



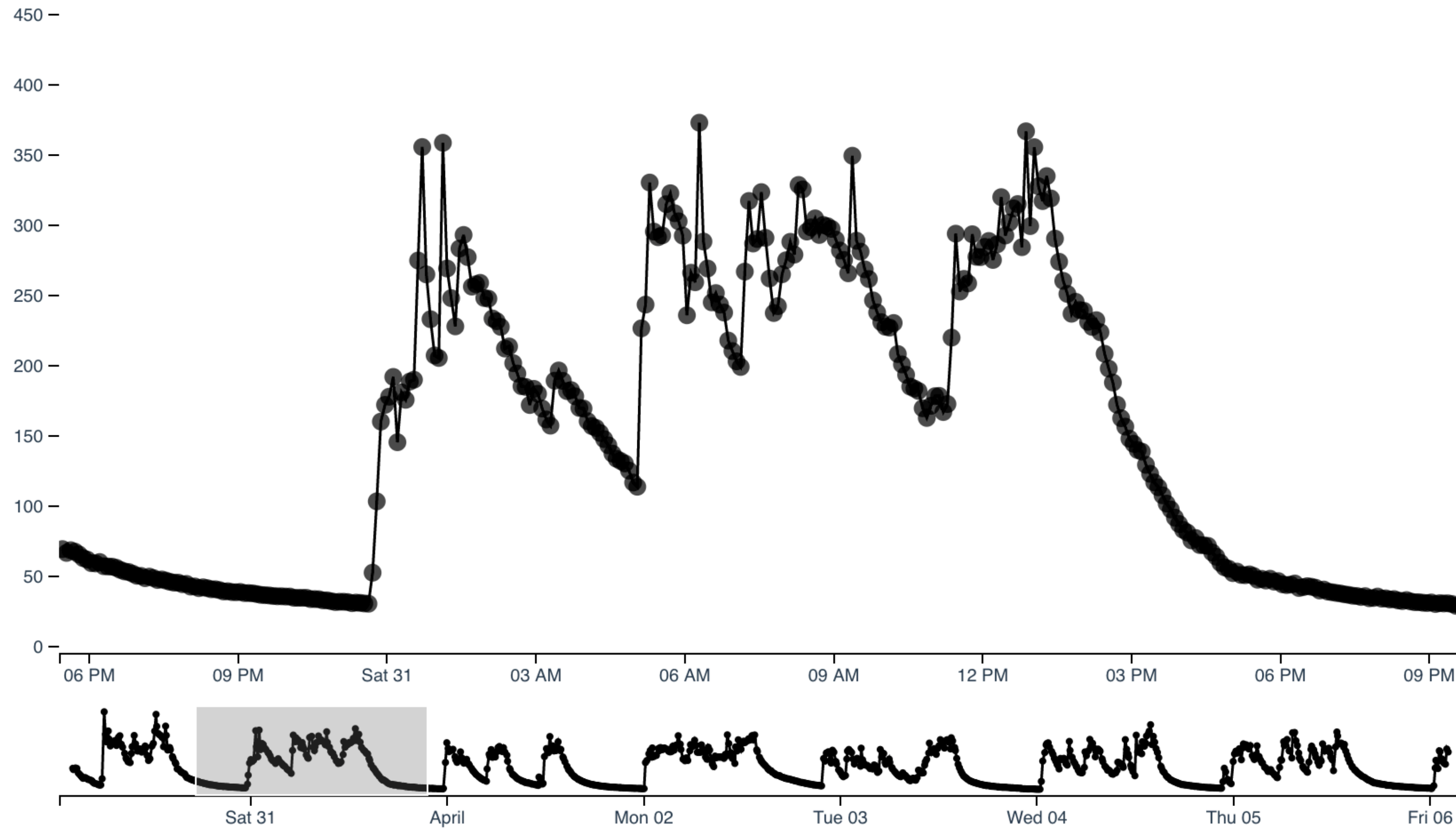
FireFinder: An Open-Source Deterministic Cooking Event Detection Algorithm

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Common Challenges of Analyzing Sensor Data

What is “cooking?”

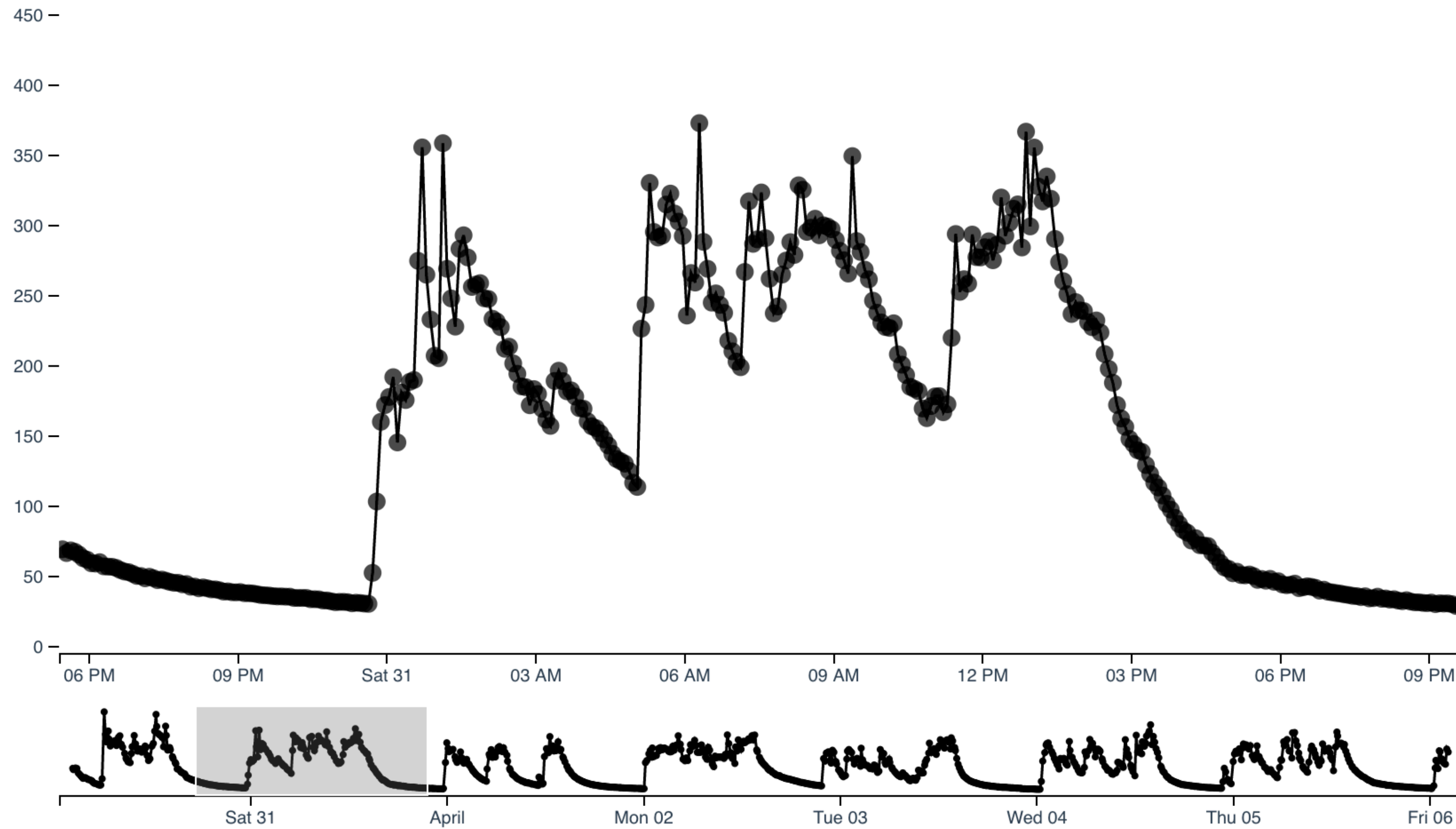
Filename: sumsarizer_v1_012993.csv



What is usage?

- When the stove is hot?
- When the fire is burning and making emissions?
- When food/drink is on the stove?
- When useful energy is being added to the pot?
- When meaningful amounts of fuel are being consumed?

Filename: sumsarizer_v1_012993.csv

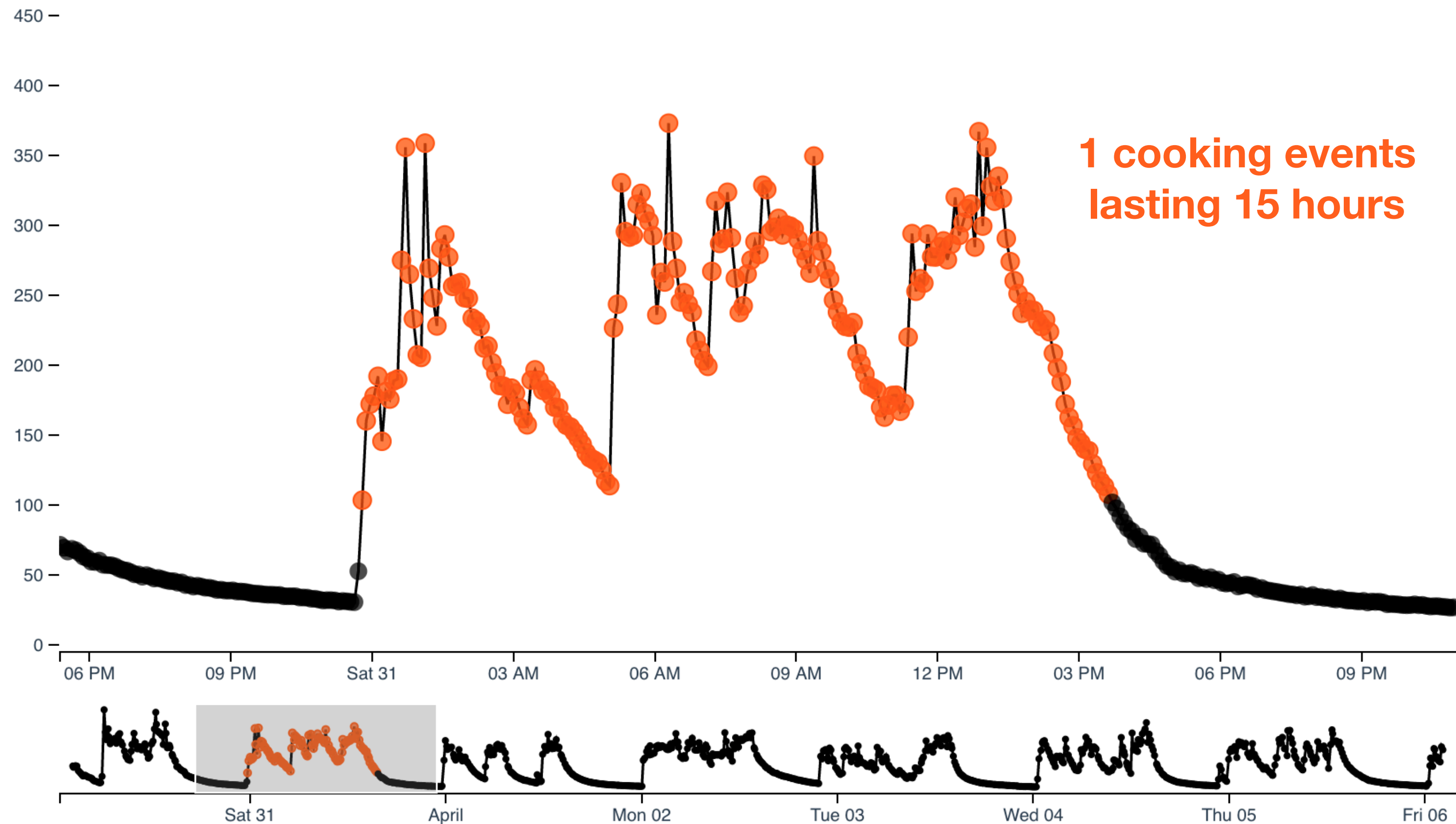


What is cooking?

- How many cooking events was that?
- How long did they last?
- What did all that mean? What was the user's behavior?

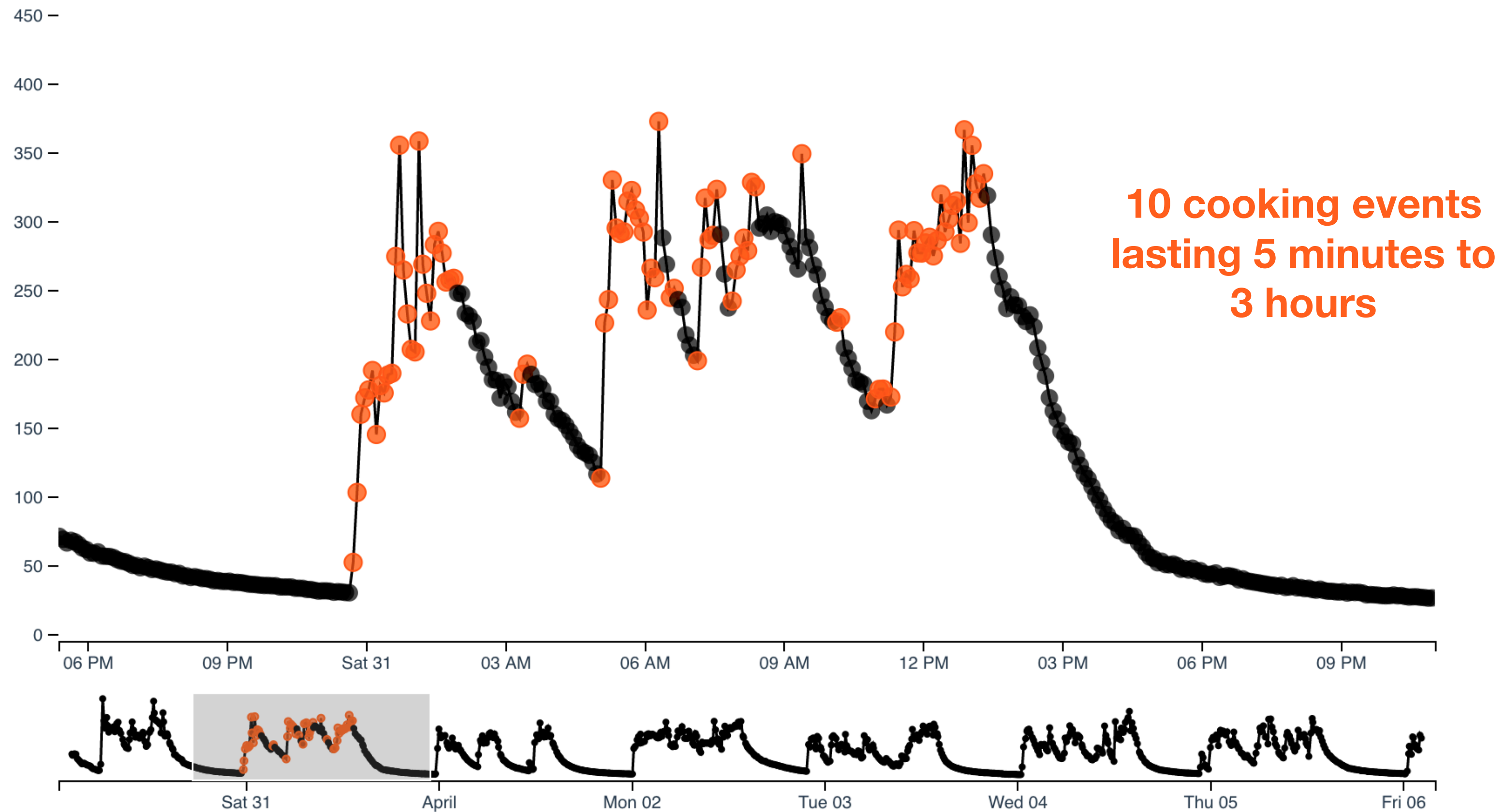
Usage - When the stove is 'hot'?

Filename: sumsarizer_v1_012993.csv



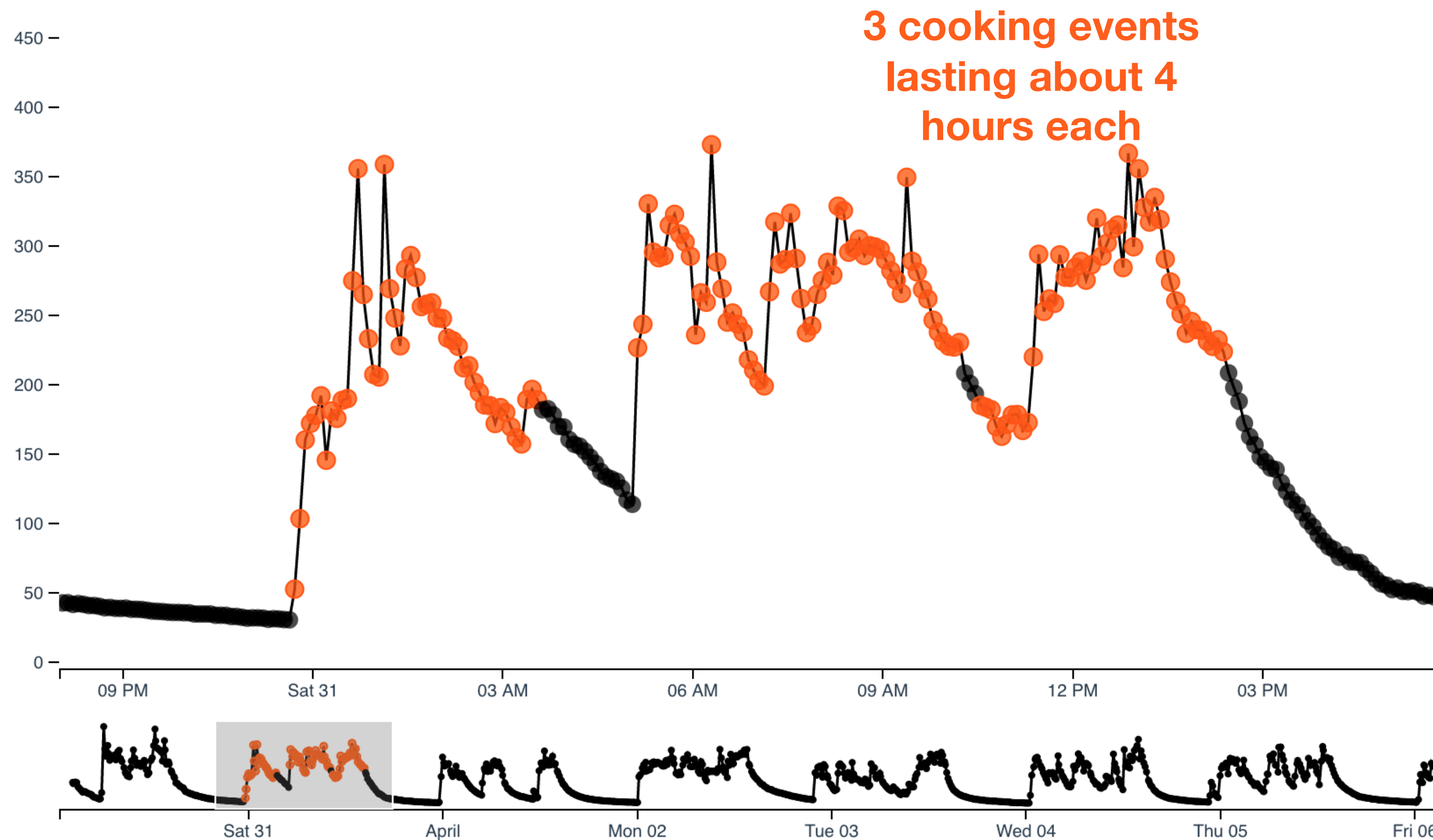
Usage - When heat is added?

Filename: sumsarizer_v1_012993.csv



Usage - when there is smoke?

Filename: sumsarizer_v1_012993.csv



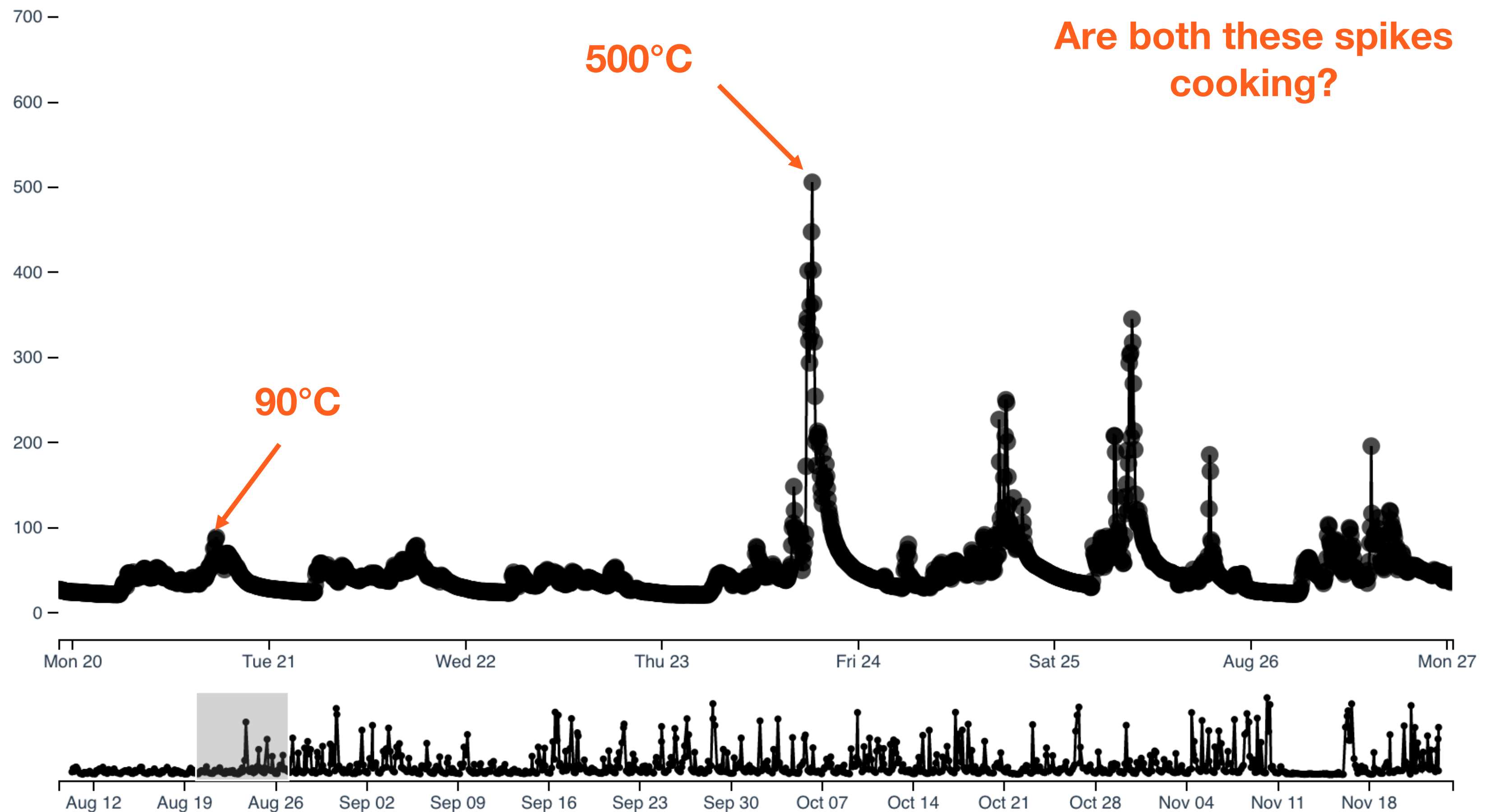
**“Cooking is whatever
you care about.”**

–Ancient Cookstove Researcher Proverb

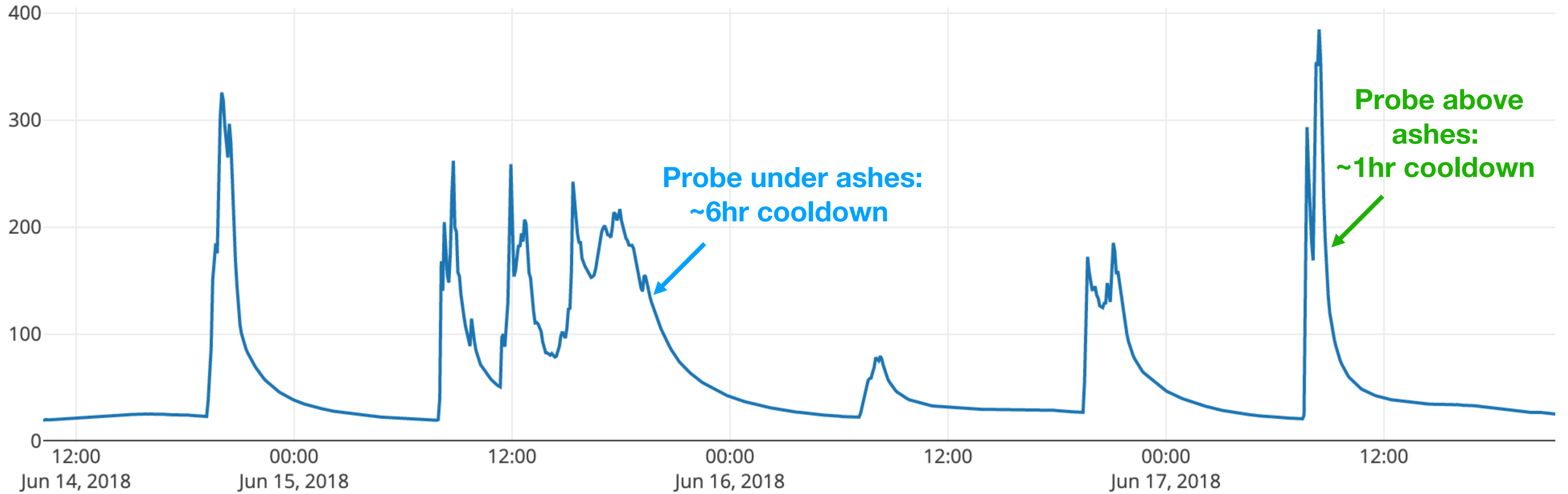
Challenges

Context changes

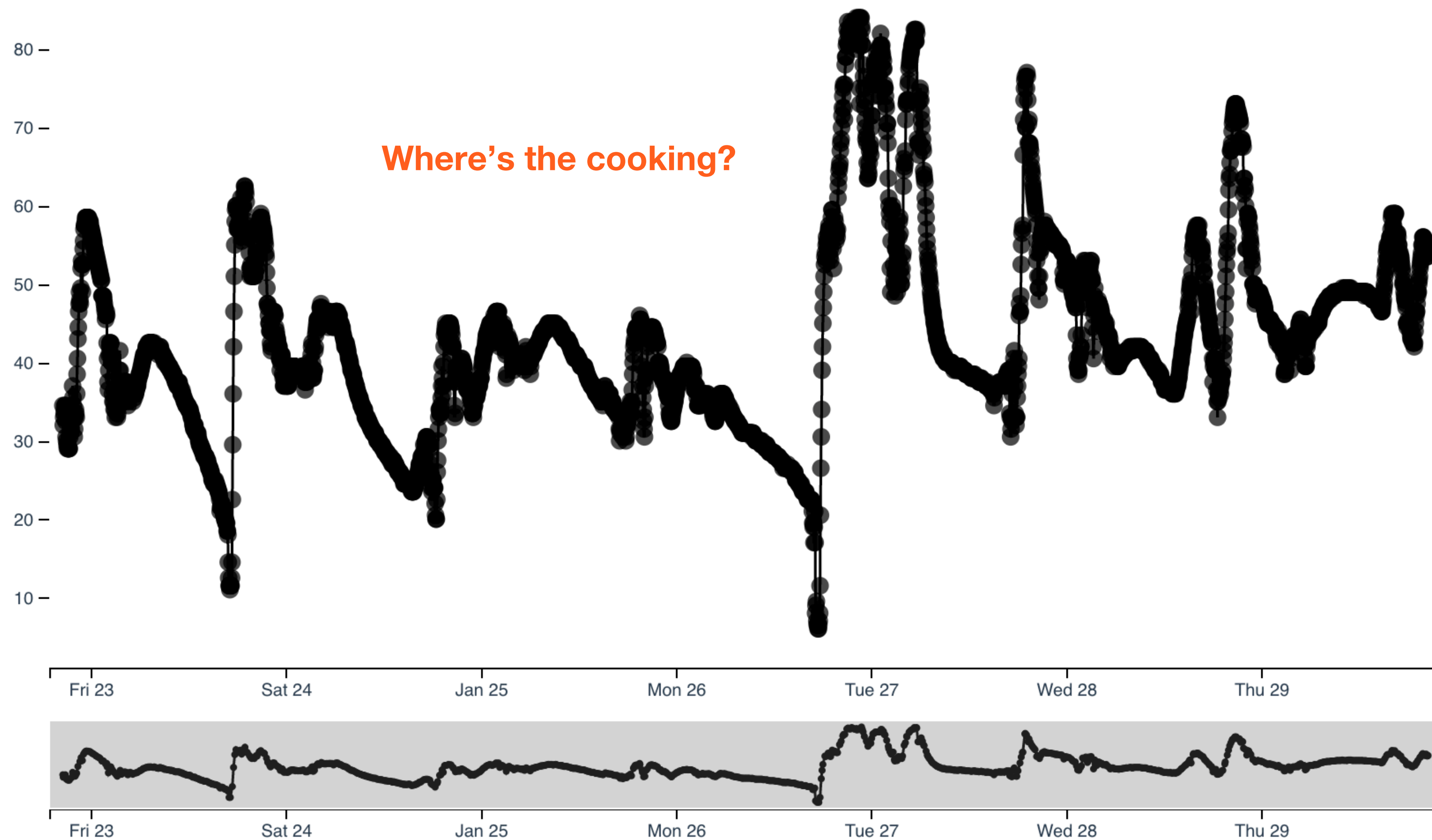
Filename: 5b6dbfae-0000-0000-0000-A0E6F850EEA5.csv



Context Changes



Bad Probe Placement & Low Temperatures



**“If your eyes can’t tell,
neither can the algorithm.”**

–(Another) Ancient Cookstove Researcher Proverb

How to Analyze Data

Primary Goals

Identify events

Limit bias: balance false positives with false negatives. You're never going to get every point perfect, but try to limit bias.

Turn time-wise event booleans into file-wise event summaries

Turn file-wise event summaries into meaningful insights

Analytics Tools

Excel/spreadsheets technical skill = moderate not realistic for more than ~10 data loggers

Code in **Python, R**, etc technical skill = very high

SUMIT technical skill = low iButtons only, R-Shiny app - not realistic for large datasets

SUMSarizer technical skill = high open-source R package. SUMSarizer *powers* Geocene Studies.

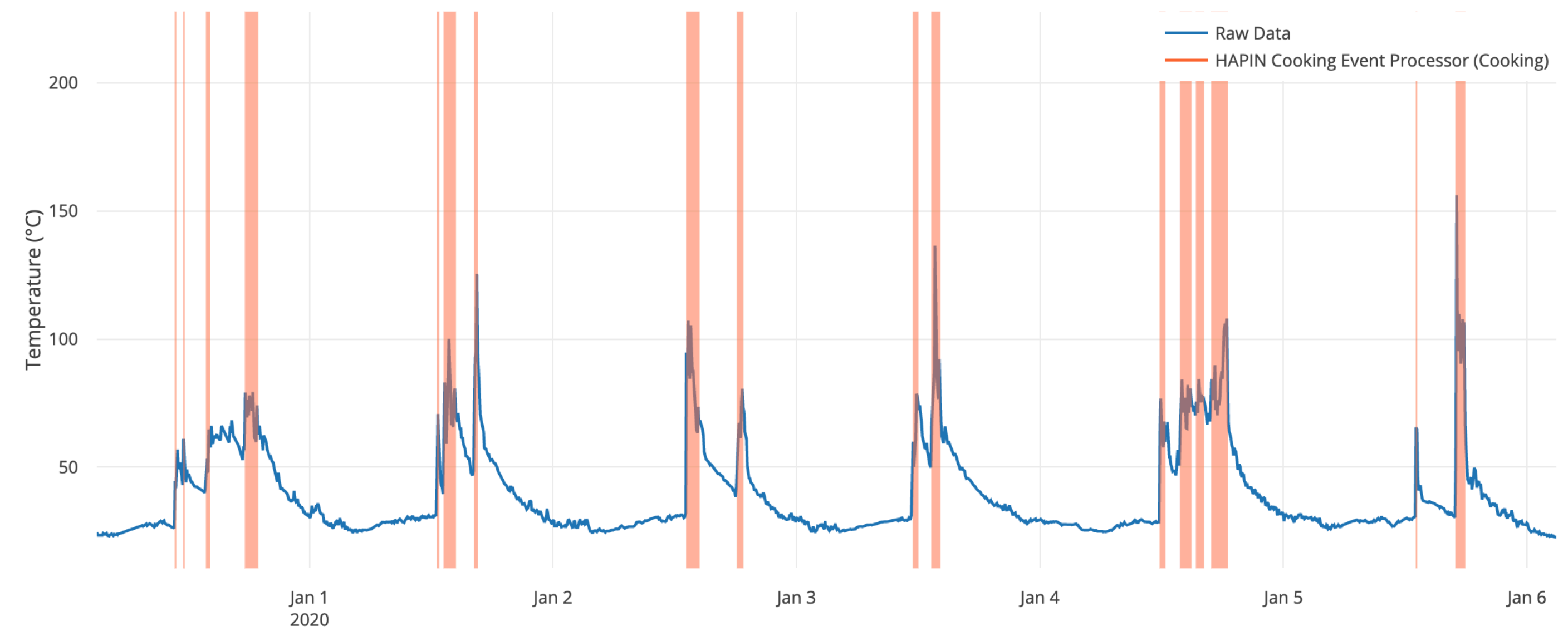
Geocene Studies technical skill = low point-and-click; no coding needed

Mission Dot-3809 | 2019-12-17 11:53

Edit Archive

Mission ID: 5df8a5b8-0000-0000-0000-CC78AB77FAAD
Created At (UTC): 01/10/2020 08:33 am
Meter Name: Dot-3809
Meter Kind: Geocene Temperature Logger, 2nd Generation
Sample Interval (sec): 300
Campaign: HAPIN-Rwanda
Tags: intervention_household:no stove_type:rondereza household_id:23753
Notes:

[Link data from another mission](#)



Common Algorithms

Ilse Ruiz Mercado's algorithm (deterministic)

Geocene FireFinder (deterministic but tunable)

- Available in SUMSarizer and Geocene
- Tuning: primary threshold, minimum event length, minimum inter-event gap, minimum event temperature.
- Currently in-use on about 7000 cookstoves worldwide ranging from rocket, TLUD, TSF, charcoal, chulha, and plancha.

Machine Learning via SUMSarizer

- Available via TRAINSET and SUMSarizer
- Tuning: use graphical tools to build a training set, then train an ML model in R.



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Geocene / **sumsarizer**

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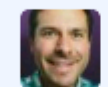
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daterdots Update README.md

Latest commit 71b6e1c on Oct 31, 2019

R	fix constant detector	6 months ago
inst/extdata	embed xgboost model in sumsarizer, make default	7 months ago
man	add functionality to process complete folders	7 months ago
tests	passing off vignette to jeremy for event-wise summaries	7 months ago
vignettes	move metadata from package to s3	6 months ago
.Rbuildignore	fix make check	12 months ago
.gitignore	vignette outlines	7 months ago

```

13 firefinder_detector = function(data,
14     primary_threshold = 75,
15     min_event_temp = NULL,
16     min_event_sec = 5*60,
17     min_break_sec = 30*60,
18     ...) {
19
20   primary_threshold <- as.numeric(primary_threshold)
21   min_event_temp <- as.numeric(min_event_temp)
22   min_event_sec <- as.numeric(min_event_sec)
23   min_break_sec <- as.numeric(min_break_sec)
24   setDT(data)
25   data <- copy(data)
26   max_run_length <- 100
27
28   #CALCULATE FEATURES
29   sample_interval <- get_sample_interval(data)
30   sample_interval_mins <- sample_interval/60
31
32   #make a column of 1st derivative (degC/minute)
33   data[, difftemps := c(0, diff(value) / sample_interval_mins)]
34
35   #make a column of delta timestamps
36   data[, difftimes := c(as.numeric(diff(data$timestamp), units = "secs"), 0)]
37
38   #look at whether or not most of the data coming up in the next
39   #hour is negative slope or 100 data points, whichever is lower
40   if (nrow(data) > 1) {
41     data$quantile_difftemps = runquantile(data$difftemps,
42     min(max_run_length,
43     min(round(60/sample_interval_mins),
44     nrow(data))),
45     probs = 0.8,
46     align = 'right')
47   } else {
48     data$quantile_difftemps = NA
49   }
50

```

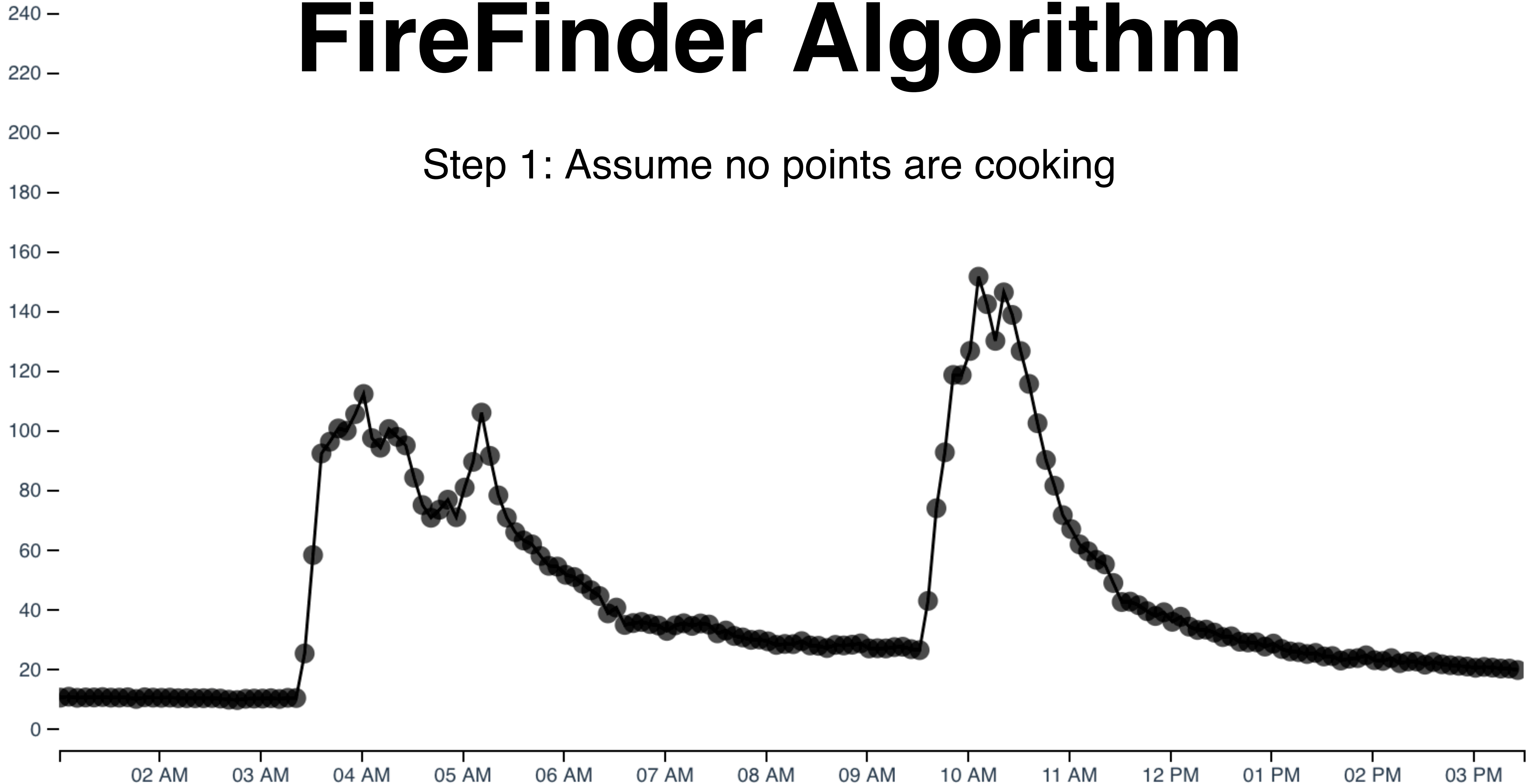
```

51   #RUN THE DECISION TREE
52
53   #just assume there is no cooking to start
54   data$event_raw = FALSE
55
56   #define points that are likely to be cooking
57   data[value > primary_threshold, event_raw := TRUE]
58
59   #get rid of long runs of negative slopes
60   data[quantile_difftemps < 0, event_raw := FALSE]
61
62   #assume cooking for highly positive slopes
63   data[difftemps > 2, event_raw := TRUE]
64
65   #get rid of highly negative slopes
66   data[difftemps < -1 * value / 500, "event_raw" := FALSE]
67
68   #remove places with gaps longer than the sample interval
69   data[difftimes > sample_interval, "event_raw" := FALSE]
70
71   data[, "event_raw" := smooth_events(event_raw, sample_interval, min_event_sec, min_break_sec)]
72
73   #remove events with very low cooking temps
74   if(!is.null(min_event_temp)){
75     data[, "event_num" := number_events(event_raw)]
76     data[, "event_max" := max(value), by=list(event_num)]
77     data[event_max < min_event_temp, "event_raw" := FALSE]
78   }
79   #remove events for data that is out of range and is probably an error
80   data[!(data$value < 1000 & data$value > -50), "event_raw" := FALSE]
81
82   return(data$event_raw)
83 }

```

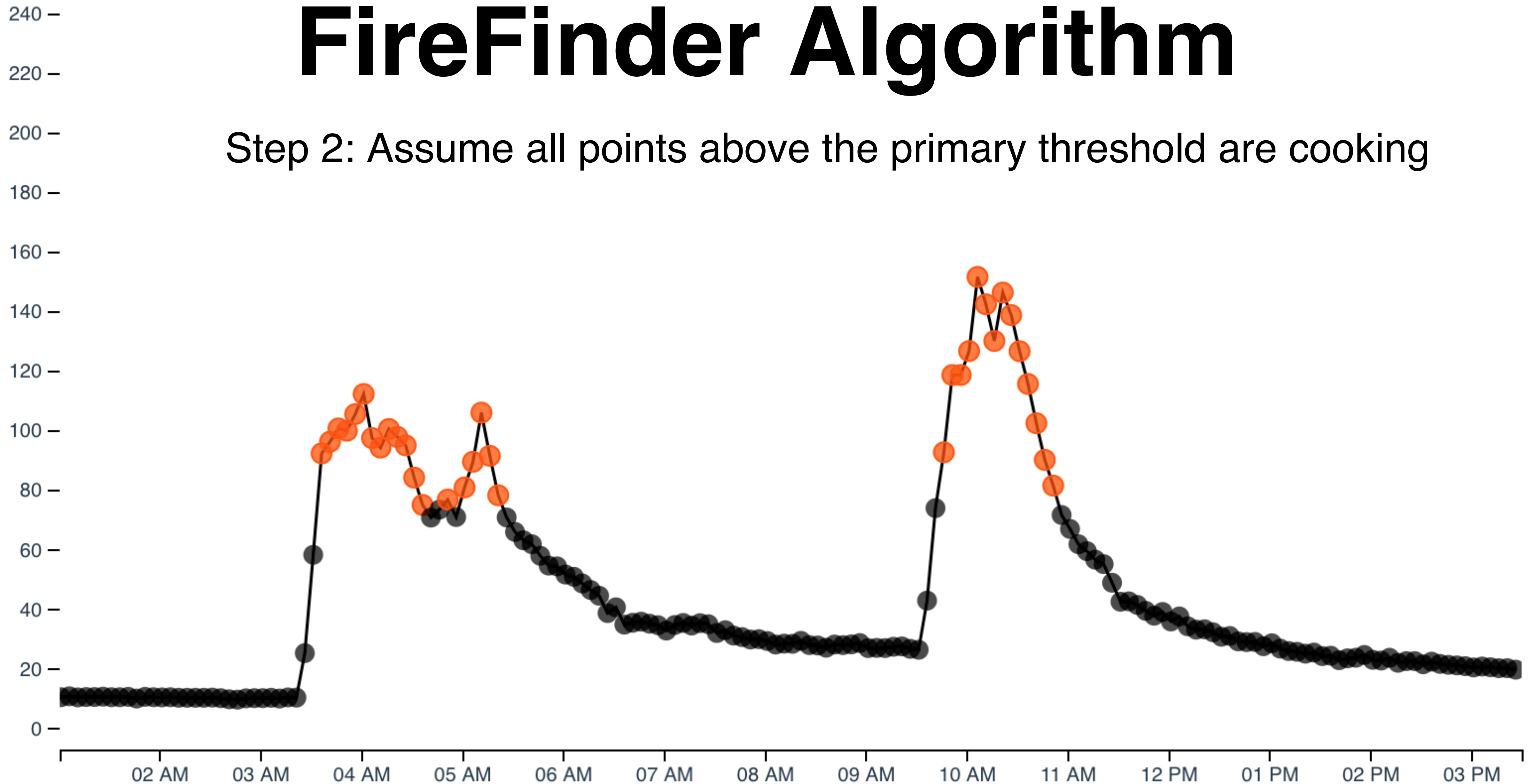
FireFinder Algorithm

Step 1: Assume no points are cooking



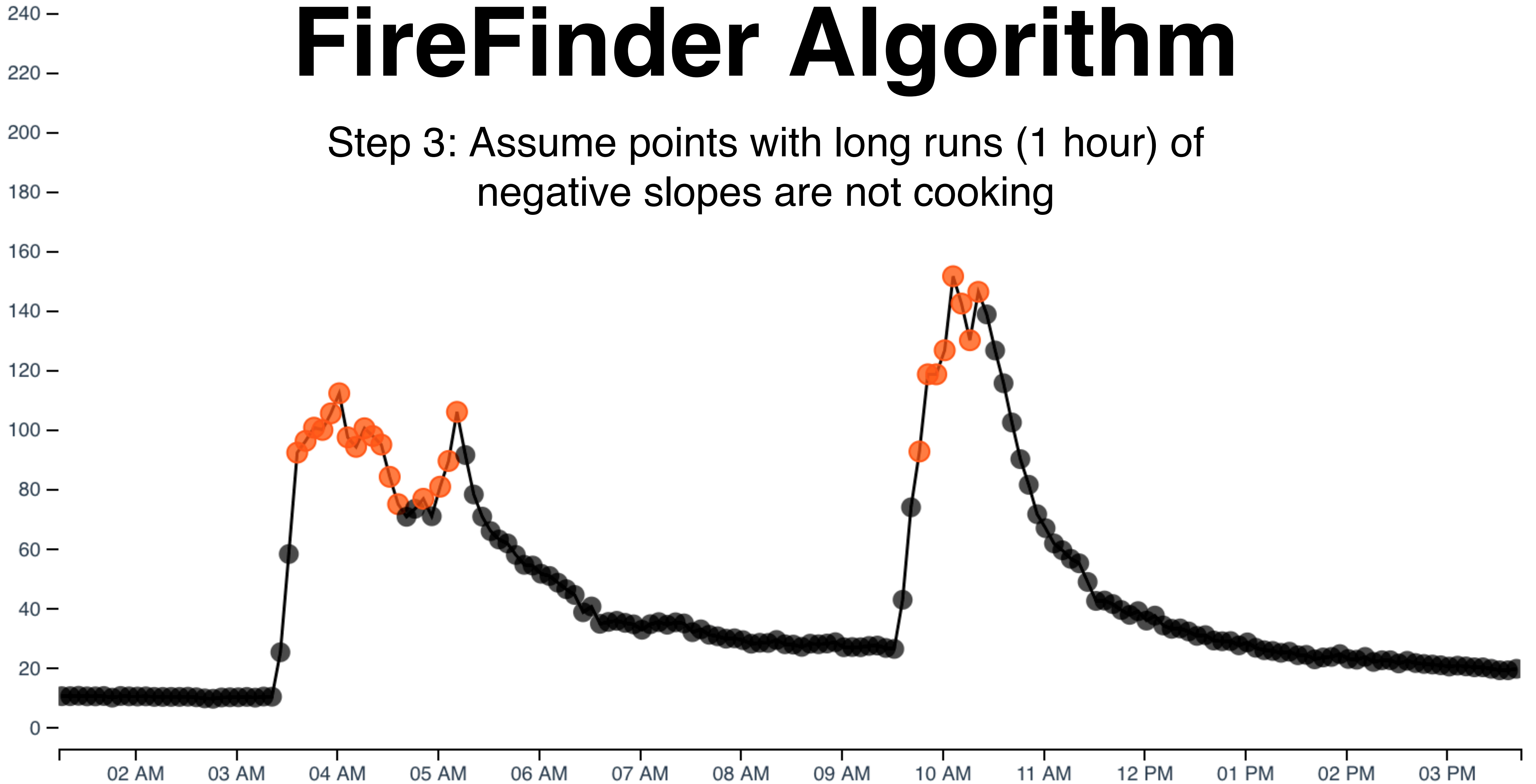
FireFinder Algorithm

Step 2: Assume all points above the primary threshold are cooking



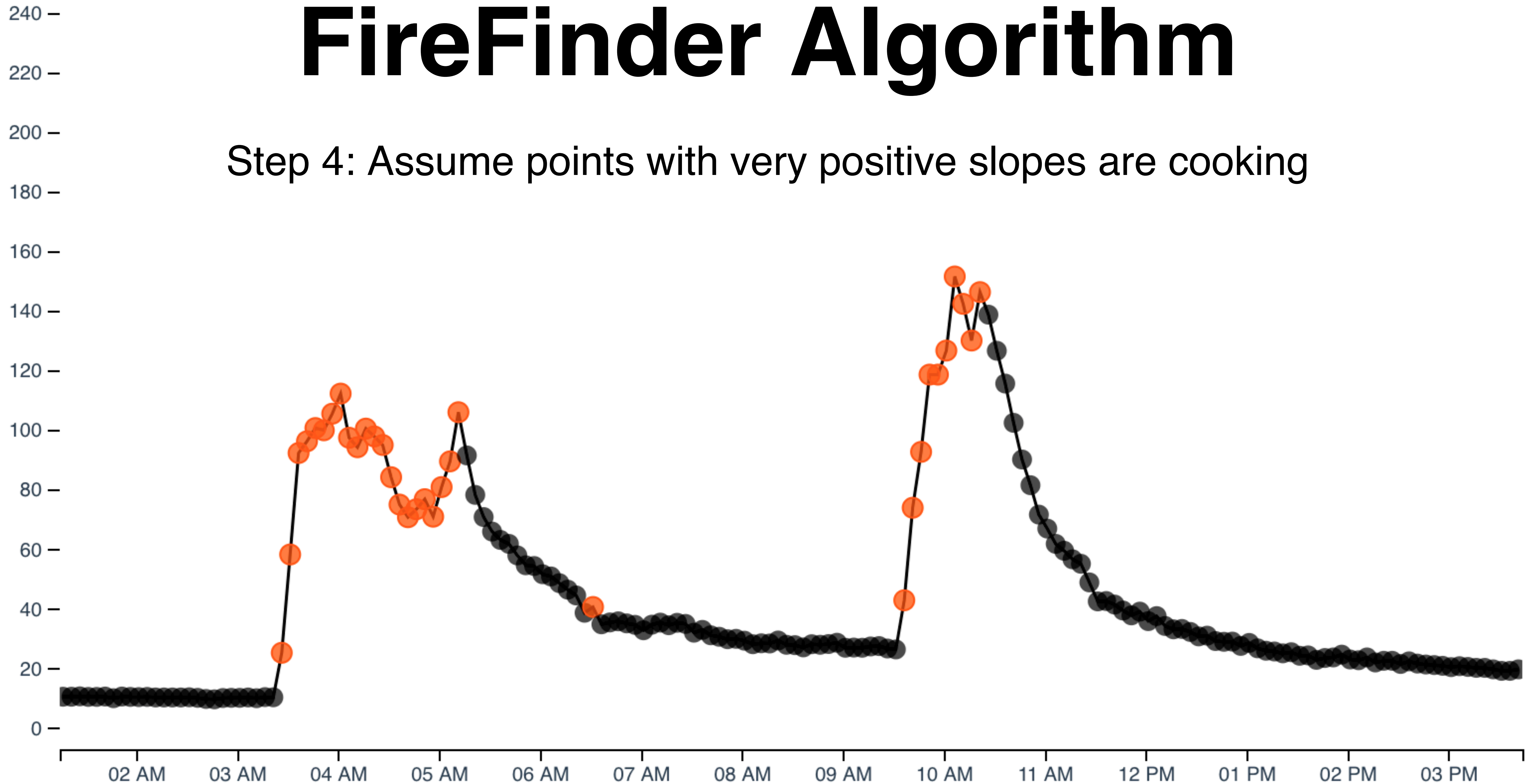
FireFinder Algorithm

Step 3: Assume points with long runs (1 hour) of negative slopes are not cooking



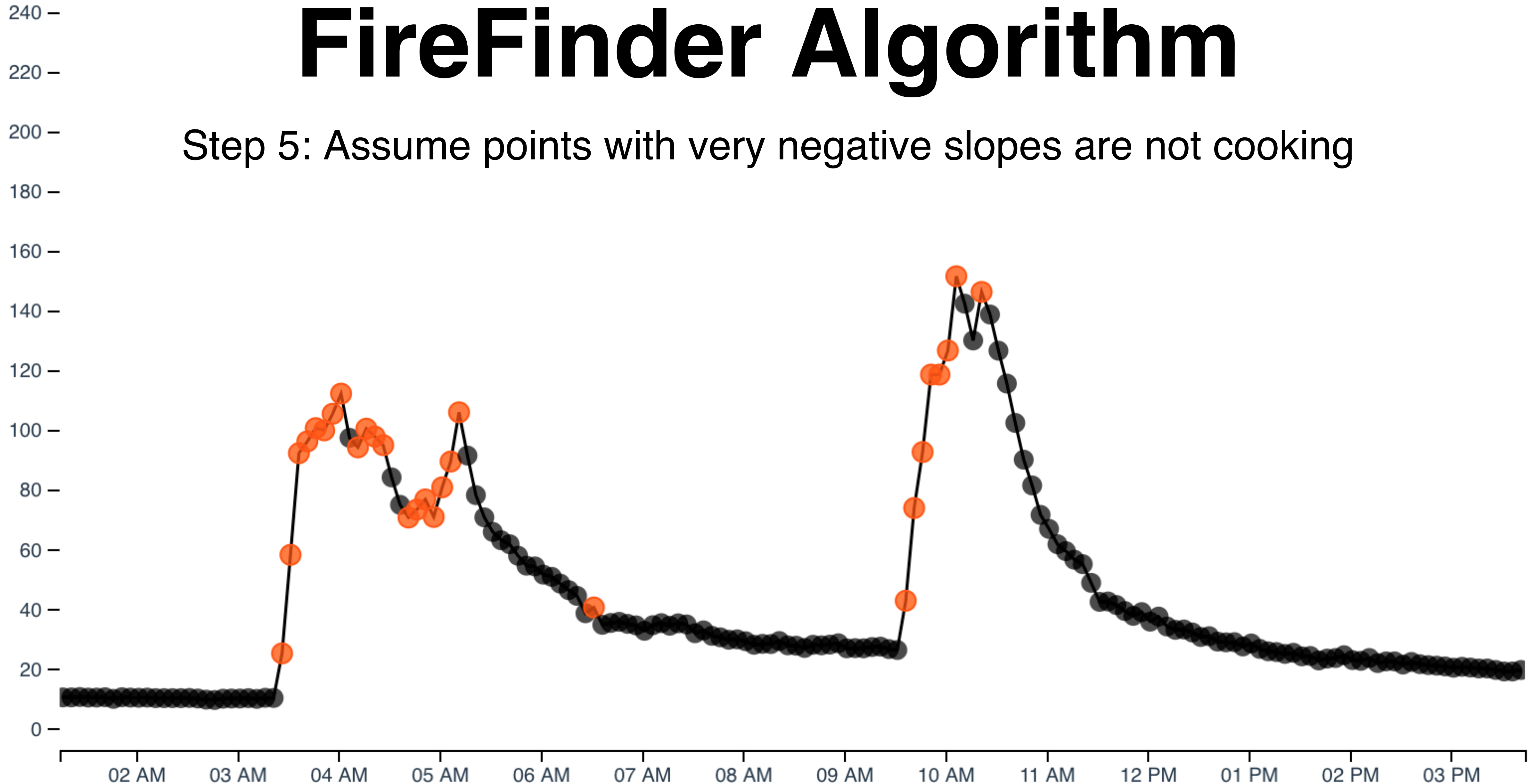
FireFinder Algorithm

Step 4: Assume points with very positive slopes are cooking



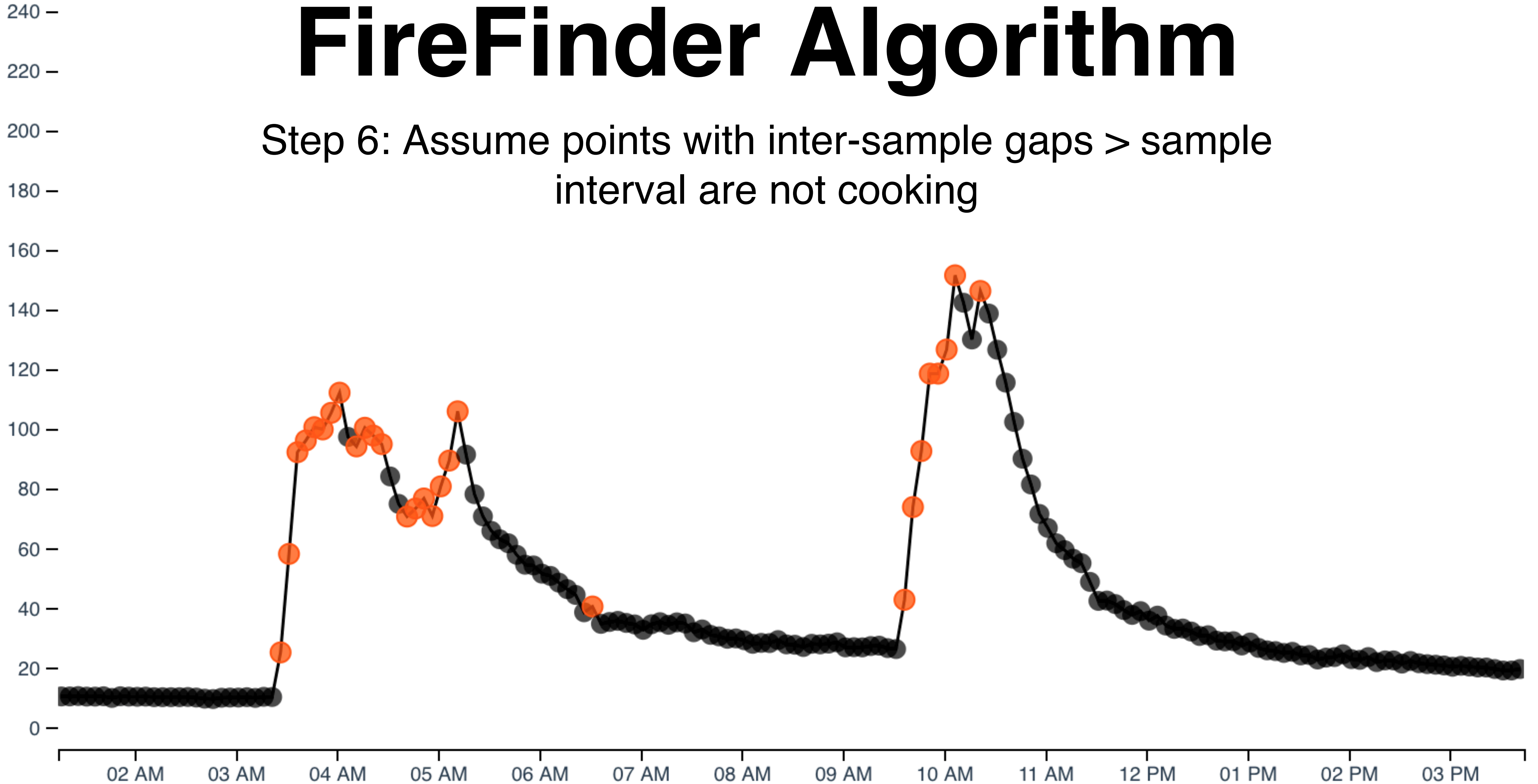
FireFinder Algorithm

Step 5: Assume points with very negative slopes are not cooking



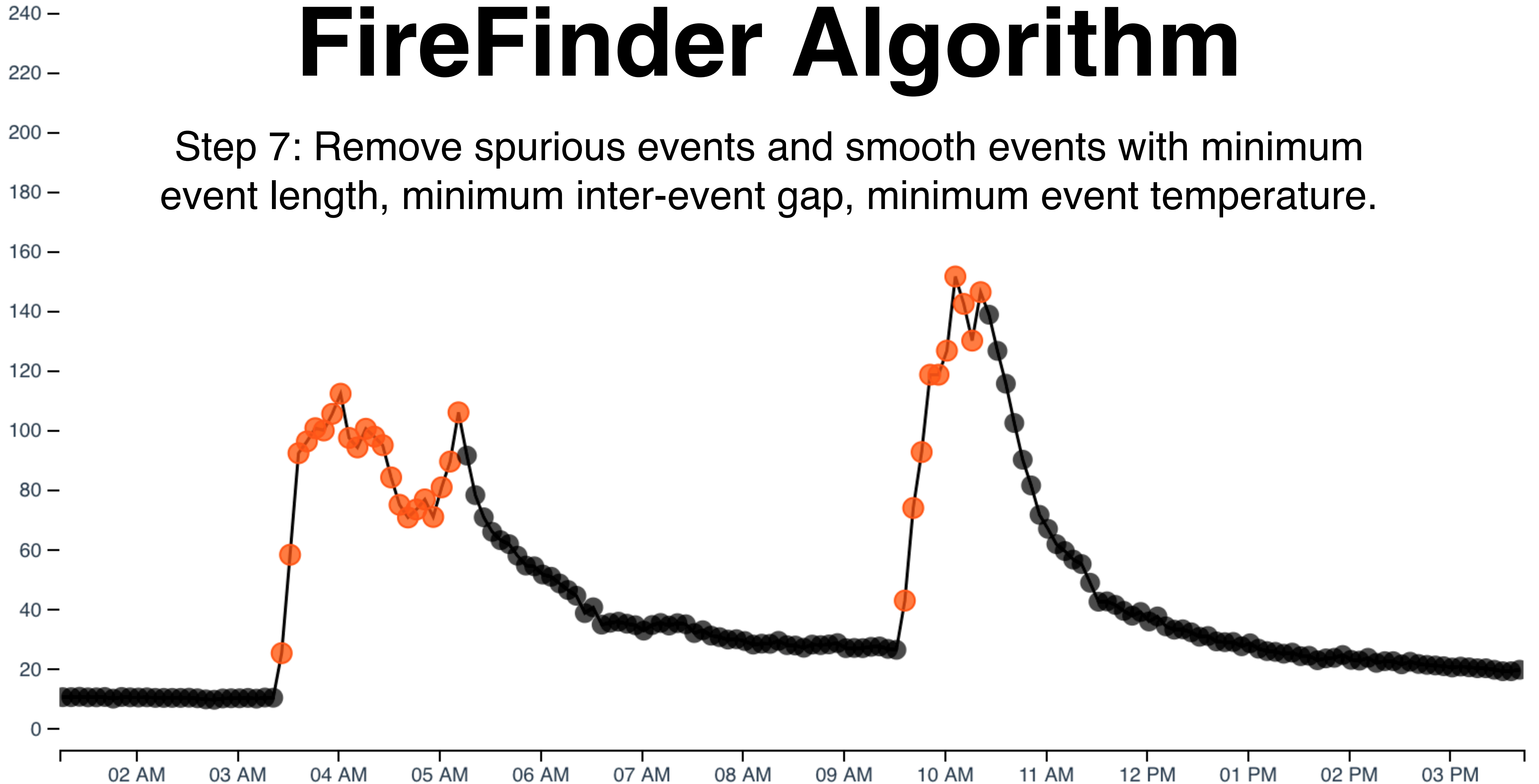
FireFinder Algorithm

Step 6: Assume points with inter-sample gaps > sample interval are not cooking



FireFinder Algorithm

Step 7: Remove spurious events and smooth events with minimum event length, minimum inter-event gap, minimum event temperature.



Tradeoffs

Better algorithms typically have better sensitivity and specificity, but not necessarily better bias!

Better algorithms are much more computationally demanding and require specialized skillsets.

Keep in mind: it's not about whether a cooking event started at 12:00 or 12:10, it's about what important insights your dataset reveals.

Understand your question: do you *really* need to know exactly how many times per day someone cooked, or do you actually need to know which cookstove is used the least/most?

Conclusion

FireFinder is a simple deterministic algorithm for detecting cooking events.

You can find the code at github.com/geocene/sumsarizer.

FireFinder has been demonstrated to work well on a wide variety of cookstove types.

You can use FireFinder for free at studies.geocene.com.