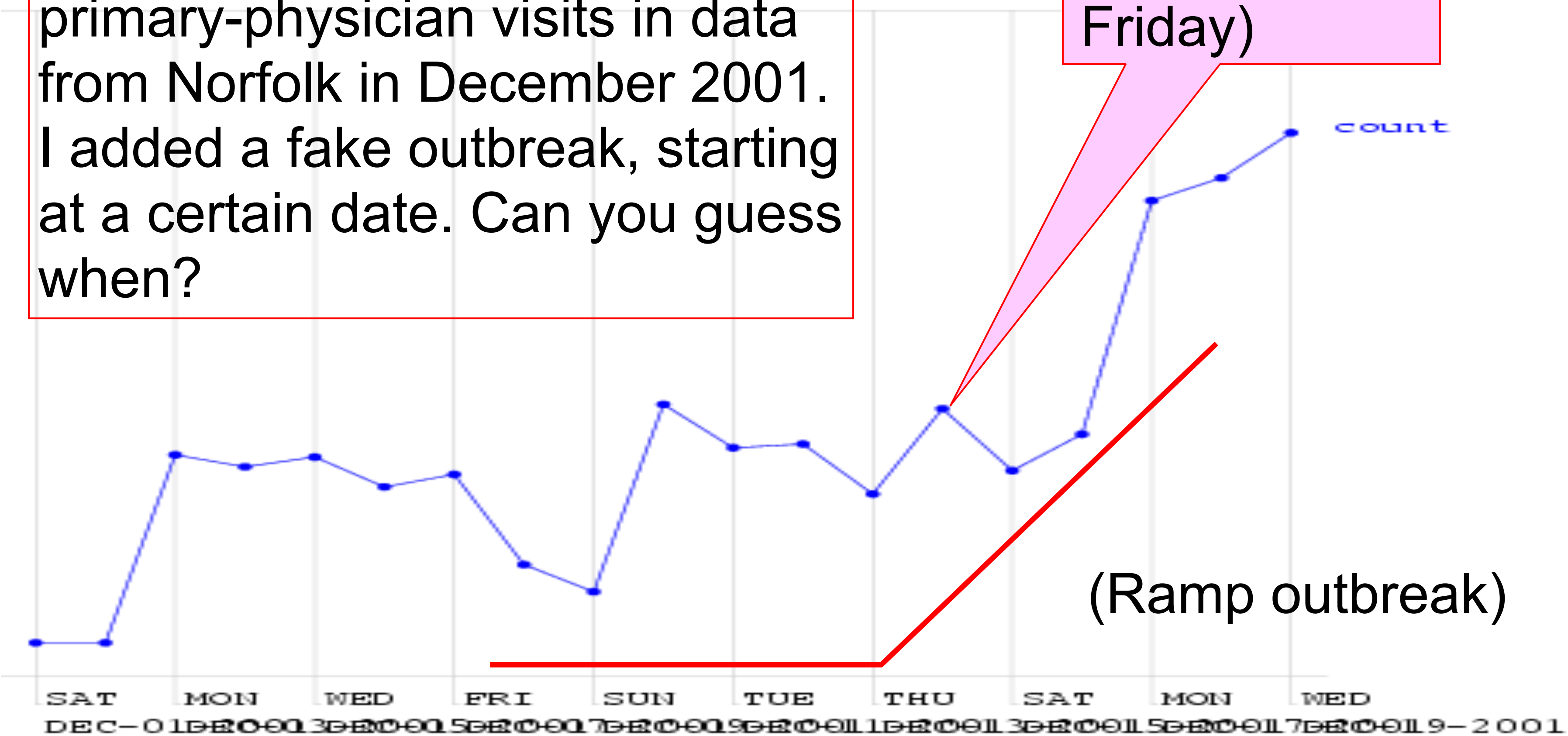
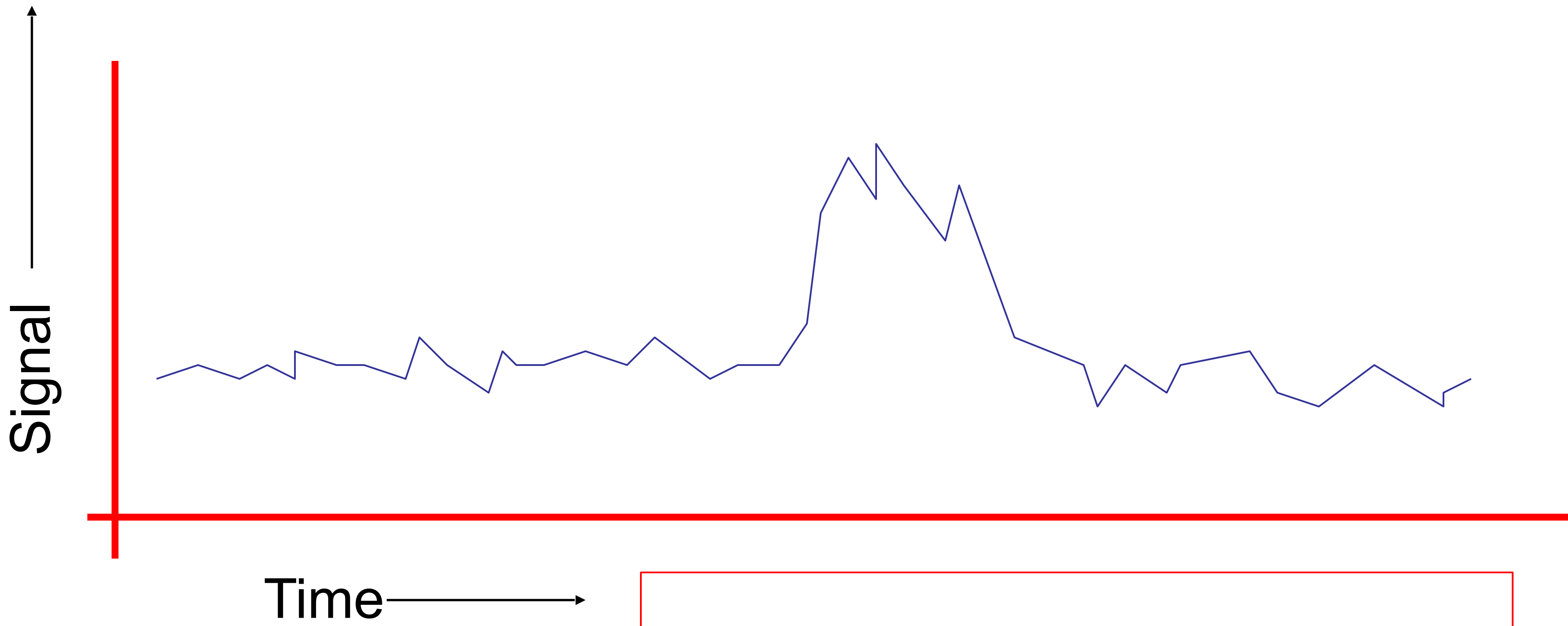
Here (much too high for a Friday)



An easy case

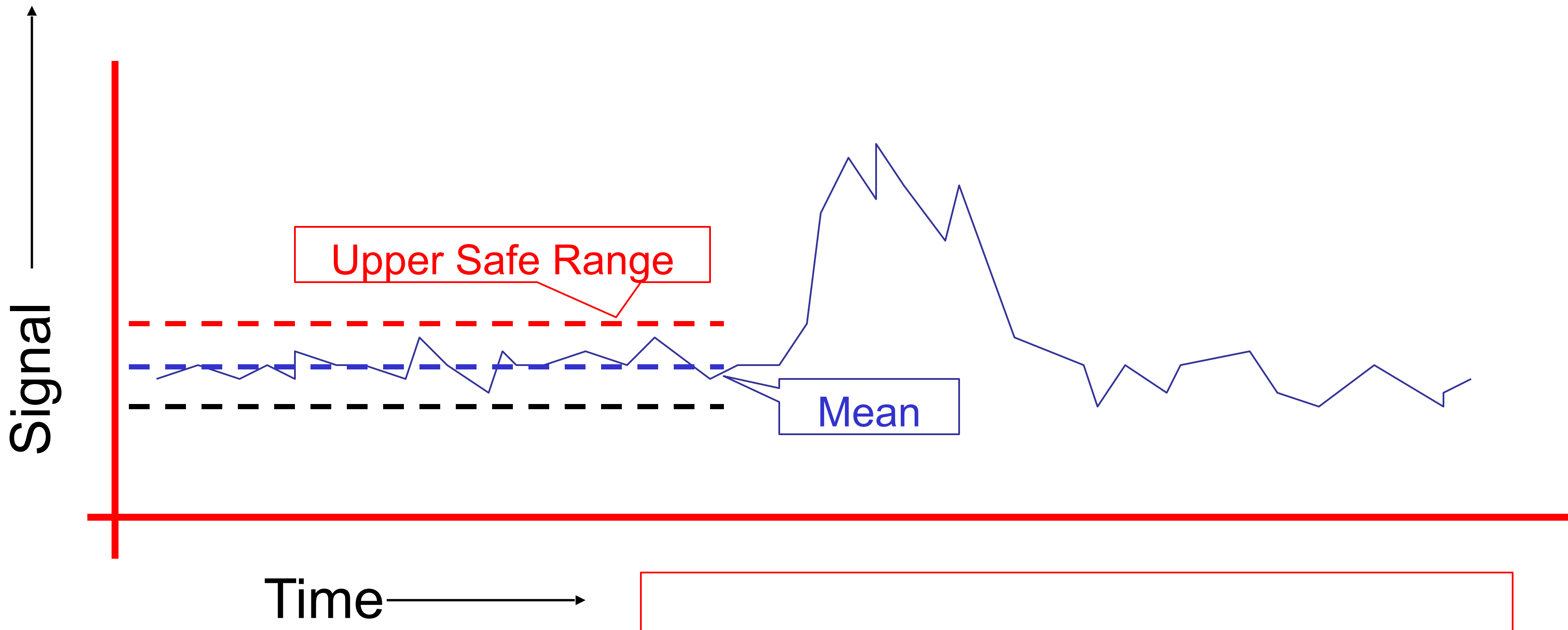


Dealt with by Statistical Quality Control

Record the mean and standard deviation up the the current time.

Signal an alarm if we go outside 3 sigmas

An easy case: Control Charts



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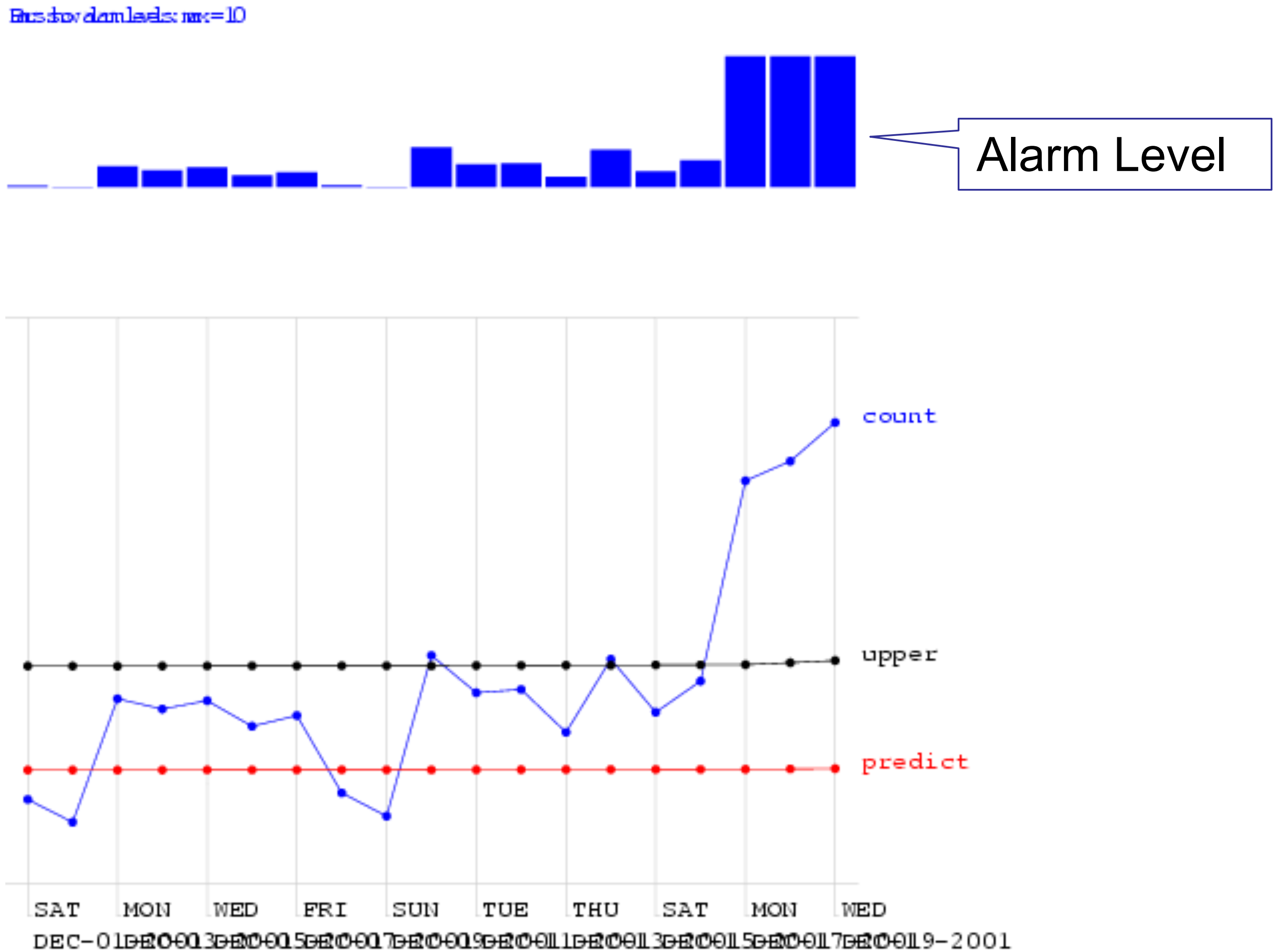
Control Charts on the Norfolk Data



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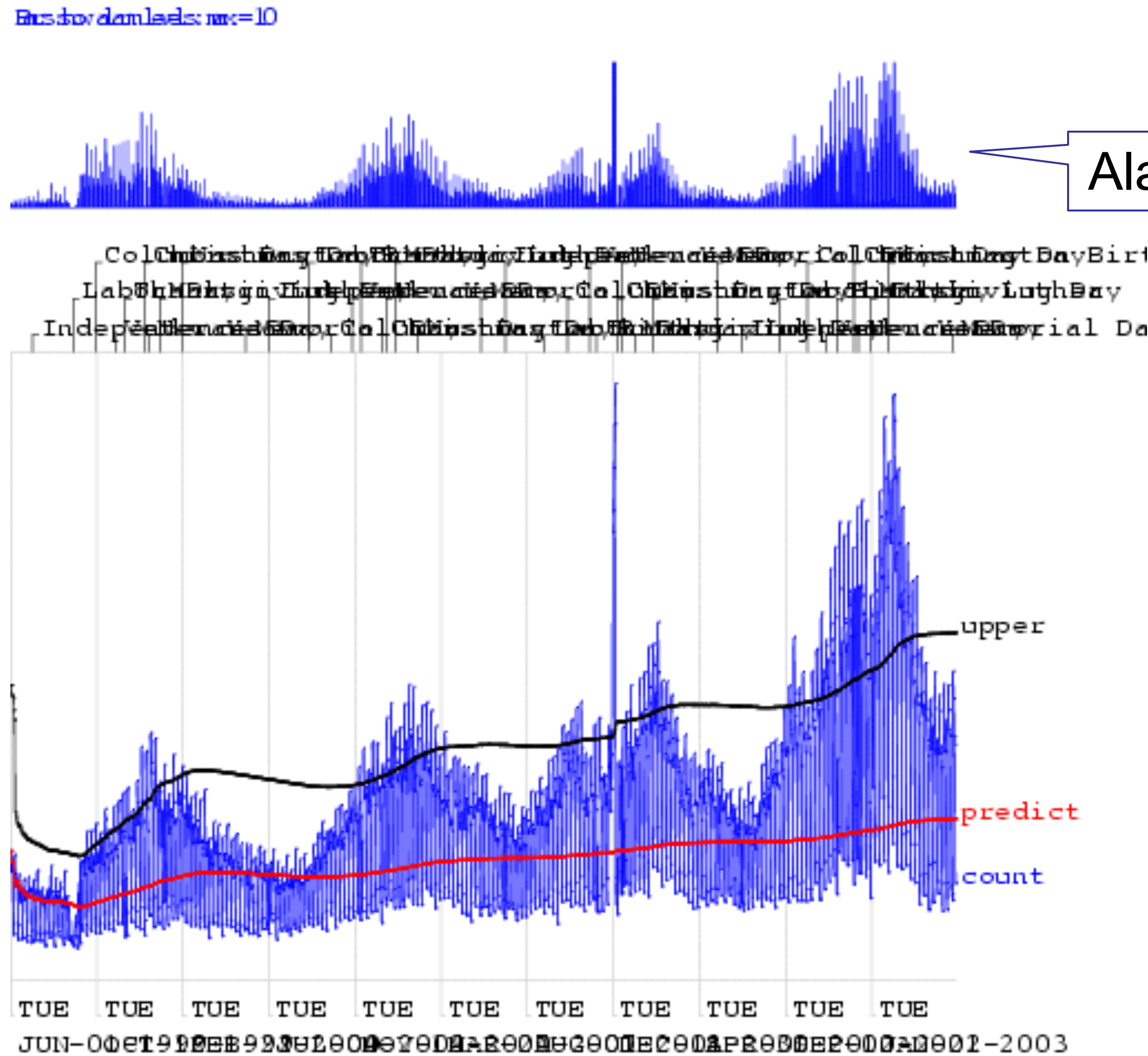

Alarm Level

Looking at changes from yesterday

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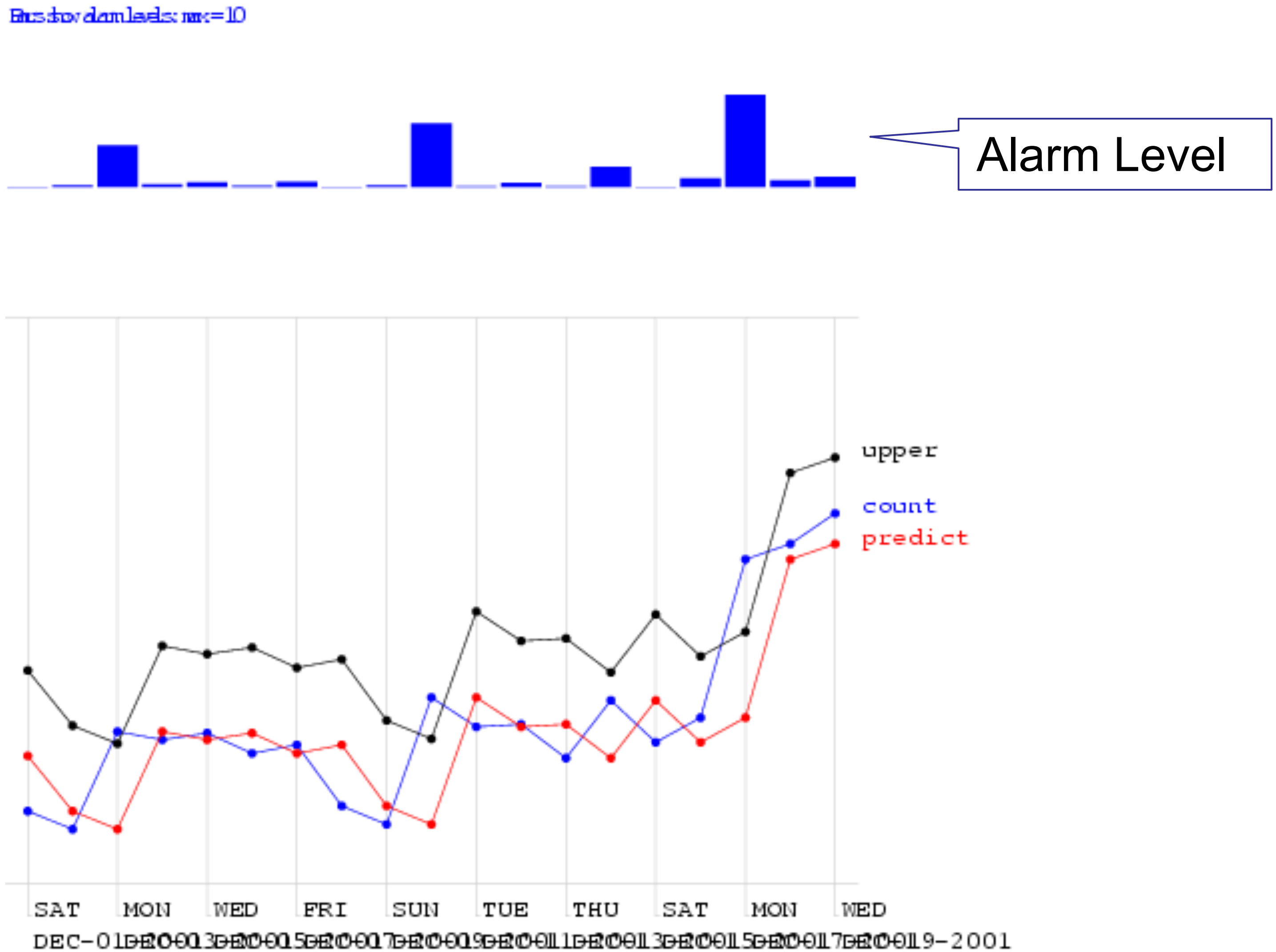

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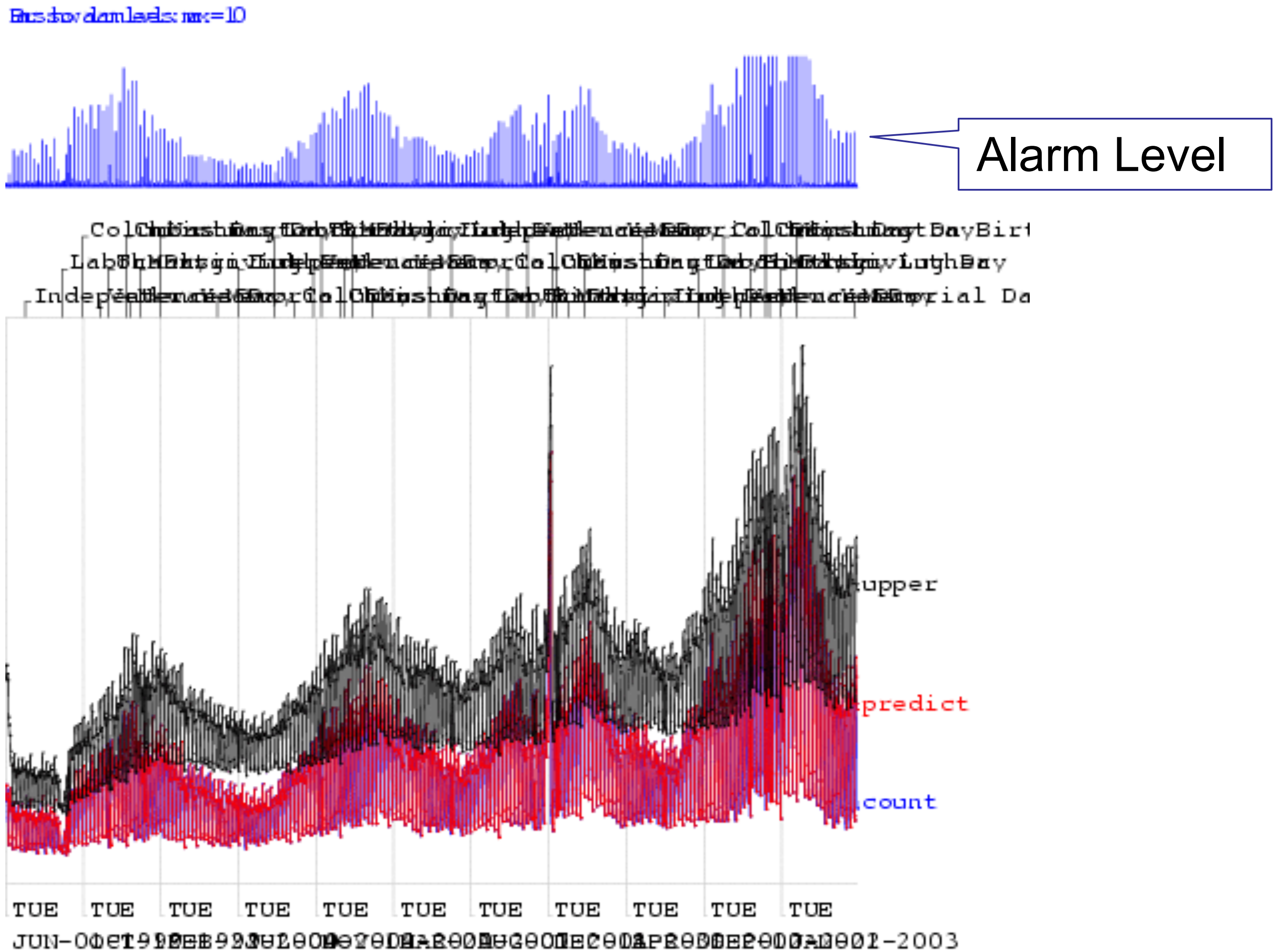
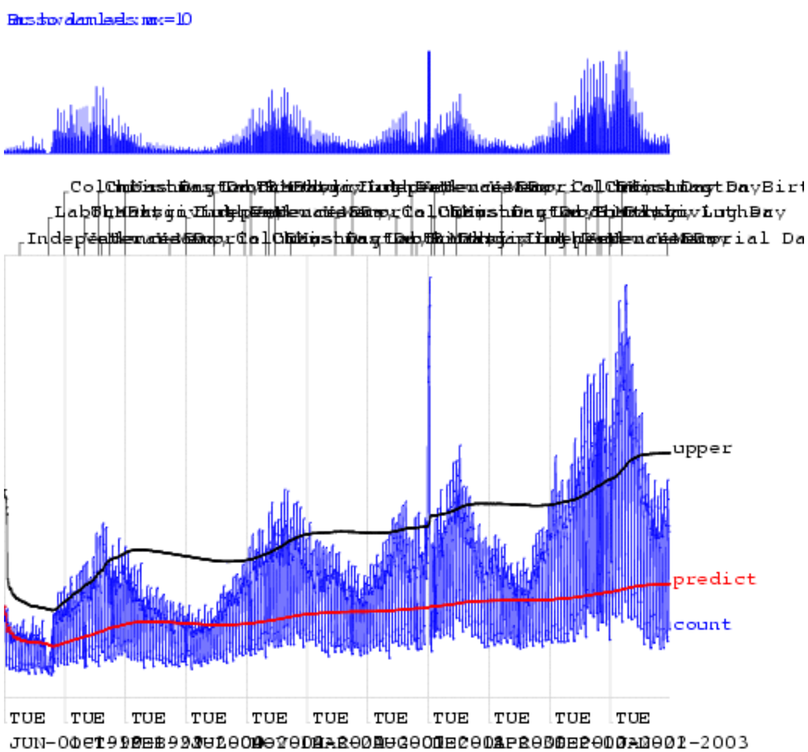
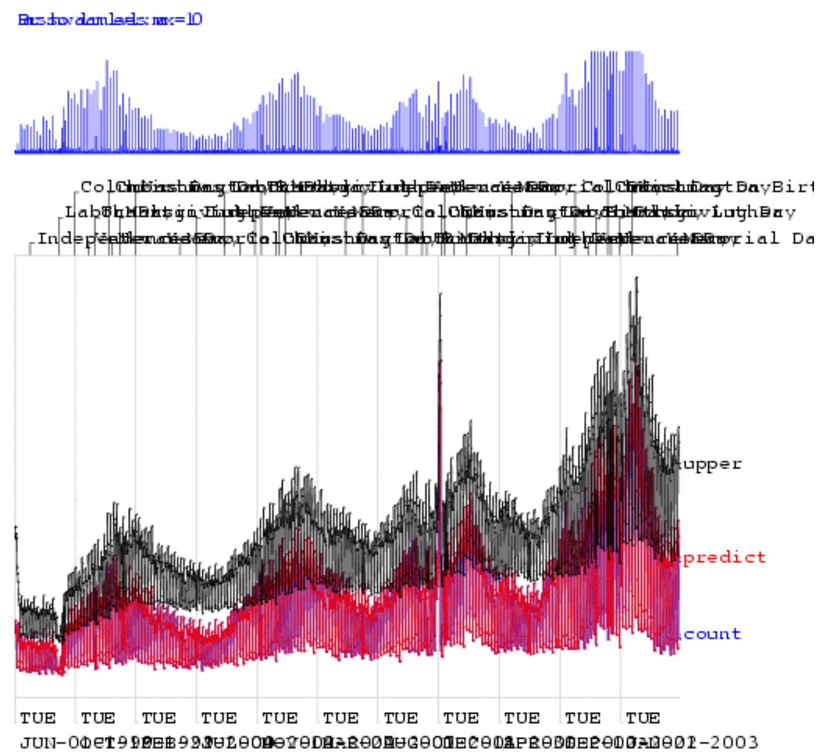


We need a happy medium:

Control Chart: Too insensitive to recent changes



Change from yesterday: Too sensitive to recent changes



Moving Average

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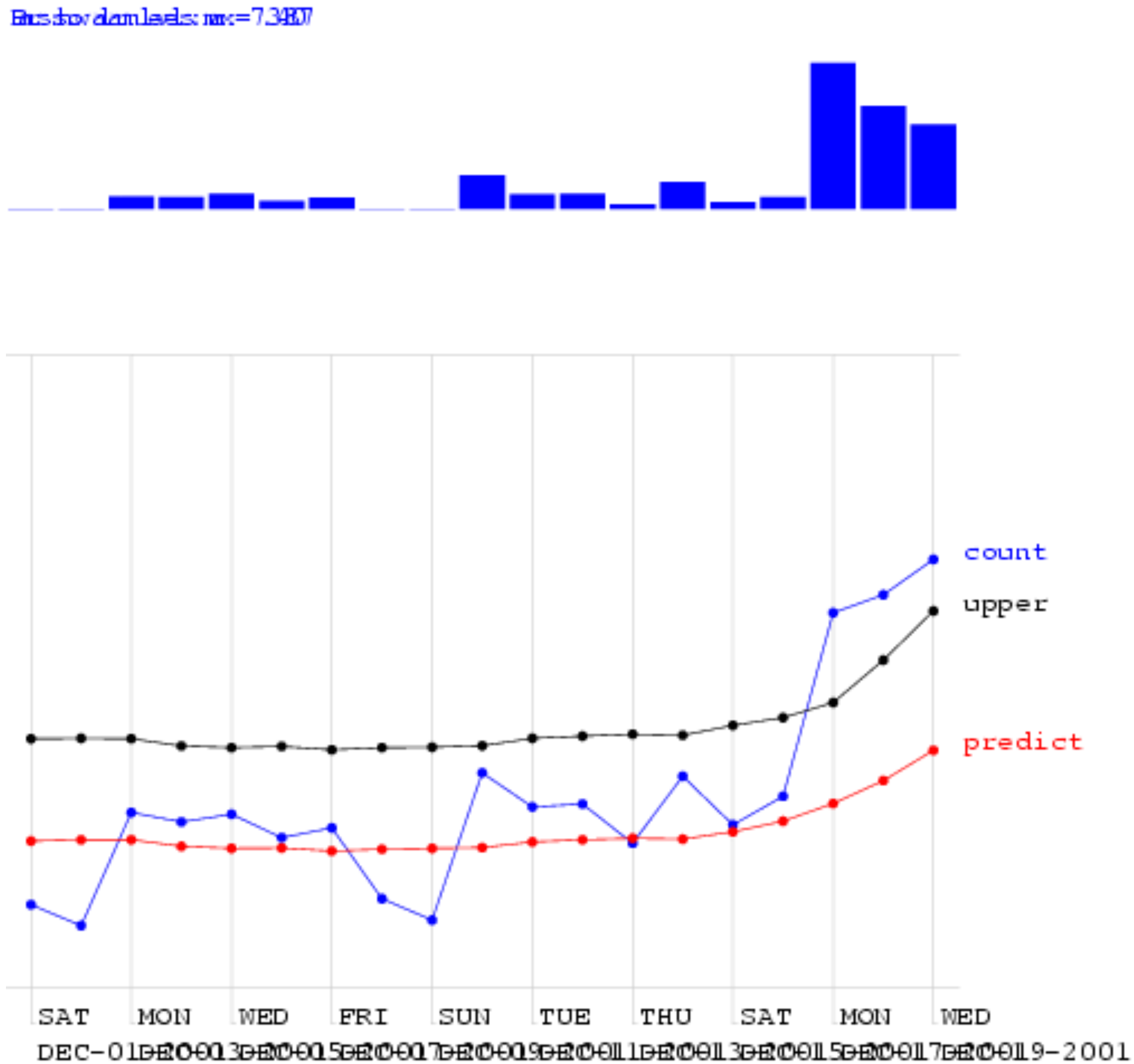

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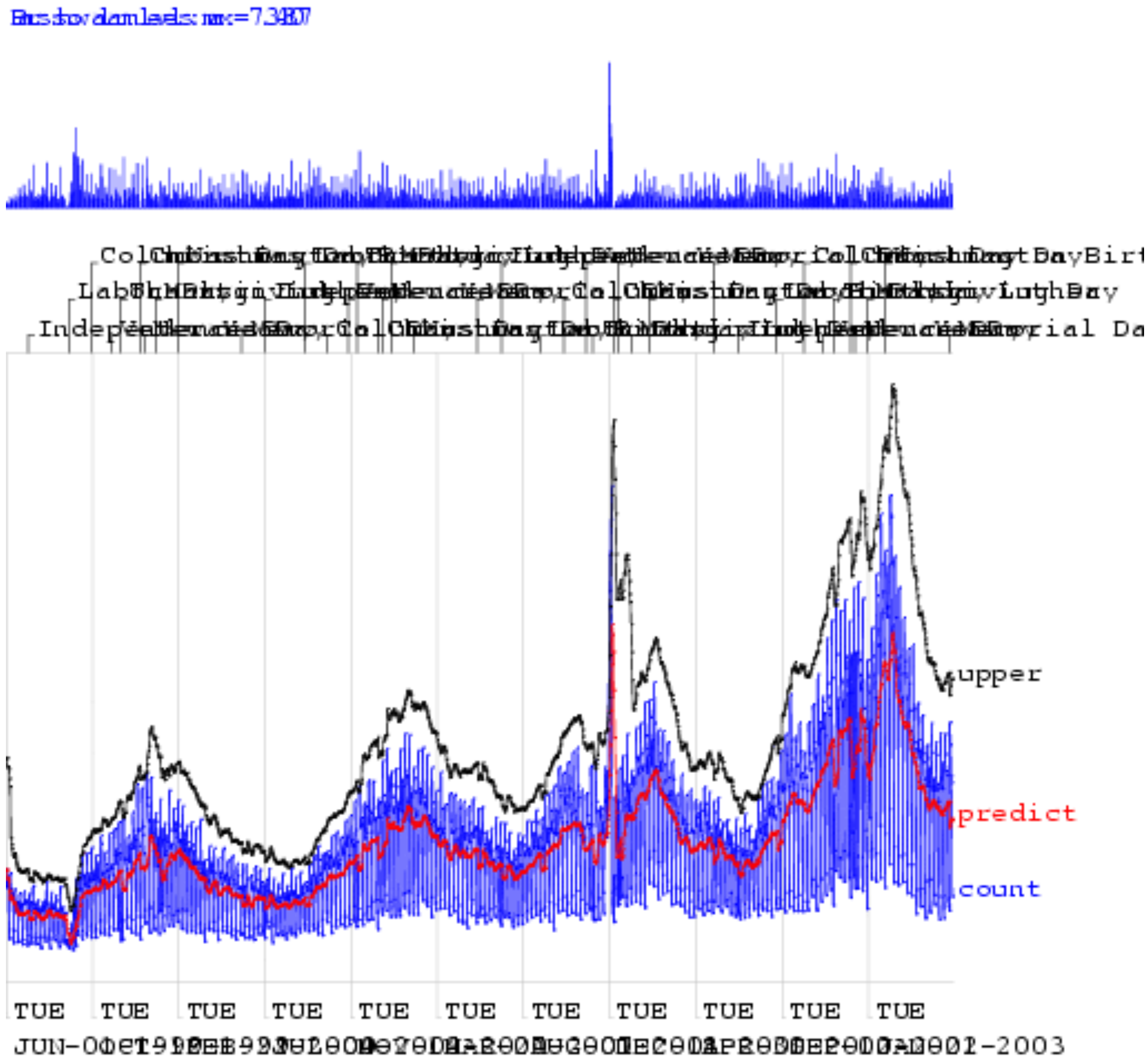

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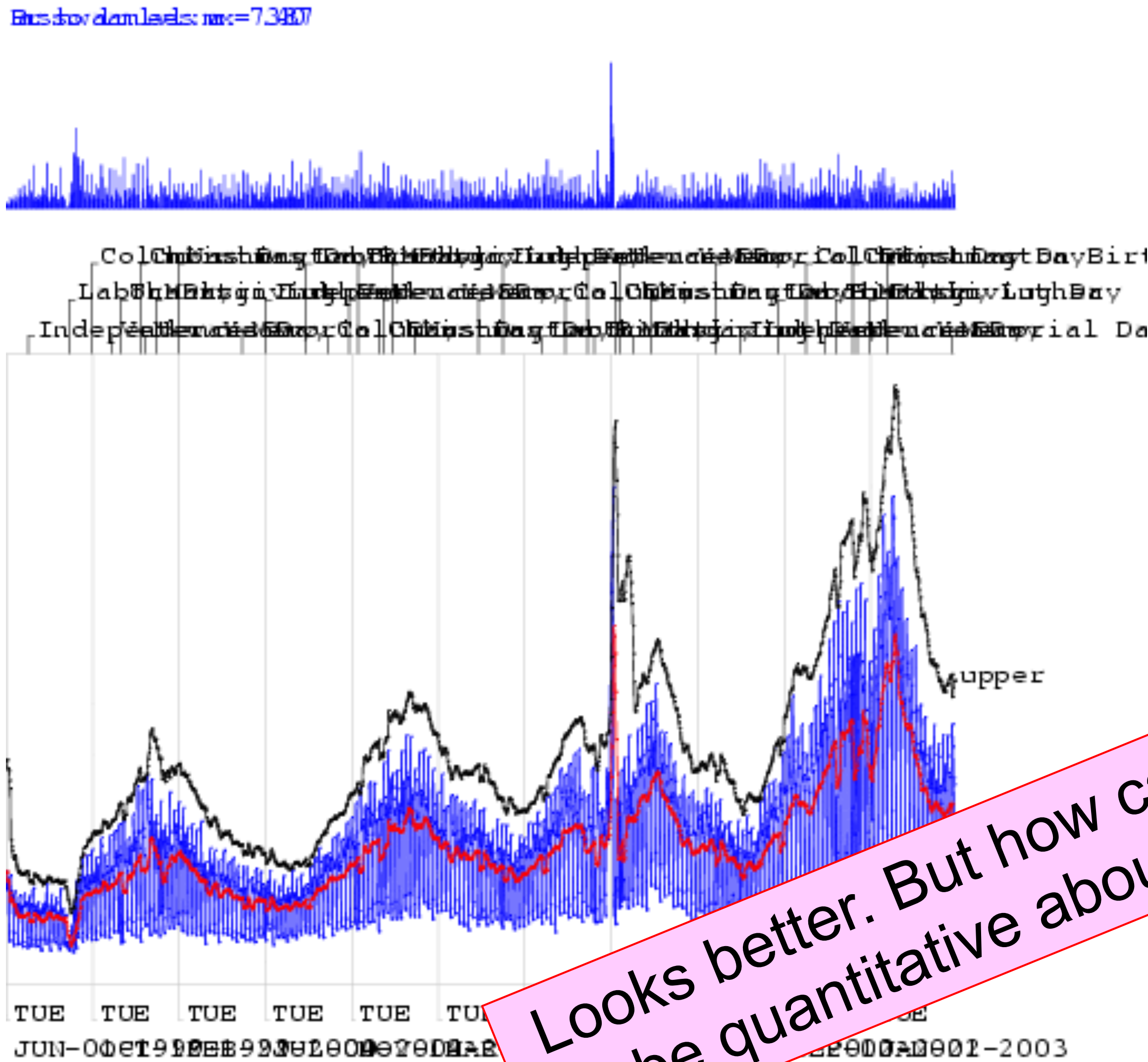

Looks better. But how can we be quantitative about this?

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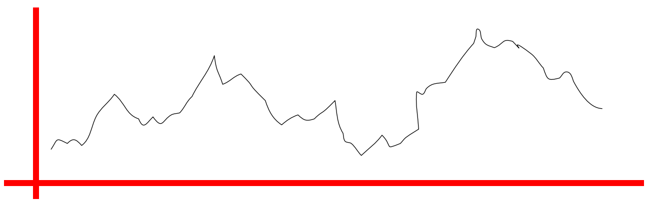
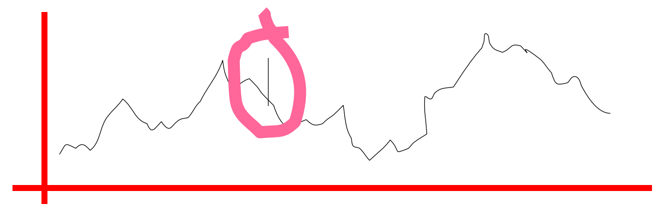
Semi-synthetic data: spike outbreaks

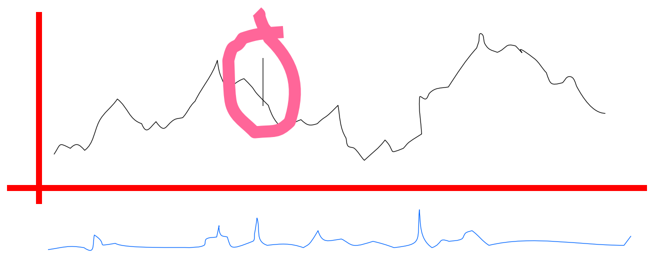
1. Take a real time series



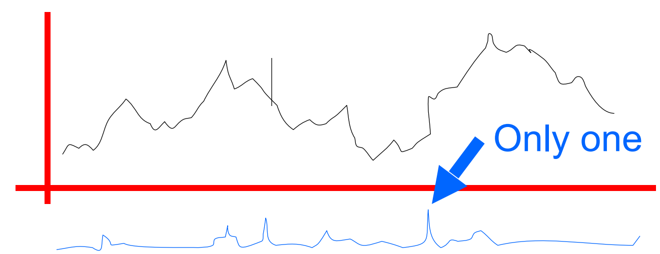
2. Add a spike of random height on a random date



3. See what alarm levels your algorithm gives on every day of the data



4. On what fraction of non-spike days is there an equal or higher alarm



5. That’s an example of the false positive rate this algorithm would need if it was going to detect the actual spike.

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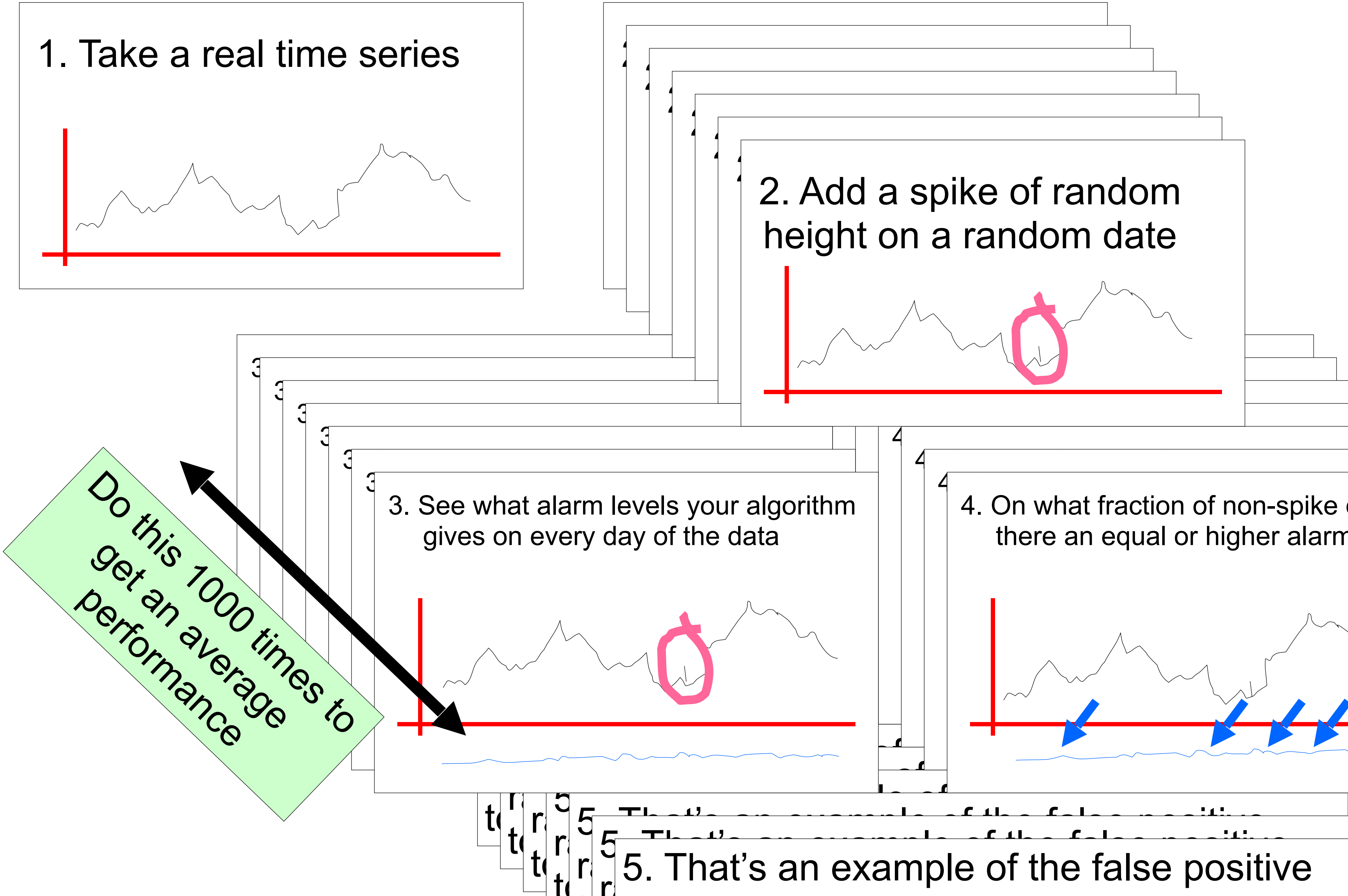

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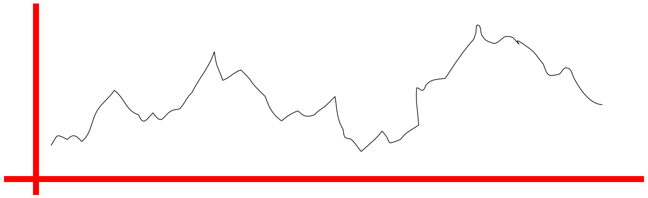

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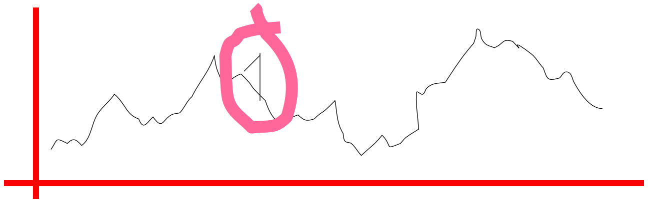

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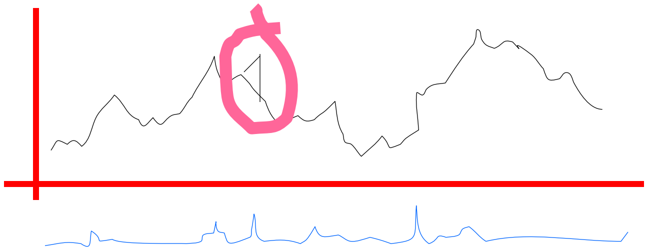
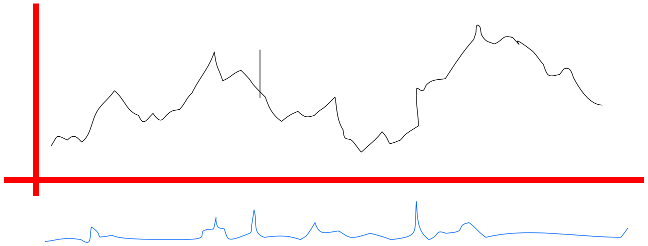


4. If you allowed a specific false positive rate, how far into the ramp would you be before you signaled an alarm?



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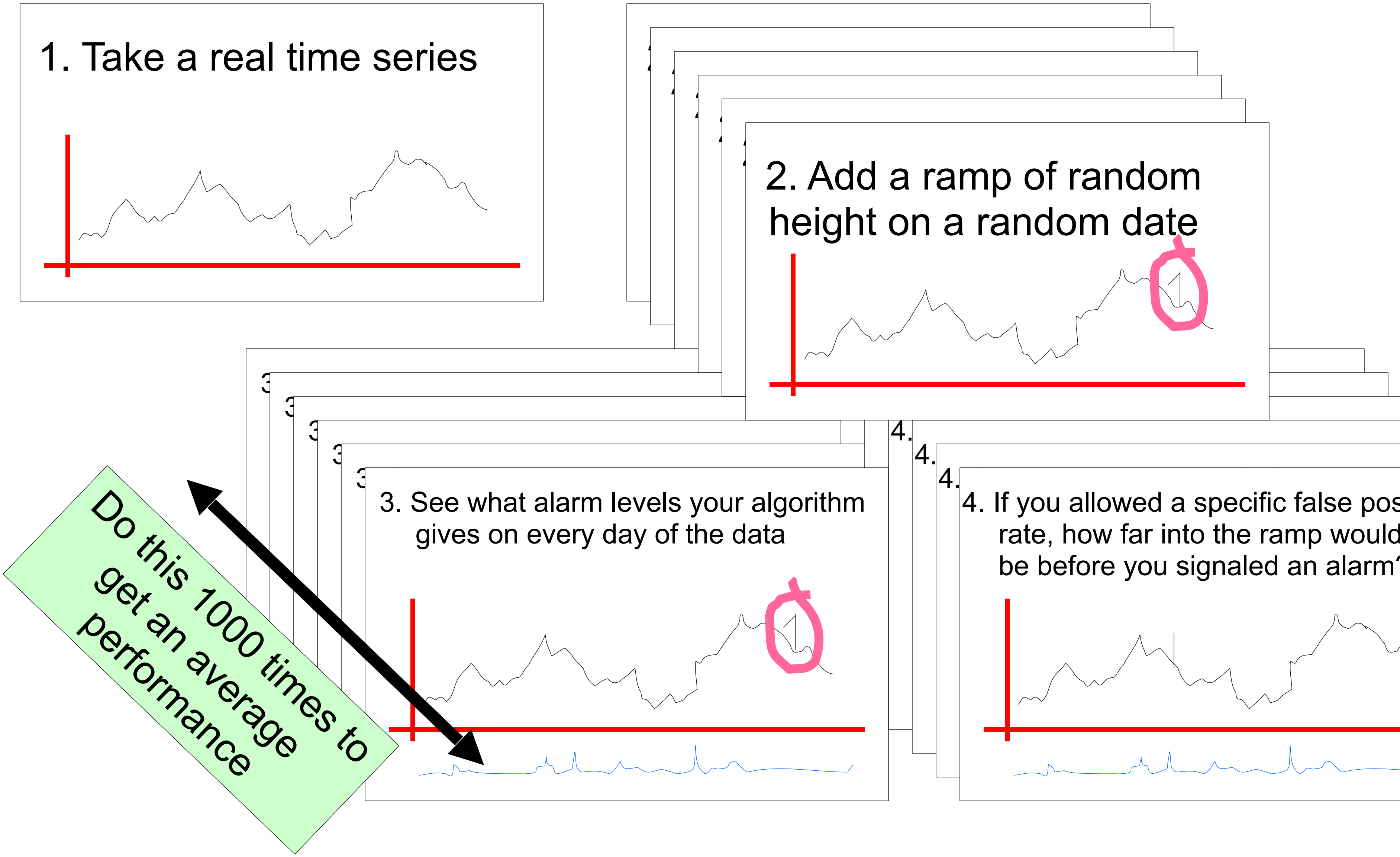

Evaluation methods

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- You can account for variation in the way the baseline will look.
- You can publish evaluation data and share results without data agreement problems
- You can easily generate large numbers of tests
- You know where the outbreaks are

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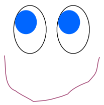

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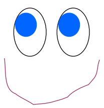

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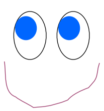

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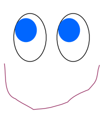

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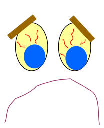

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You need experts to decide what is an outbreak

Some kinds of outbreak have no available data

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Is the test typical?

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None of these options is satisfactory.

Evaluation of Biosurveillance algorithms is really hard. It has got to be. This is a real problem, and we must learn to live with it.

Algorithm Performance

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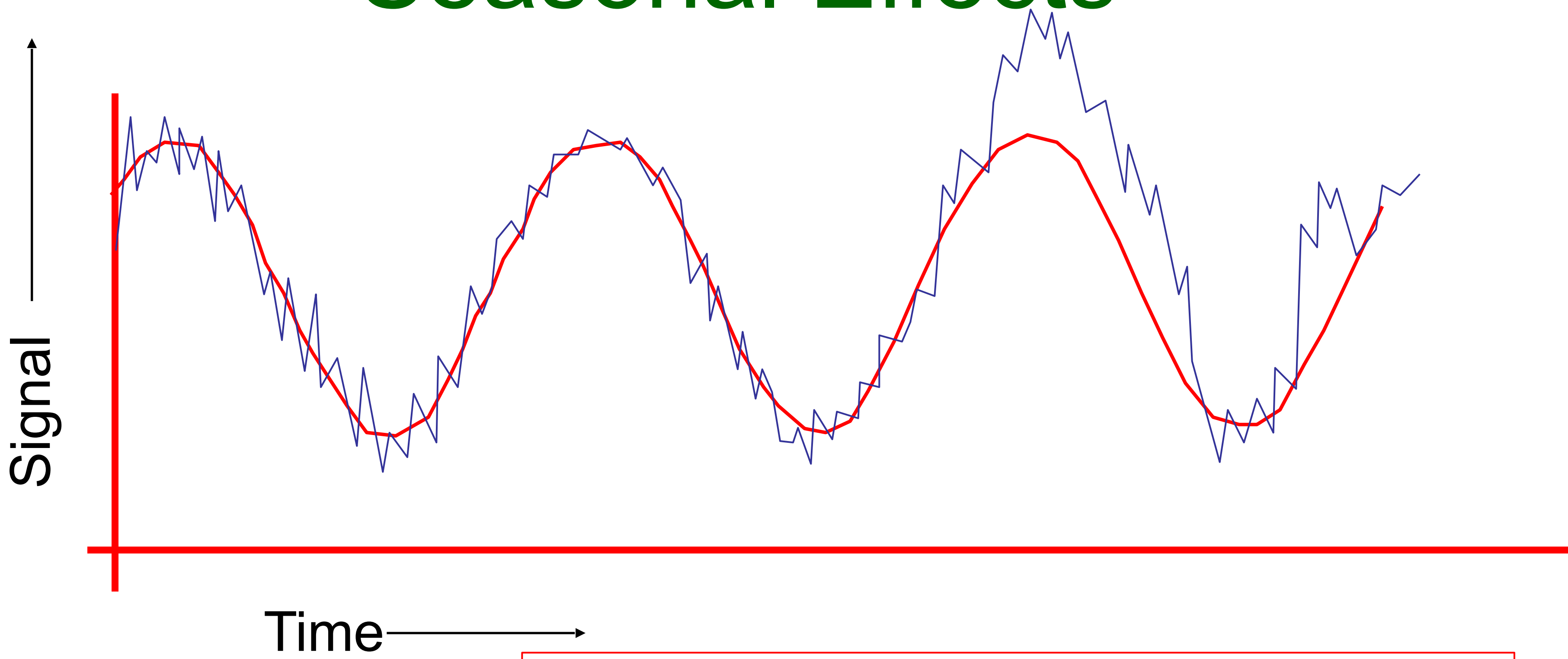
Seasonal Effects



Fit a periodic function (e.g. sine wave) to previous data. Predict today's signal and 3-sigma confidence intervals. Signal an alarm if we're off.

Reduces False alarms from Natural outbreaks.

Different times of year deserve different thresholds.

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hours_of_daylight	0.58	2.73	0.43	3.9

Day-of-week effects

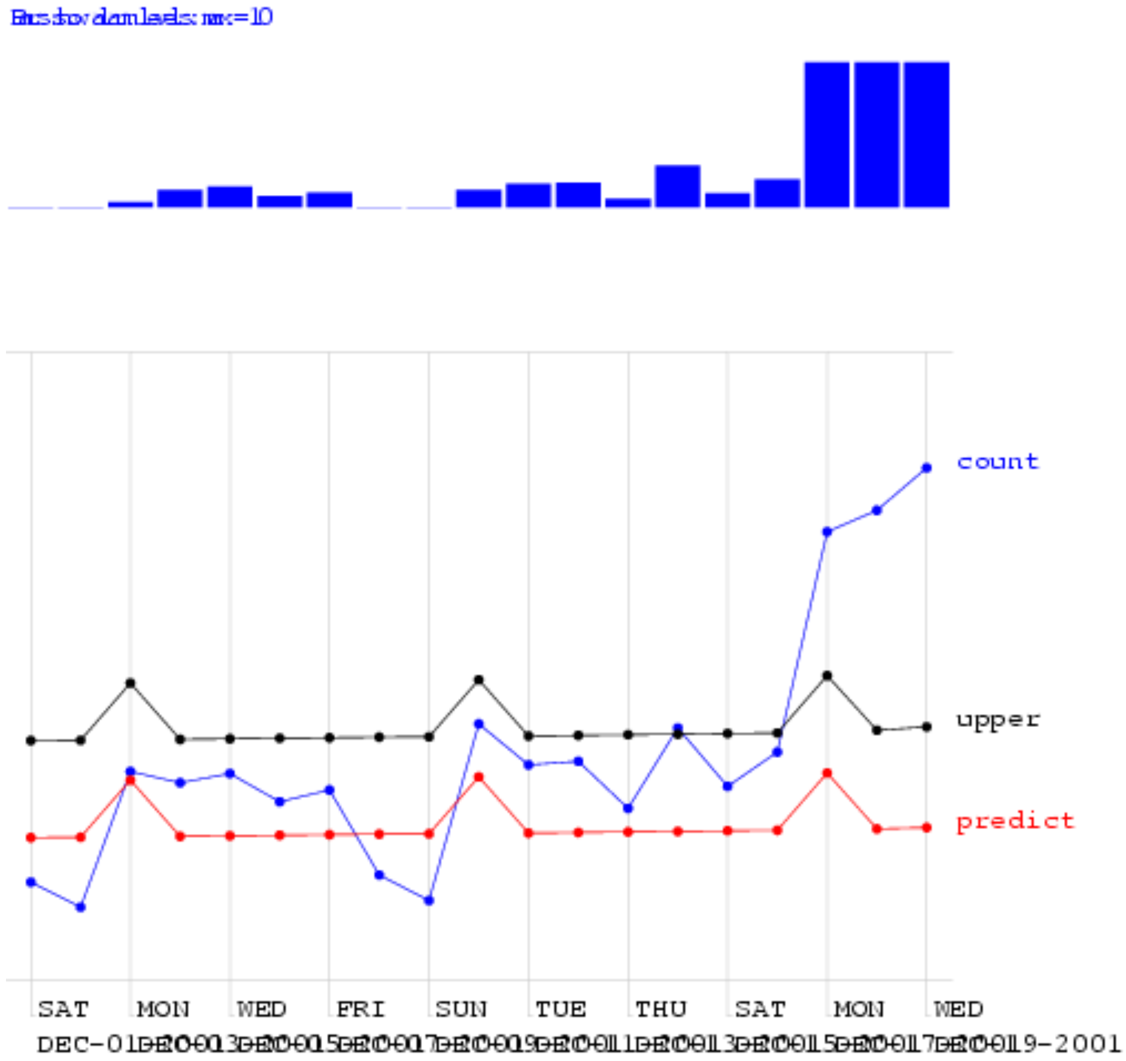
Fit a day-of-week component

$E[\text{Signal}] = a + \text{delta}_{day}$

E.G: $\text{delta}_{mon} = +5.42$, $\text{delta}_{tue} = +2.20$, $\text{delta}_{wed} = +3.33$, $\text{delta}_{thu} = +3.10$, $\text{delta}_{fri} = +4.02$, $\text{delta}_{sat} = -12.2$, $\text{delta}_{sun} = -23.42$

A simple form of ANOVA

Regression using Hours-in-day & IsMonday



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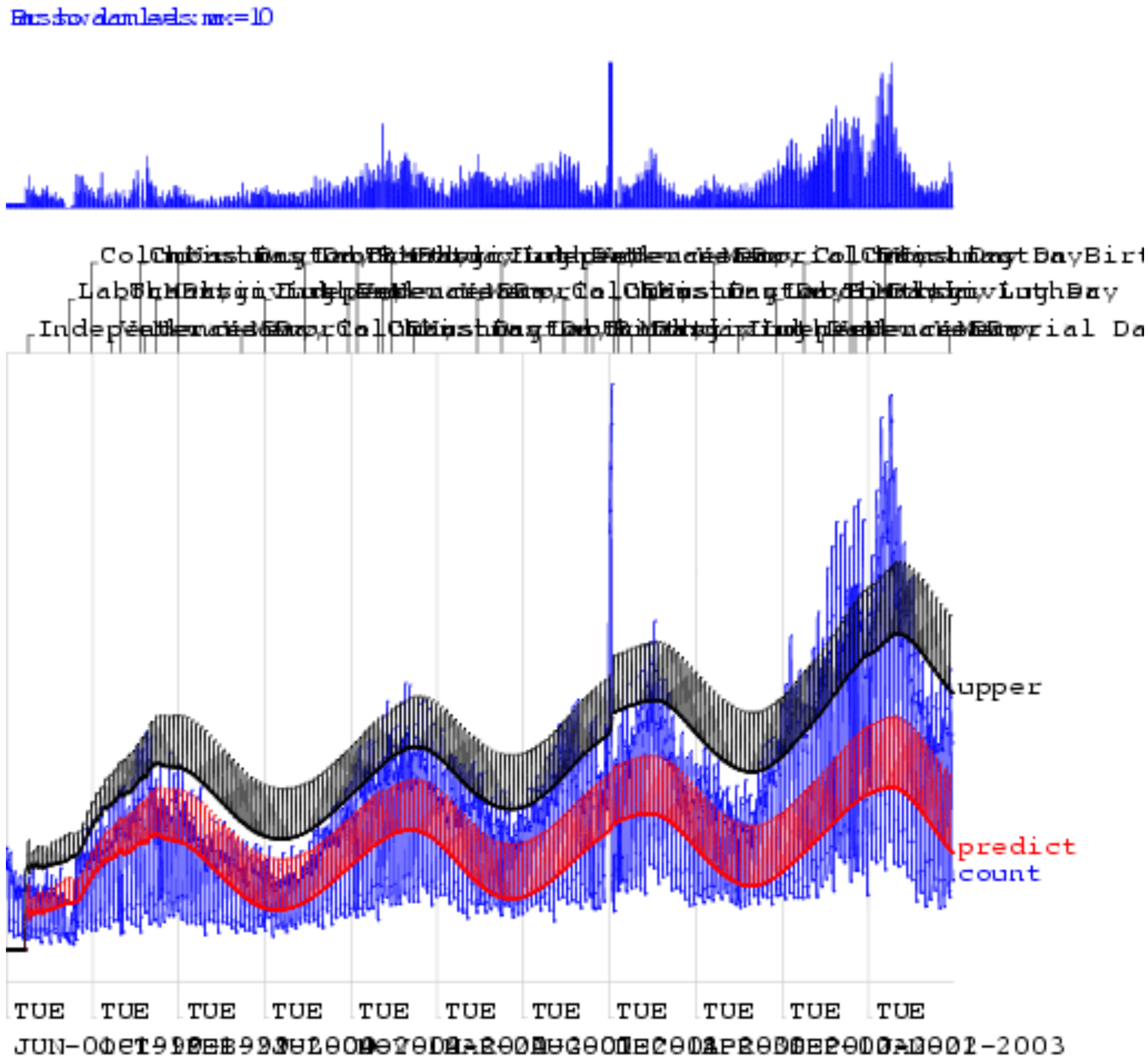

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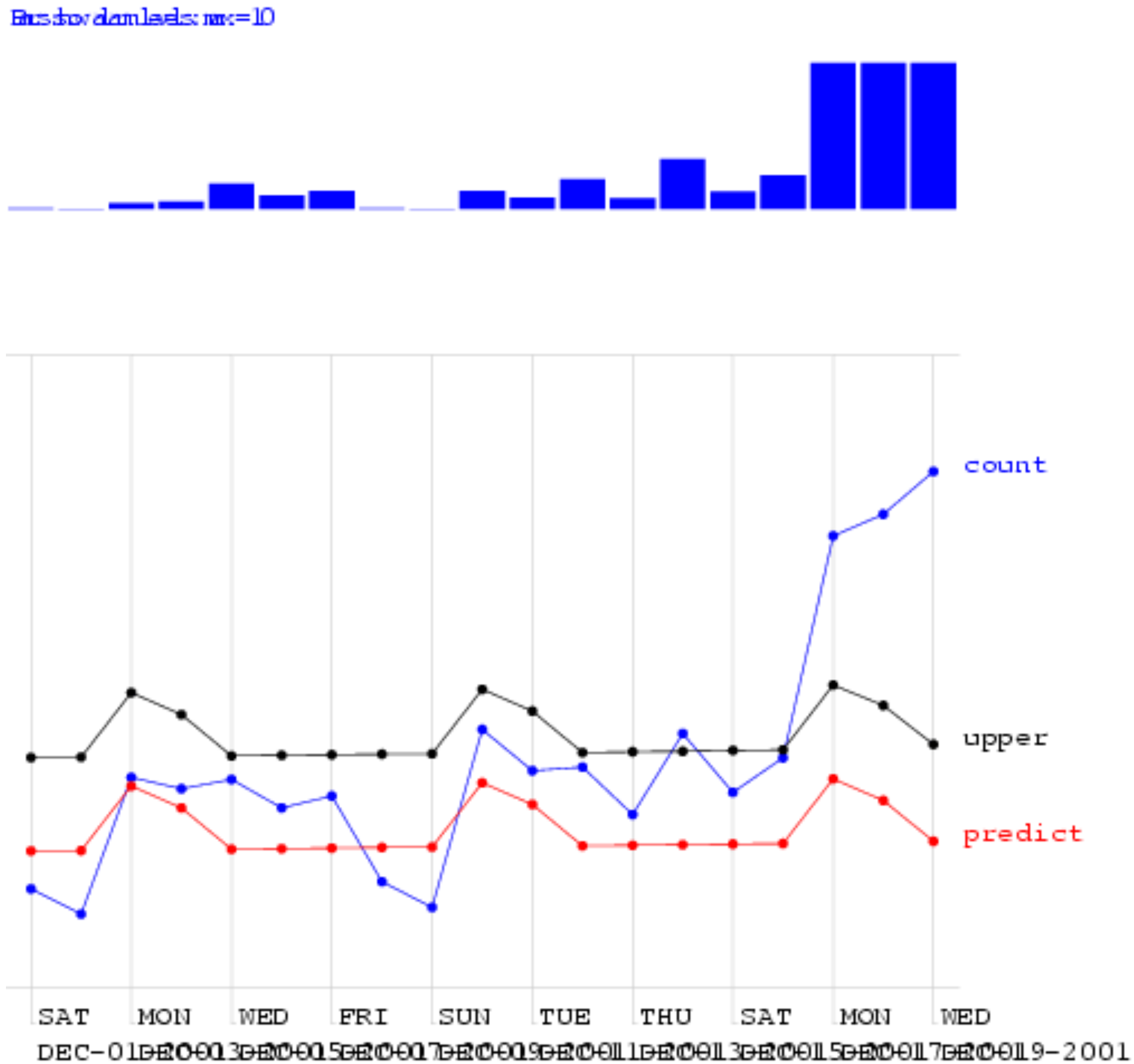
Regression using Mon-Tue



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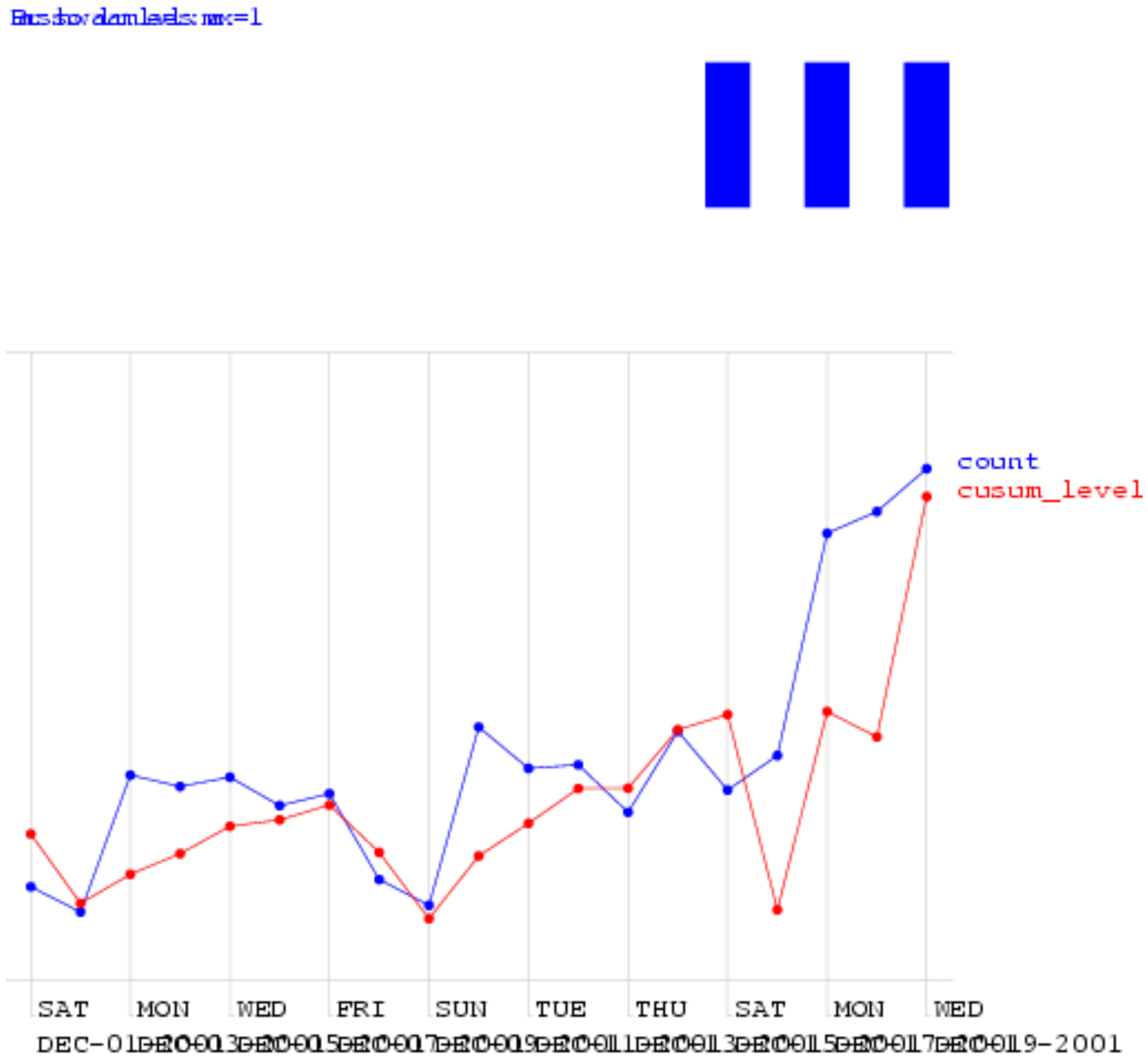
hours_of_daylight is_mon … is_tue	0.72	1.83	0.57	3.16
hours_of_daylight is_mon … is_sat	0.77	2.11	0.59	3.26

CUSUM

- CUmulative SUM Statistics

- Keep a running sum of “surprises”: a sum of excesses each day over the prediction
- When this sum exceeds threshold, signal alarm and reset sum

CUSUM



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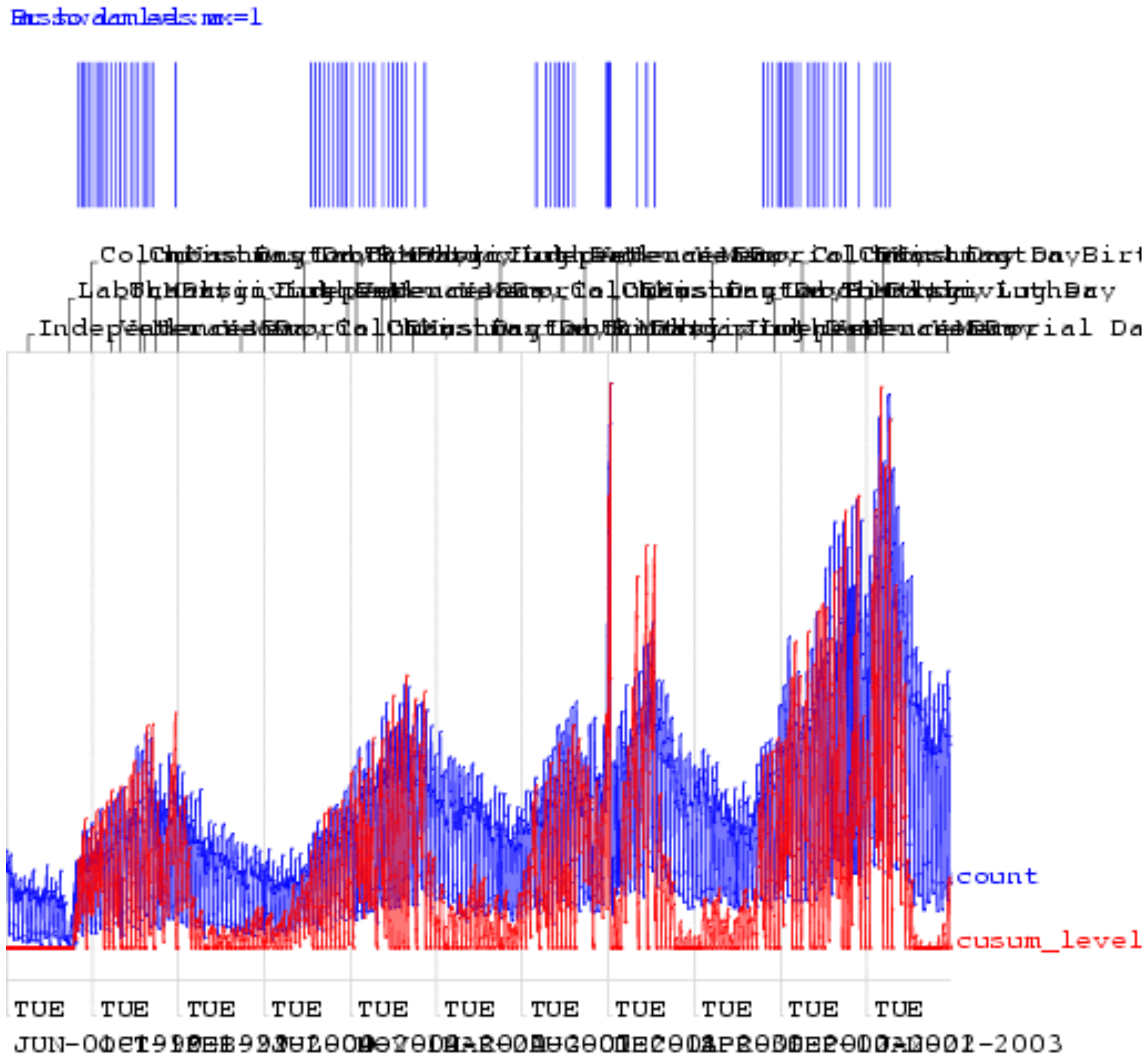

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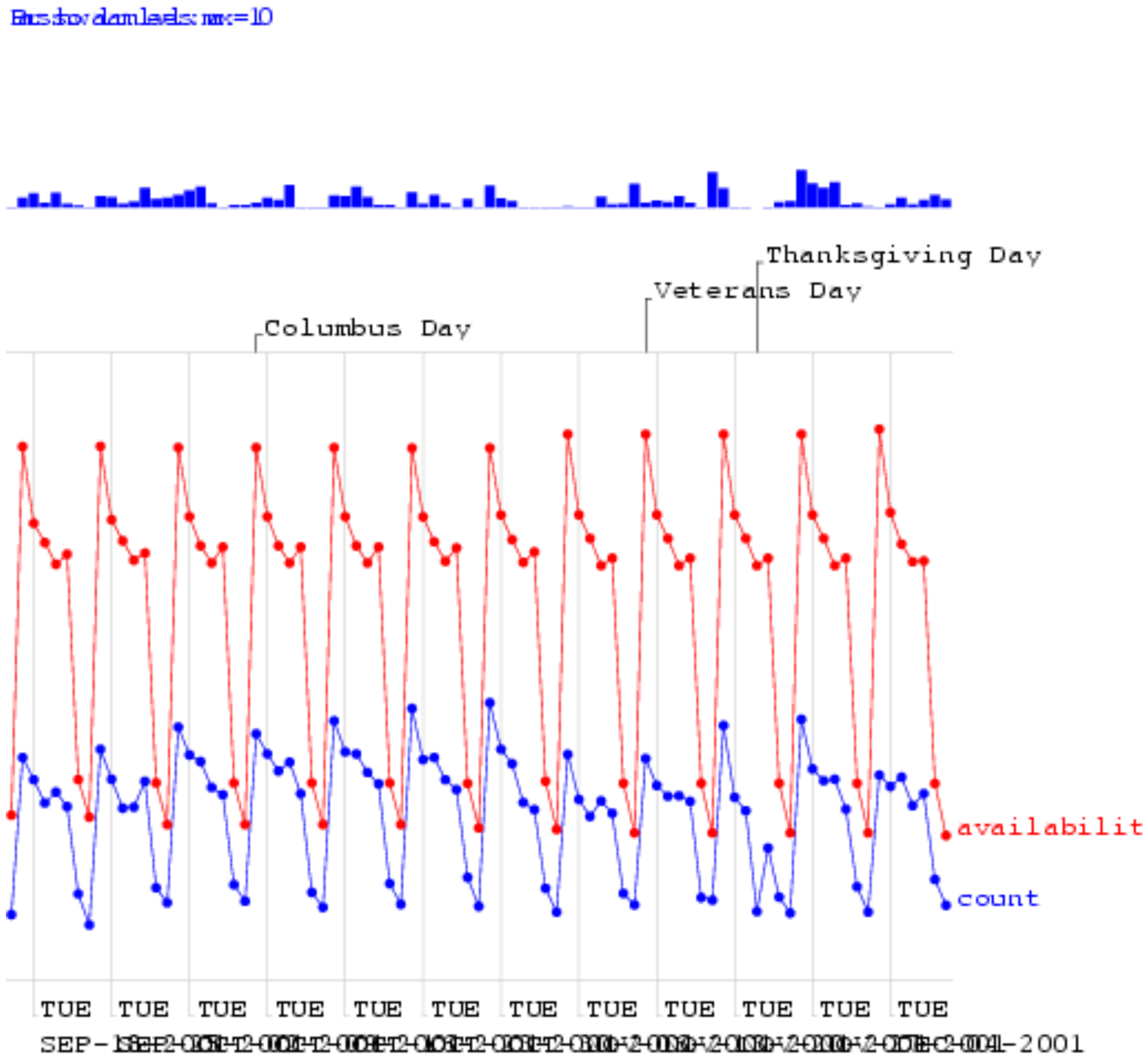

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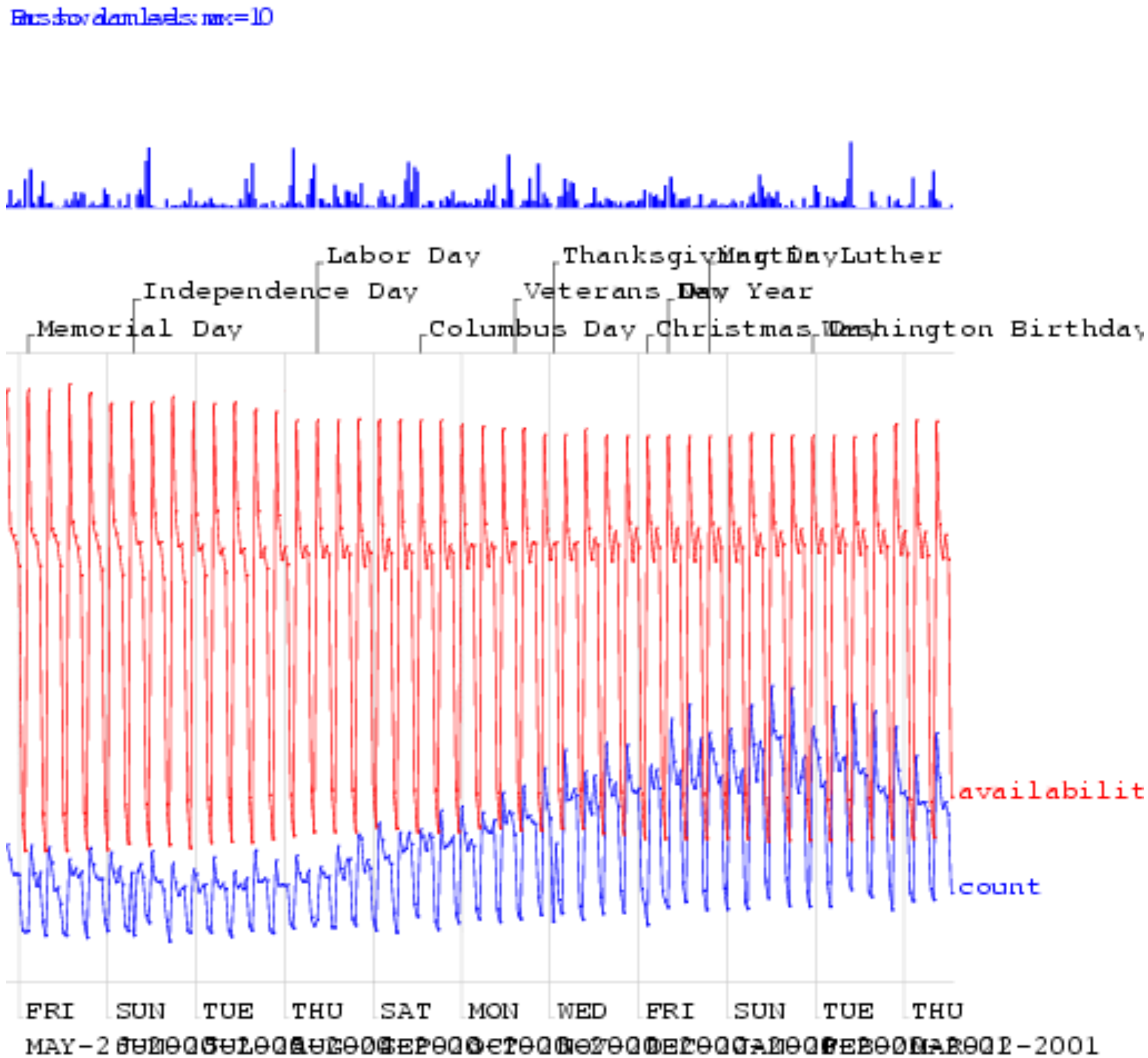

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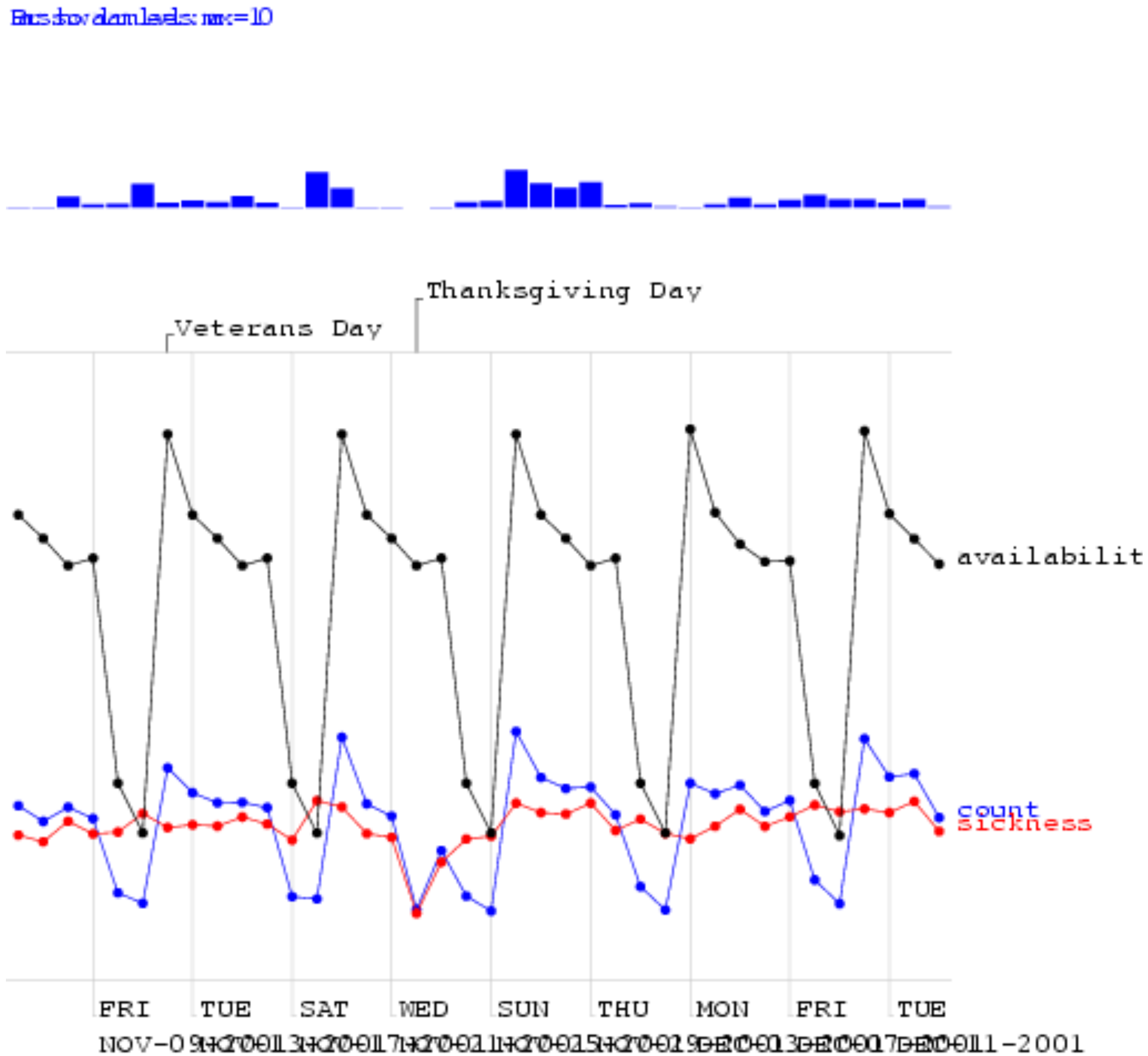

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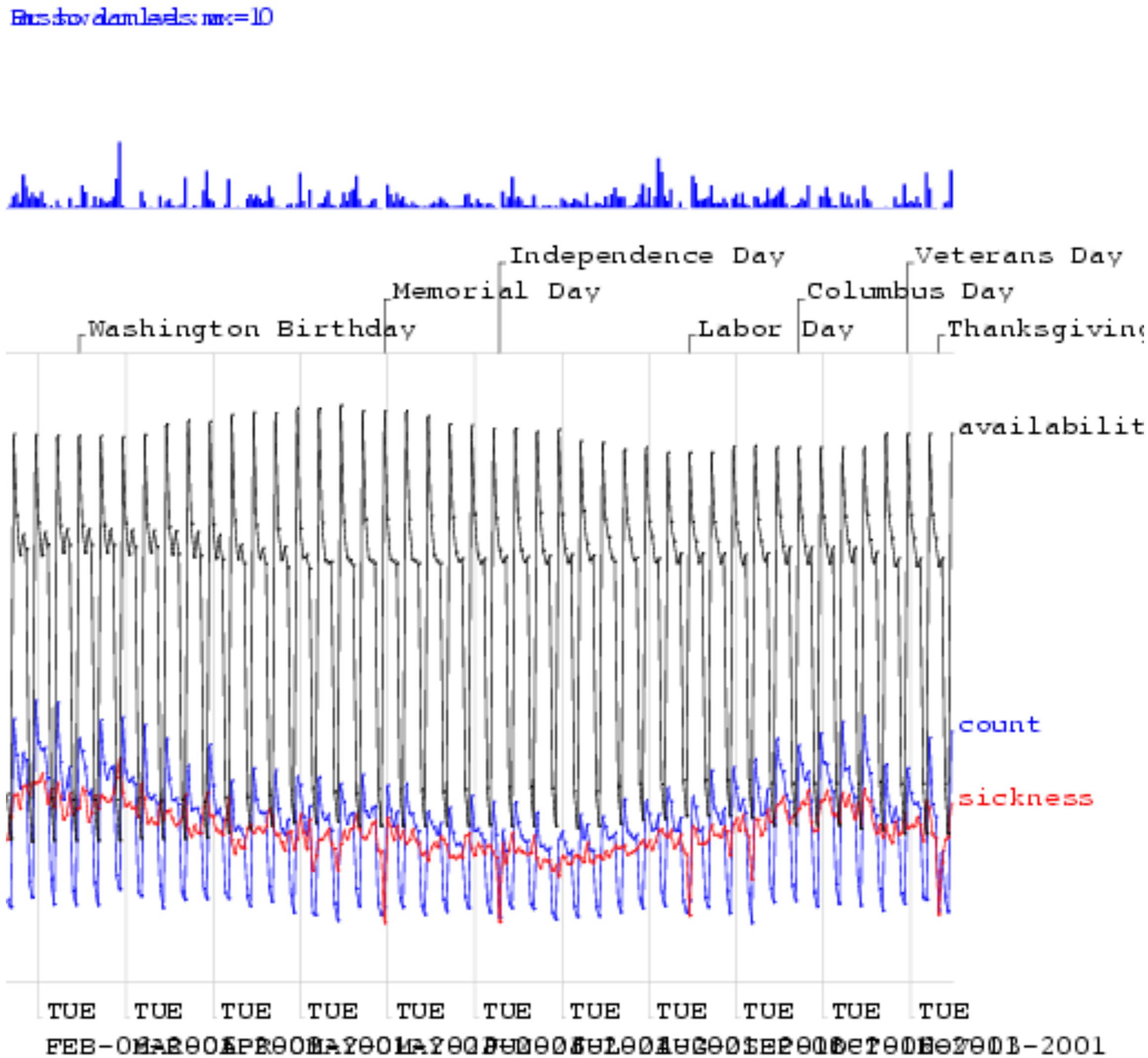

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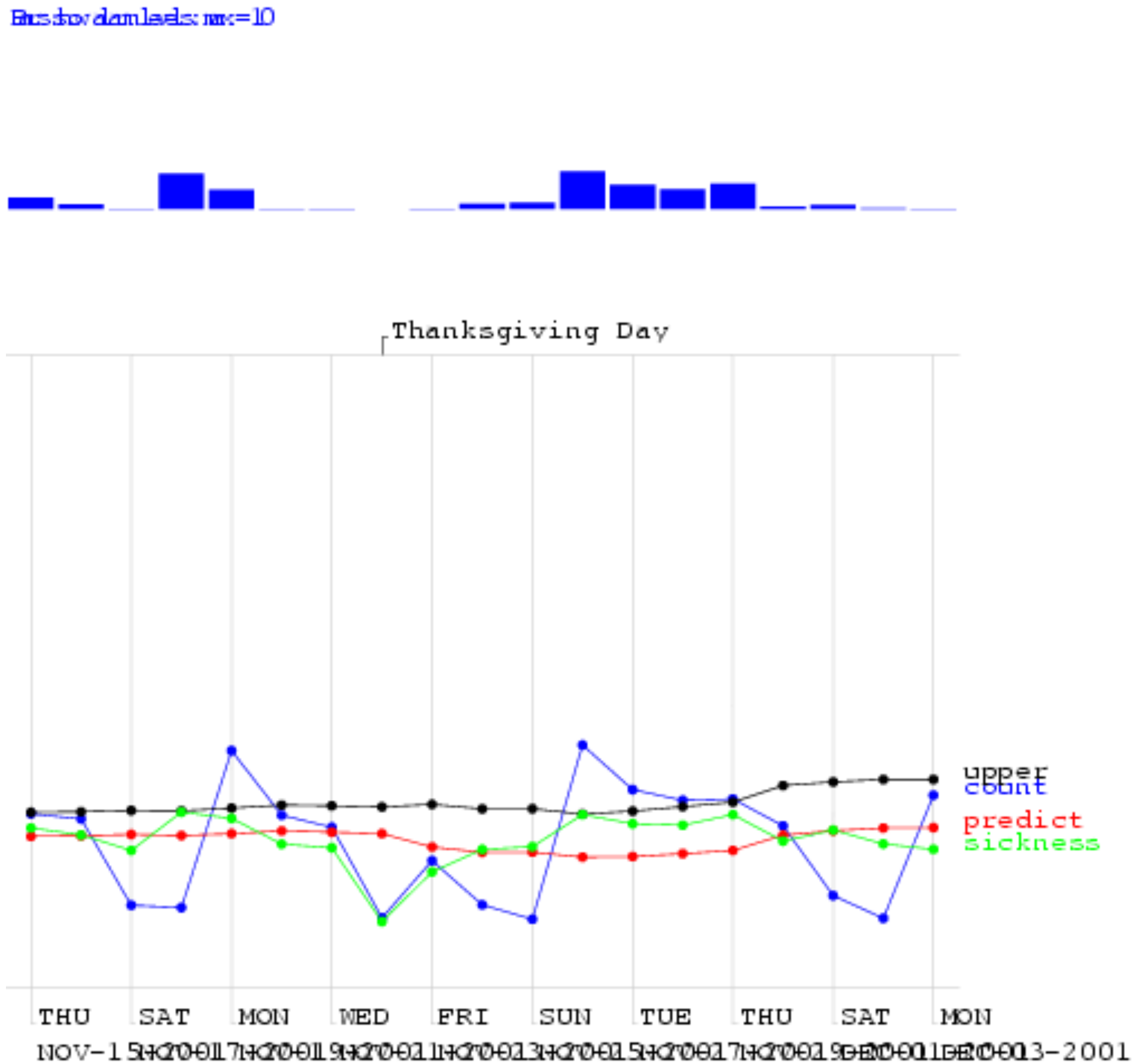

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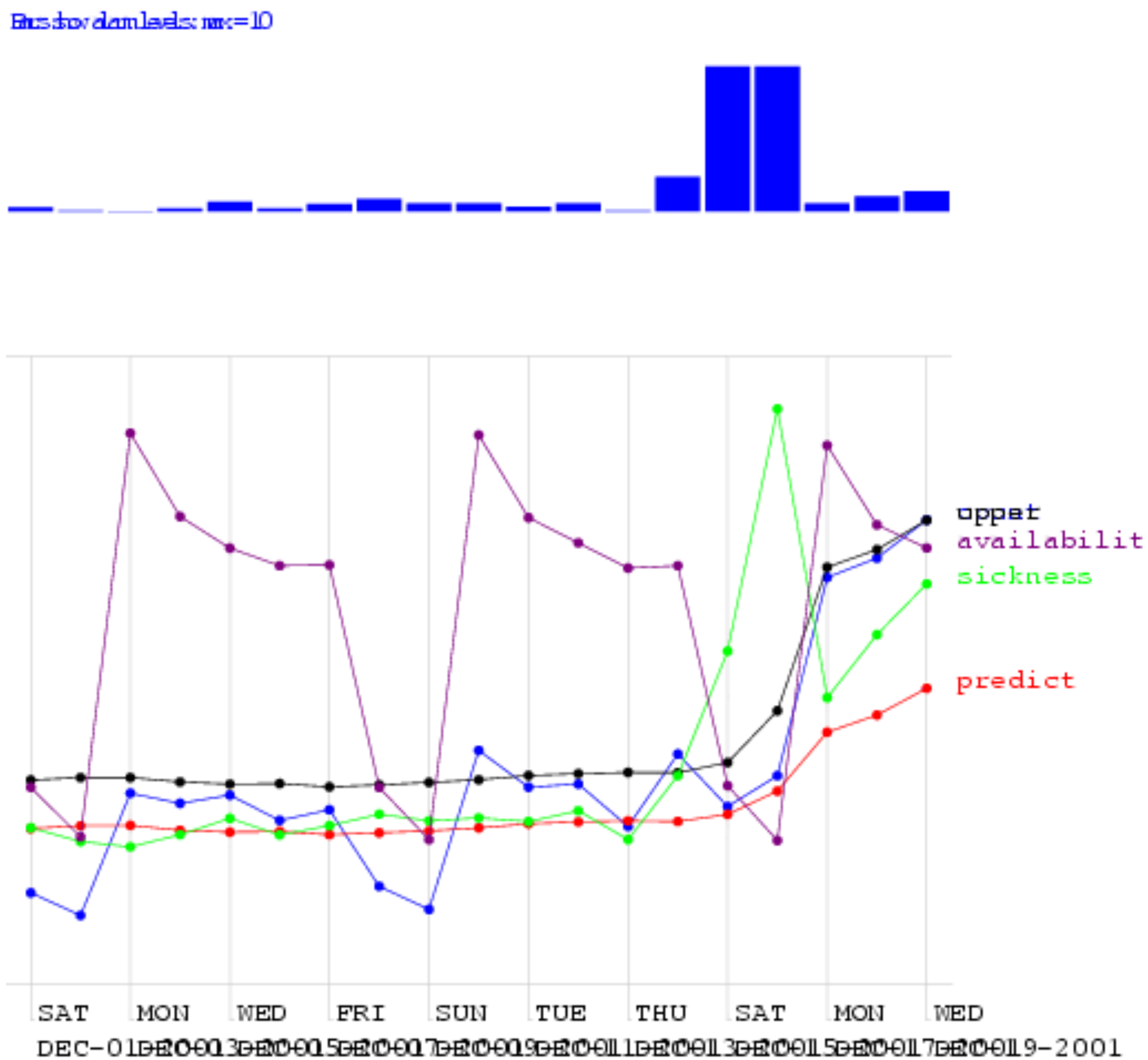

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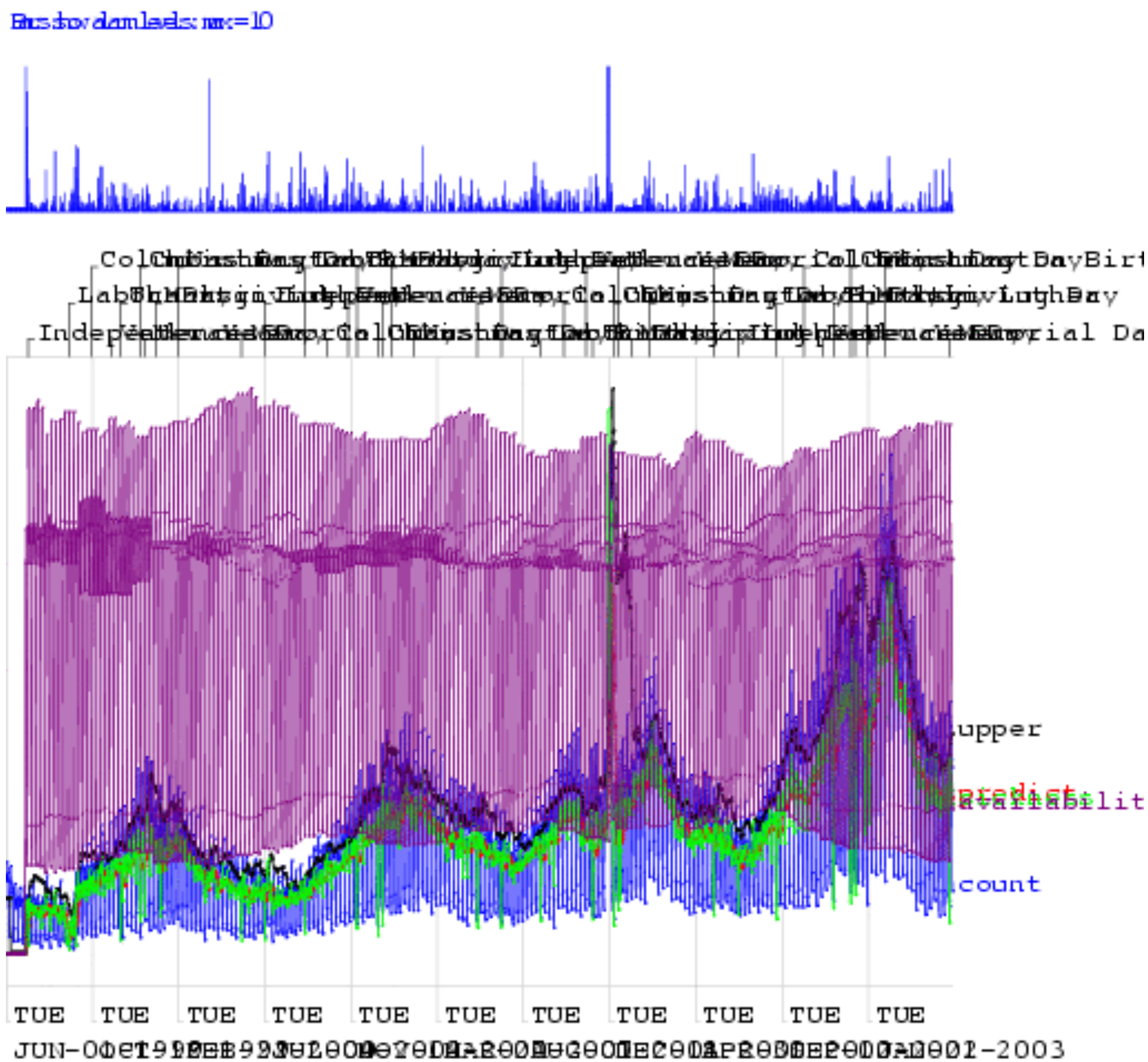

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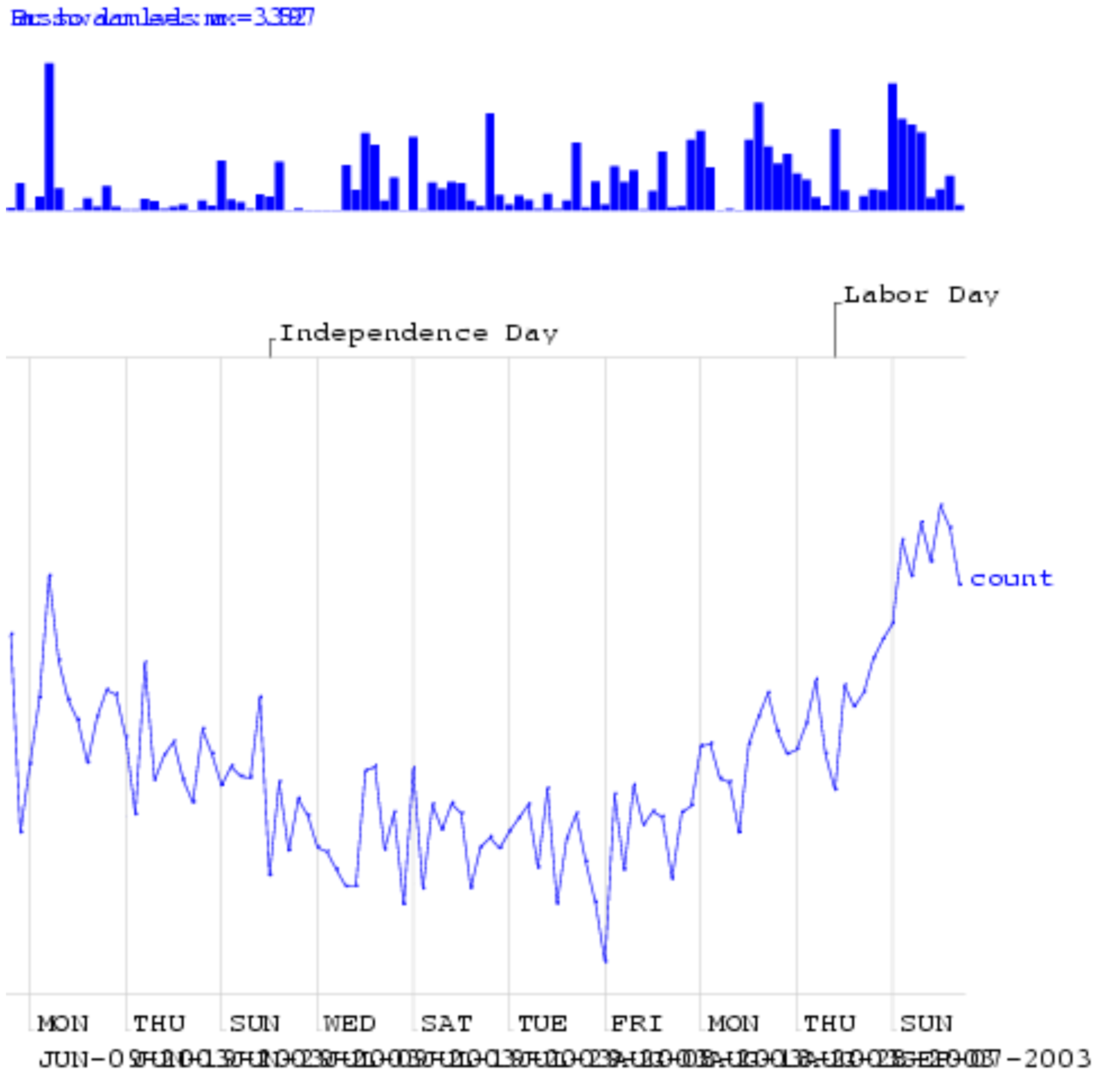
Moving Average 56	0.54	2.72	0.44	3.54
hours_of_daylight	0.58	2.73	0.43	3.9
hours_of_daylight is_mon	0.7	2.25	0.57	3.12
hours_of_daylight is_mon … is_tue	0.72	1.83	0.57	3.16
hours_of_daylight is_mon … is_sat	0.77	2.11	0.59	3.26
CUSUM	0.45	2.03	0.15	3.55
sa-mav-1	0.86	1.88	0.74	2.73
sa-mav-7	0.87	1.28	0.83	1.87
sa-mav-14	0.86	1.27	0.82	1.62

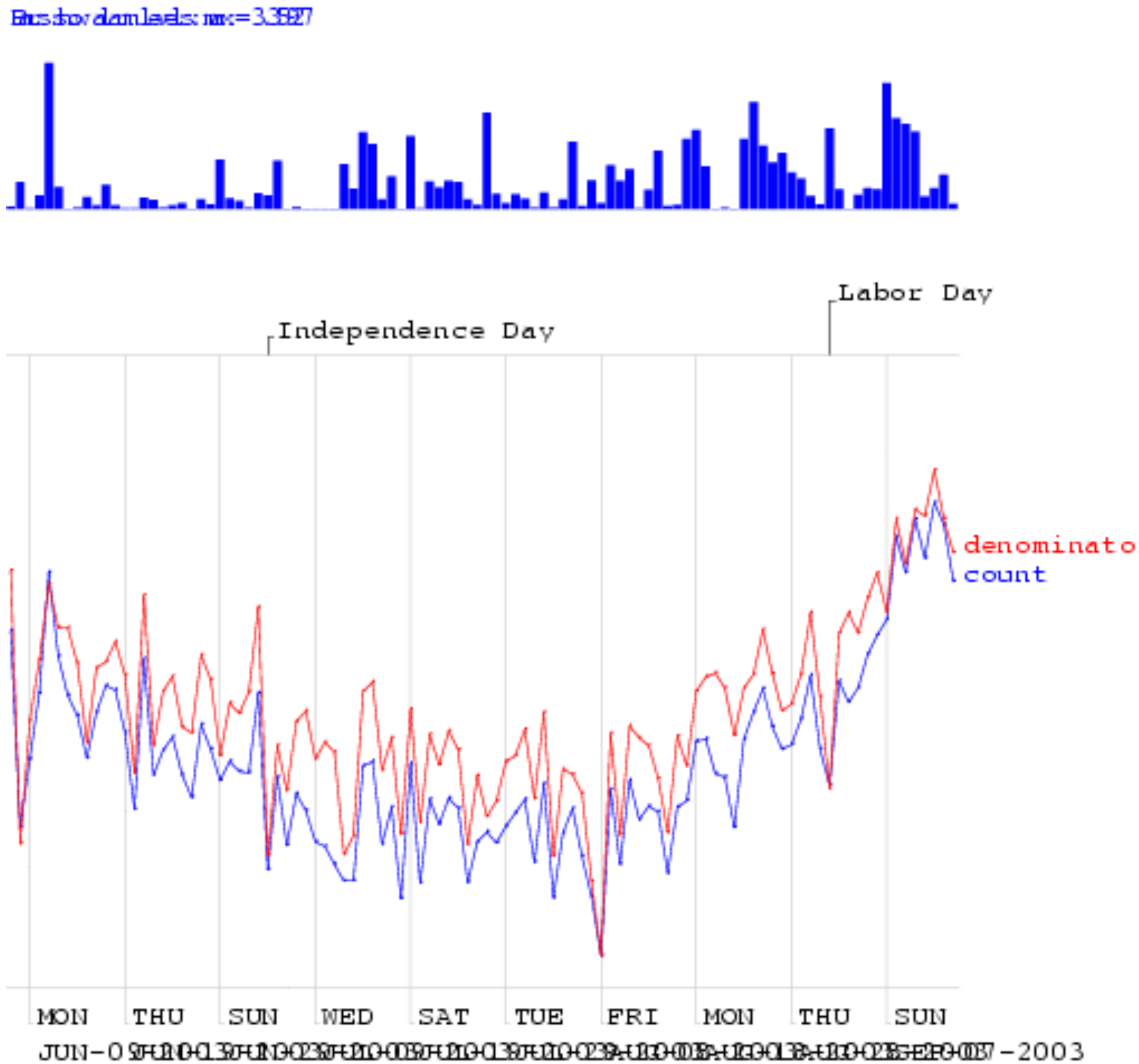
Algorithm Performance

	Allowing one False Alarm per TWO weeks…		Allowing one False Alarm per SIX weeks…	
	Fraction of spikes detected	Days to detect a ramp outbreak	Fraction of spikes detected	Days to detect a ramp outbreak
standard control chart	0.39	3.47	0.22	4.13
using yesterday	0.14	3.83	0.1	4.7
Moving Average 3	0.36	3.45	0.33	3.79
Moving Average 7	0.58	2.79	0.51	3.31
Moving Average 56	0.54	2.72	0.44	3.54
hours_of_daylight	0.58	2.73	0.43	3.9
hours_of_daylight is_mon	0.7	2.25	0.57	3.12
hours_of_daylight is_mon … is_tue	0.72	1.83	0.57	3.16
hours_of_daylight is_mon … is_sat	0.77	2.11	0.59	3.26
CUSUM	0.45	2.03	0.15	3.55
sa-mav-1	0.86	1.88	0.74	2.73
sa-mav-7	0.87	1.28	0.83	1.87
sa-mav-14	0.86	1.27	0.82	1.62
sa-regress	0.73	1.76	0.67	2.21

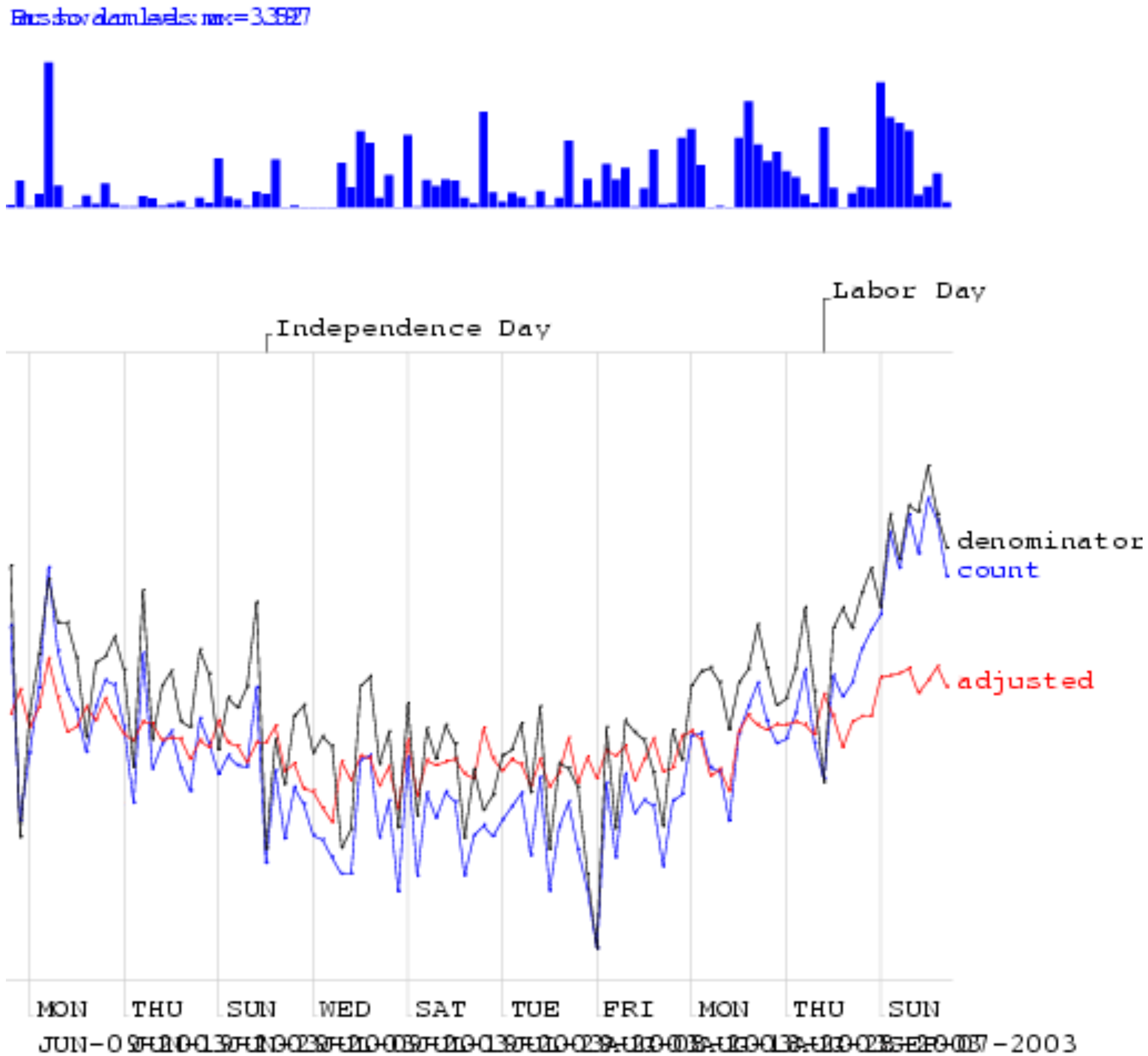
Exploiting Denominator Data



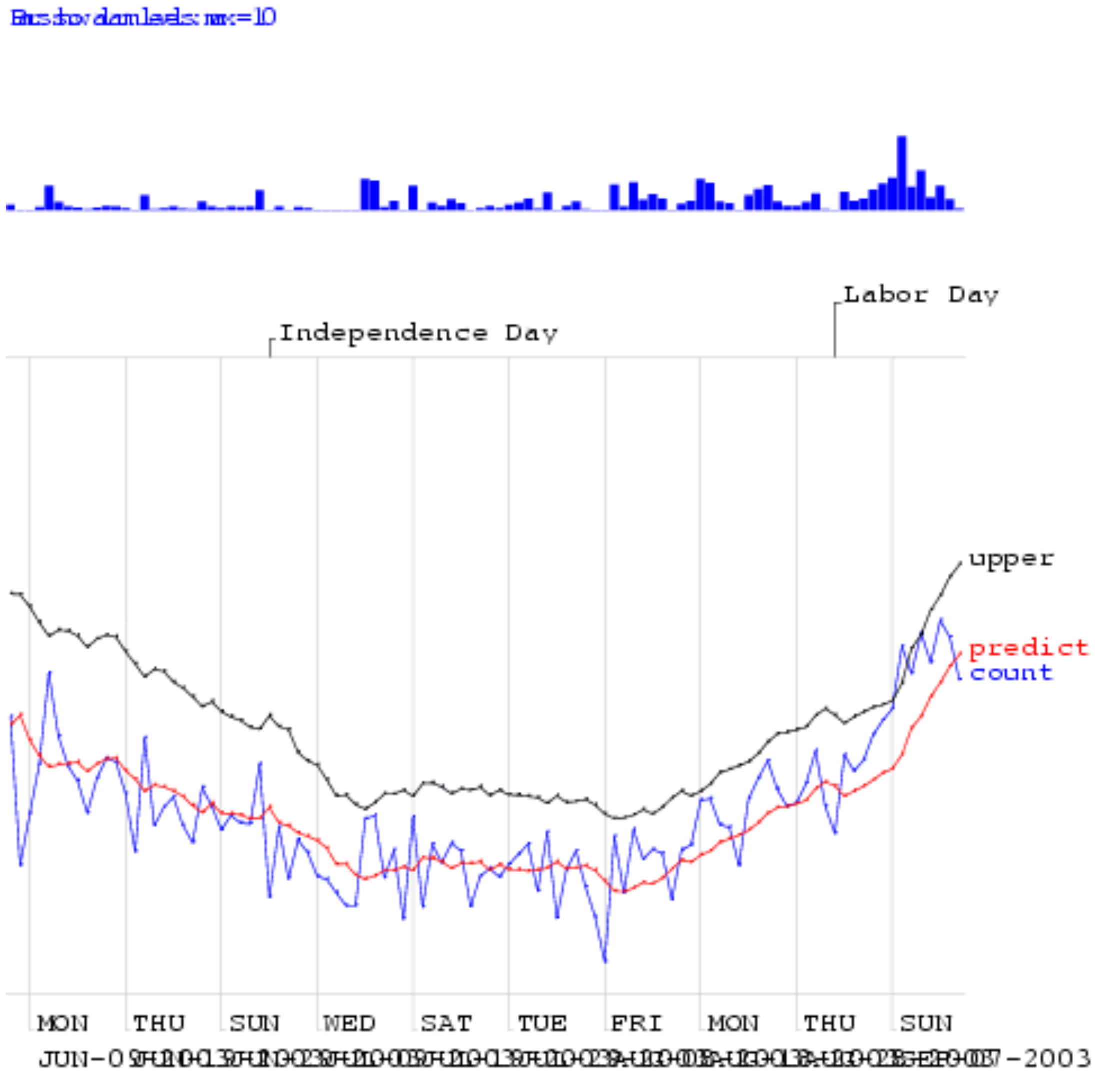
Exploiting Denominator Data



Exploiting Denominator Data



Exploiting Denominator Data



Algorithm Performance

	Allowing one False Alarm per TWO weeks… Fraction of spikes detected	Allowing one False Alarm per TWO weeks… Days to detect a ramp outbreak	Allowing one False Alarm per SIX weeks… Fraction of spikes detected	Allowing one False Alarm per SIX weeks… Days to detect a ramp outbreak
standard control chart	0.39	3.47	0.22	4.13
using yesterday	0.14	3.83	0.1	4.7
Moving Average 3	0.36	3.45	0.33	3.79
Moving Average 7	0.58	2.79	0.51	3.31
Moving Average 56	0.54	2.72	0.44	3.54
hours_of_daylight	0.58	2.73	0.43	3.9
hours_of_daylight is_mon	0.7	2.25	0.57	3.12
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hours_of_daylight is_mon … is_sat	0.77	2.11	0.59	3.26
CUSUM	0.45	2.03	0.15	3.55
sa-mav-1	0.86	1.88	0.74	2.73
sa-mav-7	0.87	1.28	0.83	1.87
sa-mav-14	0.86	1.27	0.82	1.62
sa-regress	0.73	1.76	0.67	2.21
Cough with denominator	0.78	2.15	0.59	2.41
Cough with MA	0.65	2.78	0.57	3.24

Show Walkerton Results

Other state-of-the-art methods

- Wavelets
- Change-point detection
- Kalman filters
- Hidden Markov Models