THE UNIVERSITY OF MELBOURNE

v1.0

Sensors and Signal Processing

Tilman Dingler

Mobile Computing | 13-Aug-2018

COMP90018 - Mobile Computing Systems Programming

"The materials on LMS for tutorials are confusing. I heard they're mixed with last year/semester's."

Microblog: Feedback

“For some complex mobile devices, maybe it's difficult to determine a single goal or it is multi-functional, in this case, the execution and evaluation should be separated for each goal or integrate them together? And how?”

Microblog: Question

1. Technology inevitably alters our perception of reality.

SpiderSense, 2013

Observations

Mateevitsi et al.: „Sensing the environment through SpiderSense“, Augmented Human Conference, ACM 2013

1. Technology inevitably alters our perception of reality.

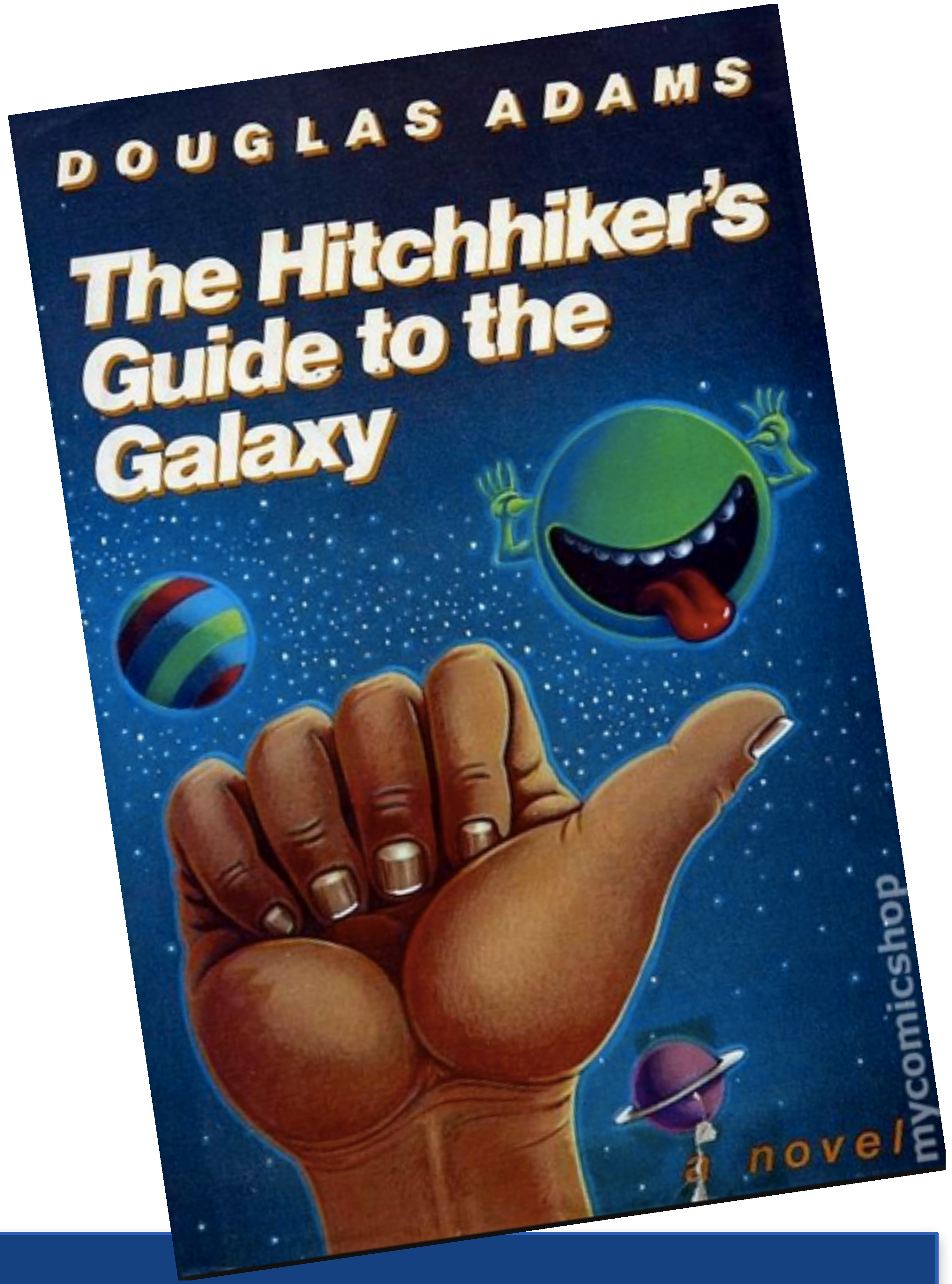
2. Computers are increasingly defining our experiences in the real world.

Observations

1. Technology inevitably alters our perception of reality.

2. Computers are increasingly defining our experiences in the real world.

3. We engineer a world where humans live in the I/O system of a giant computer.



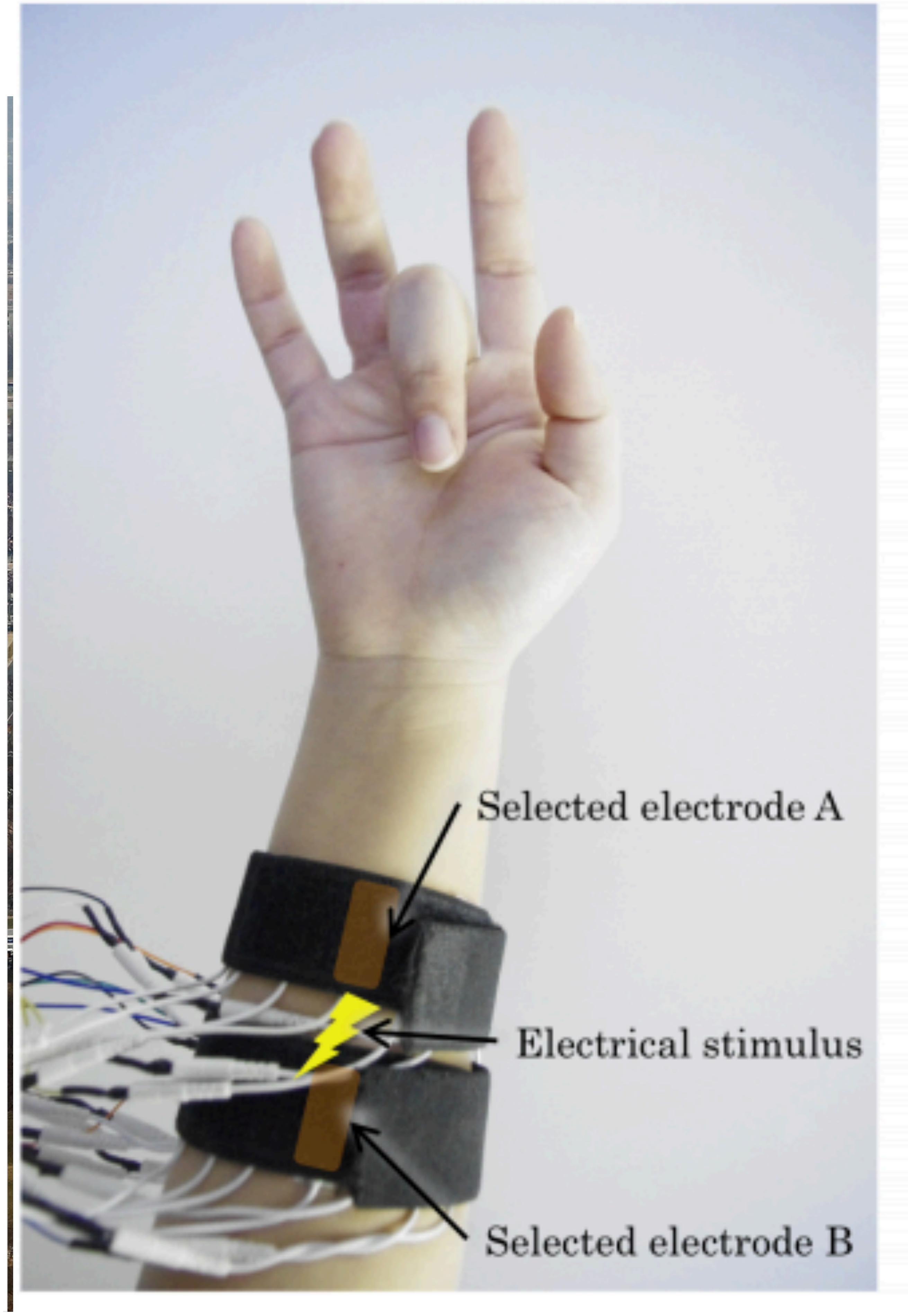
Observations

1. Technology inevitably alters our perception of reality.

2. Computers are increasingly defining our experiences in the real world.

3. We engineer a world where humans live in the I/O system of a giant computer.

4. With computers and technologies we manipulate humans.



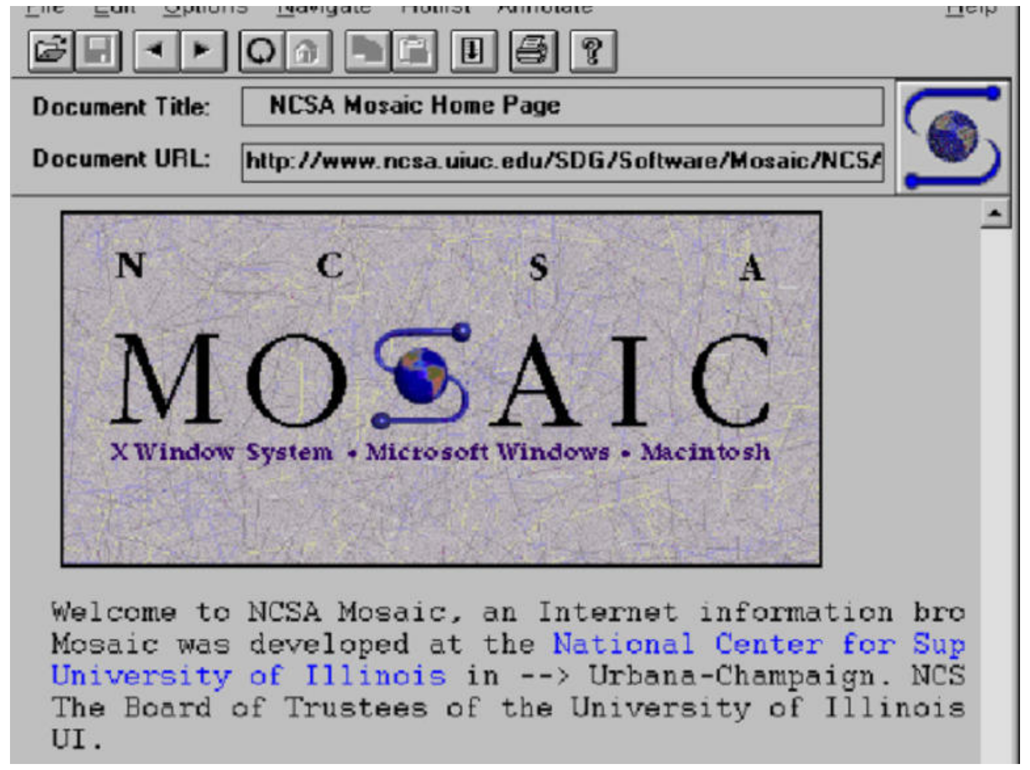
Observations

http://time.com/4641381/donald-trump-inauguration-crowd/

Tamaki et al.: „PossessedHand: techniques for controlling human hands using electrical muscle stimuli.“ CHI Conference, ACM, 2011

1. Sensors as a Driver for Ubiquitous Computing Technologies
2. What Constitutes a Sensor?
3. Challenges when Dealing with Sensor Data
4. Sensor Signal Processing: Dealing with these challenges

Learning Outcomes



Recap: Ubiquitous Computing - The Third Wave

In the Environment

IBM PC

On the User

Osborne 1

Two fundamentally different approaches for ubiquitous interaction

In the Environment

Kinect

On the User

PS Vita

Two fundamentally different approaches for ubiquitous interaction

In the Environment

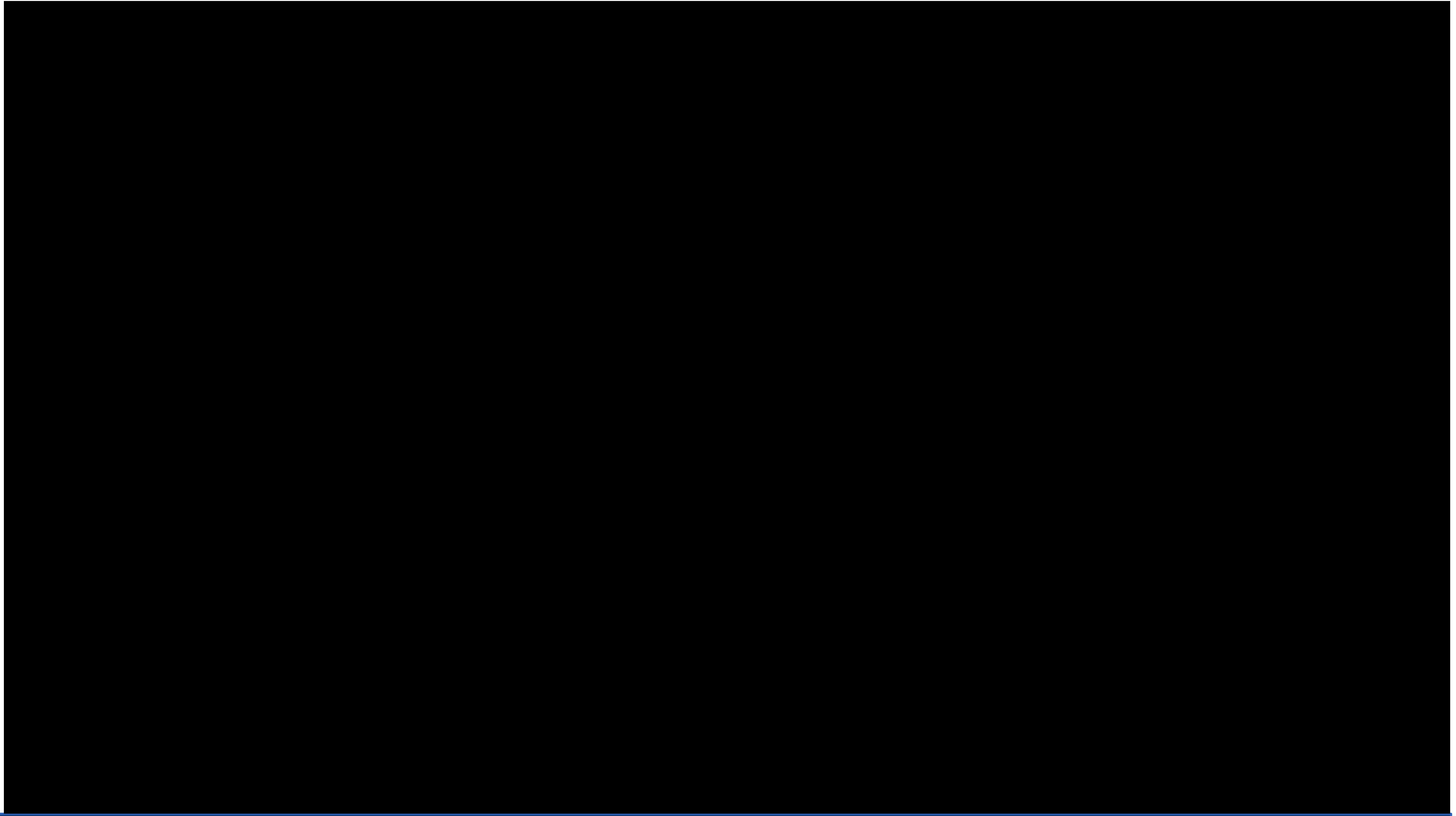
Illumiroom

On the User

Junaio by Metaio

Two fundamentally different approaches for ubiquitous interaction

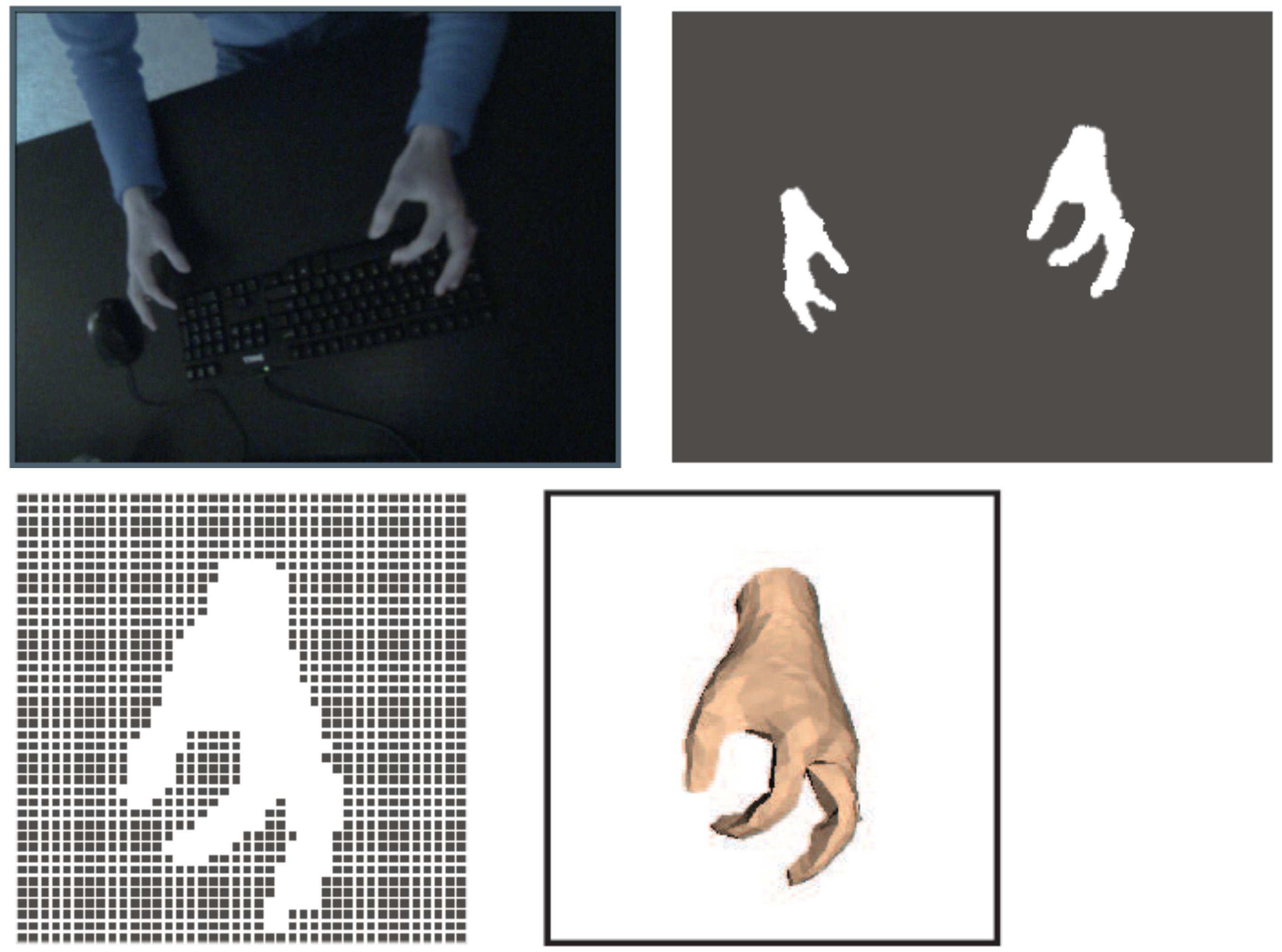
Jones, Brett R., et al. "IllumiRoom: peripheral projected illusions for interactive experiences." Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, 2013.



IllumiRoom

Jones, Brett R., et al. "IllumiRoom: peripheral projected illusions for interactive experiences." Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, 2013.

In the Environment



On the User

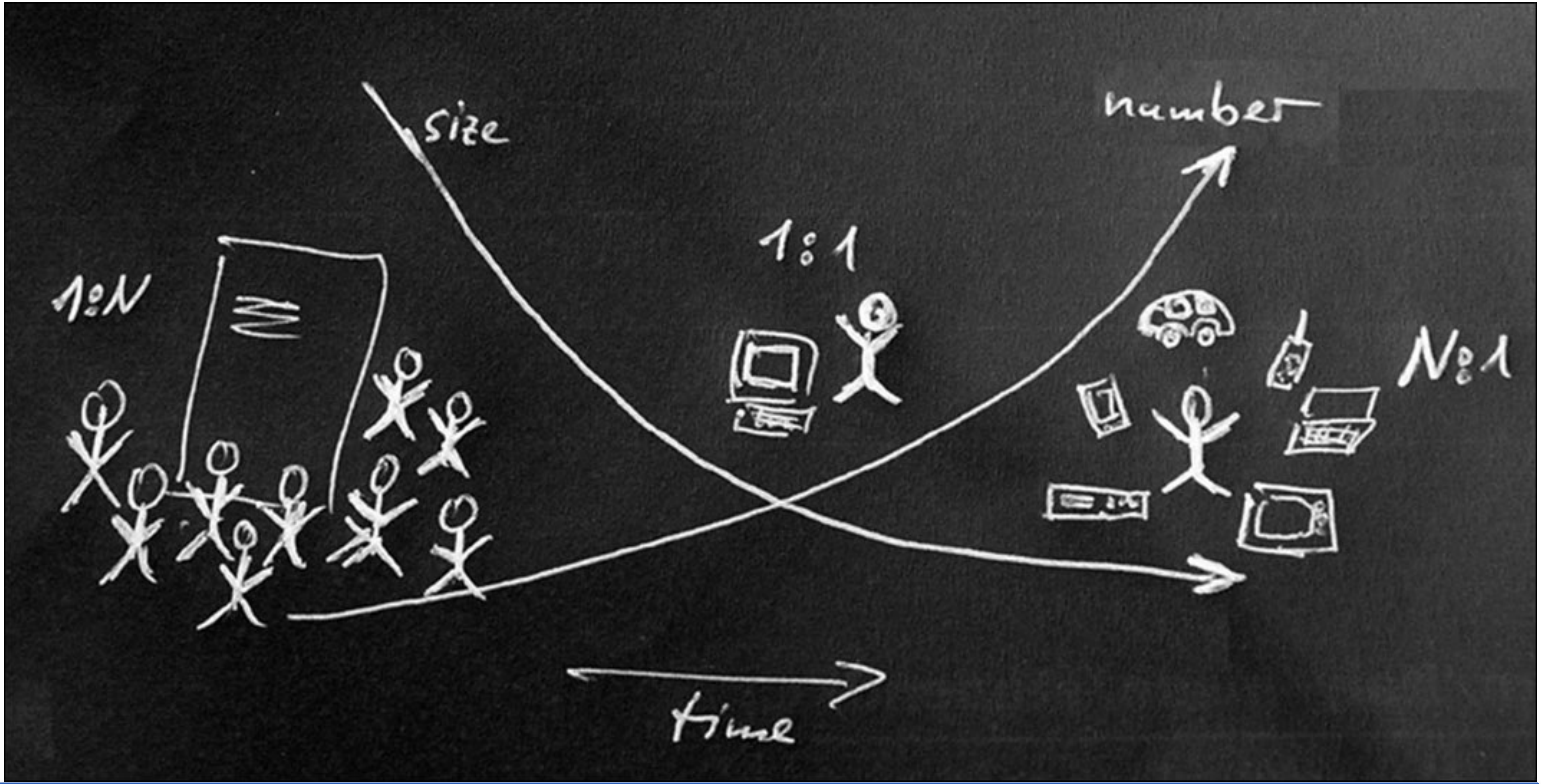
Gesture Recognition

Two fundamentally different approaches for ubiquitous interaction

In the Environment

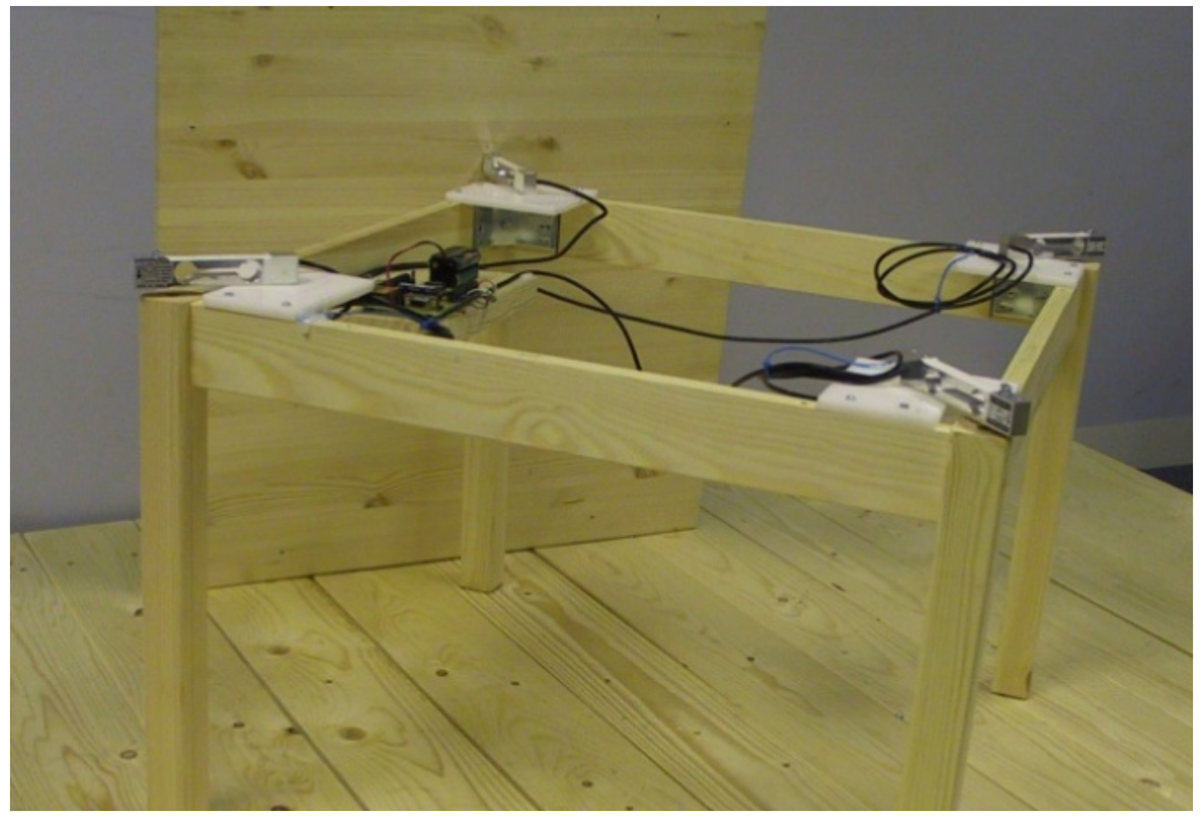
On the User

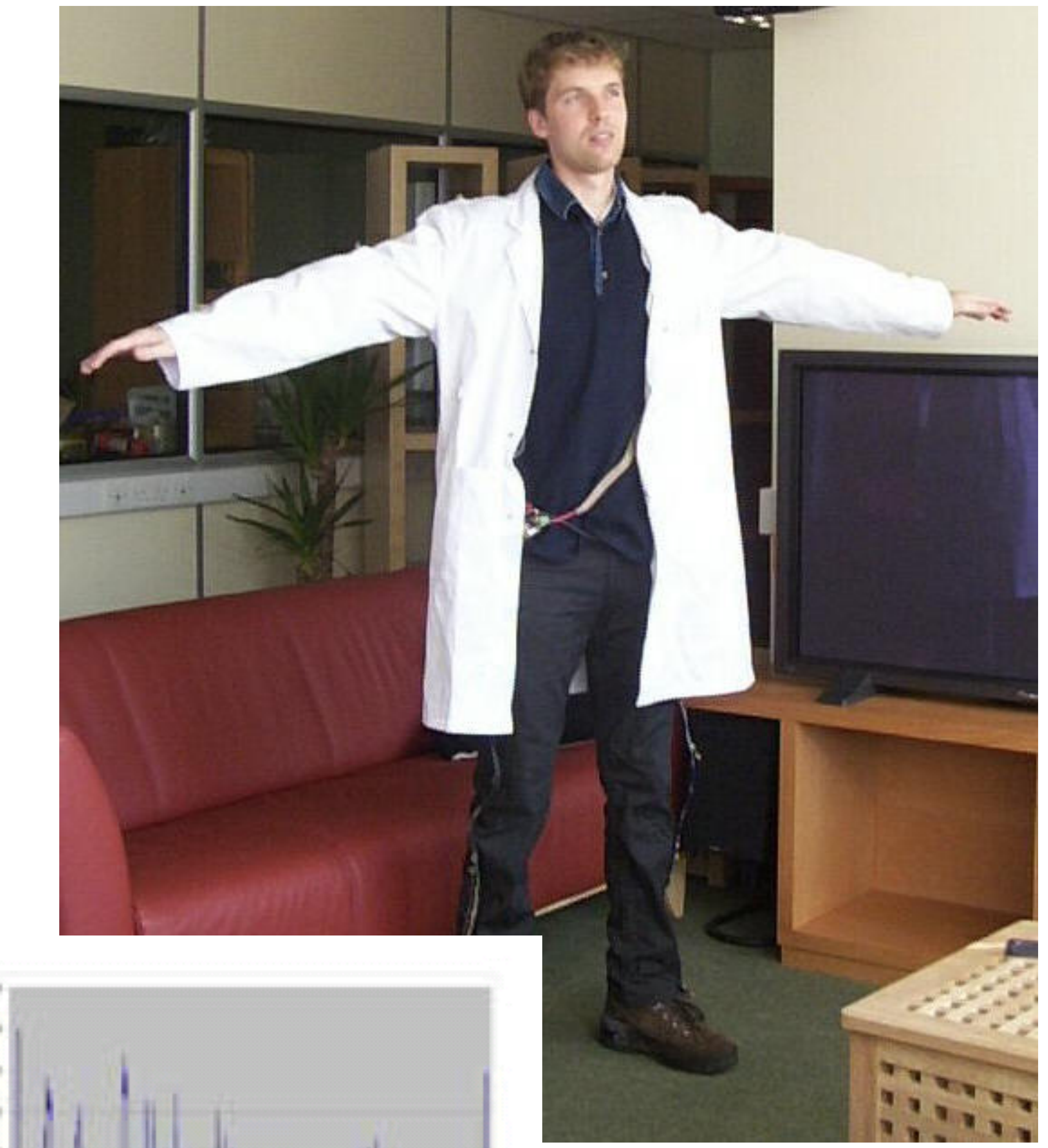
Two fundamentally different approaches for ubiquitous interaction

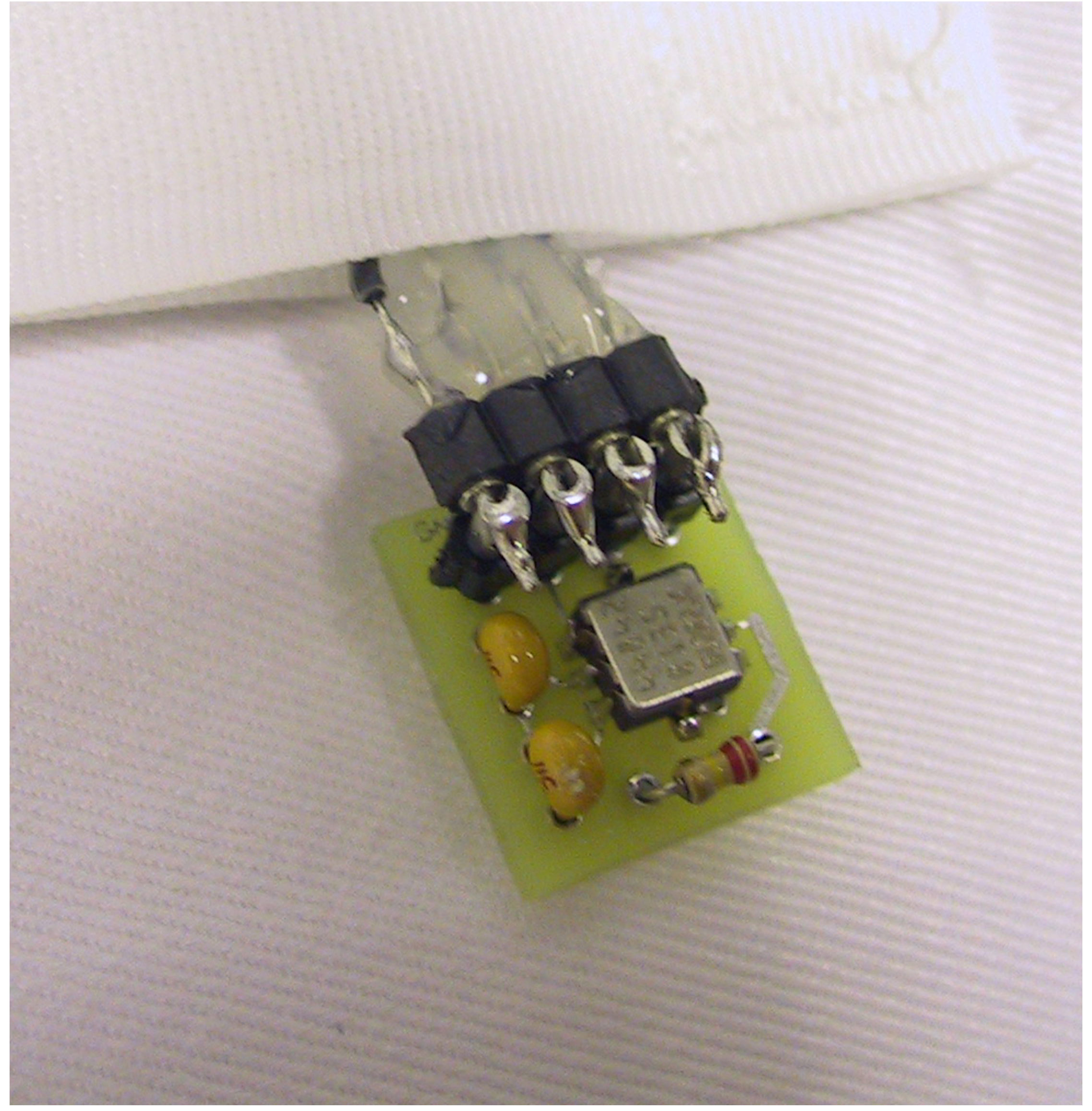


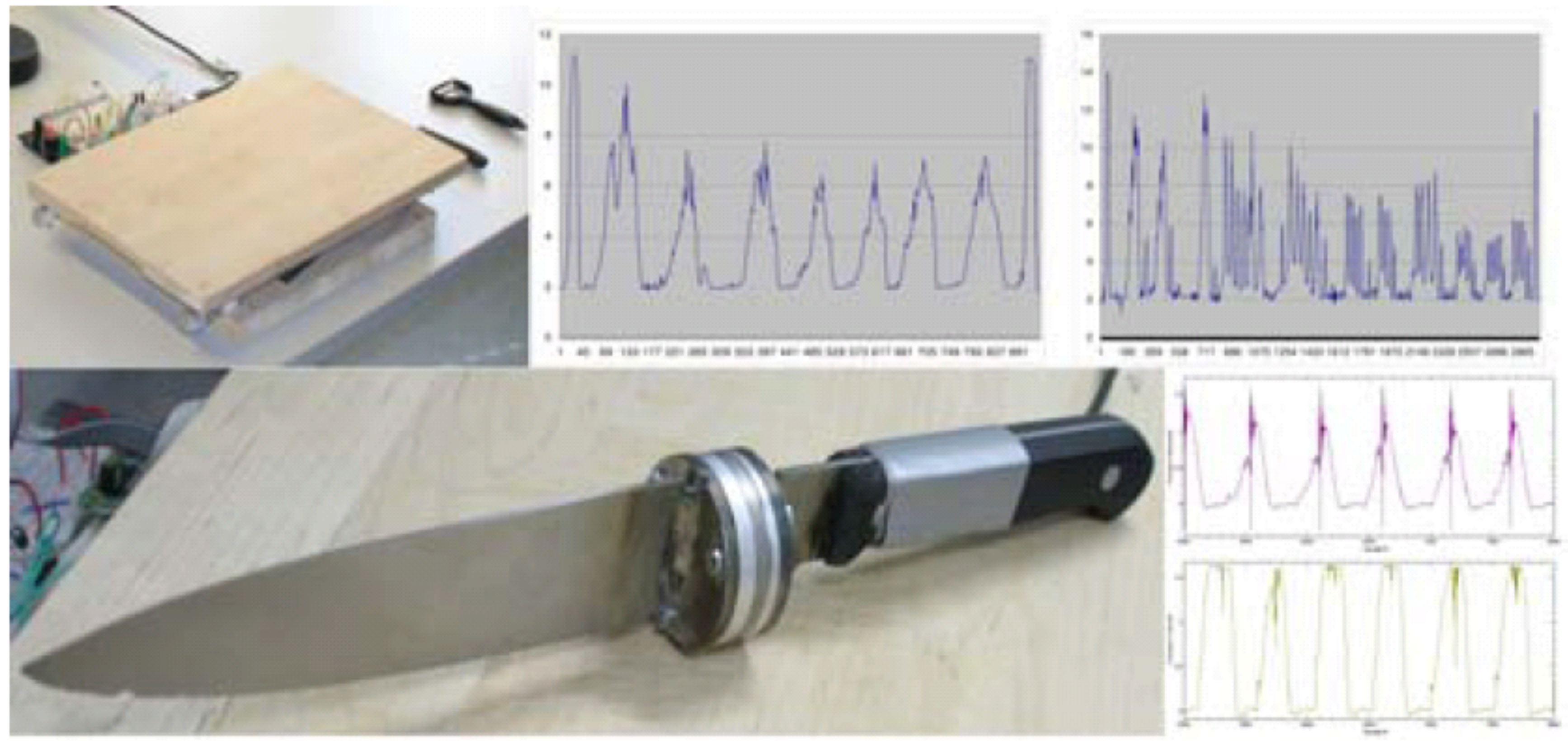
Ubiquitous Computing

Illustration by Albrecht Schmidt









Aware – Everything

Trends and Drivers

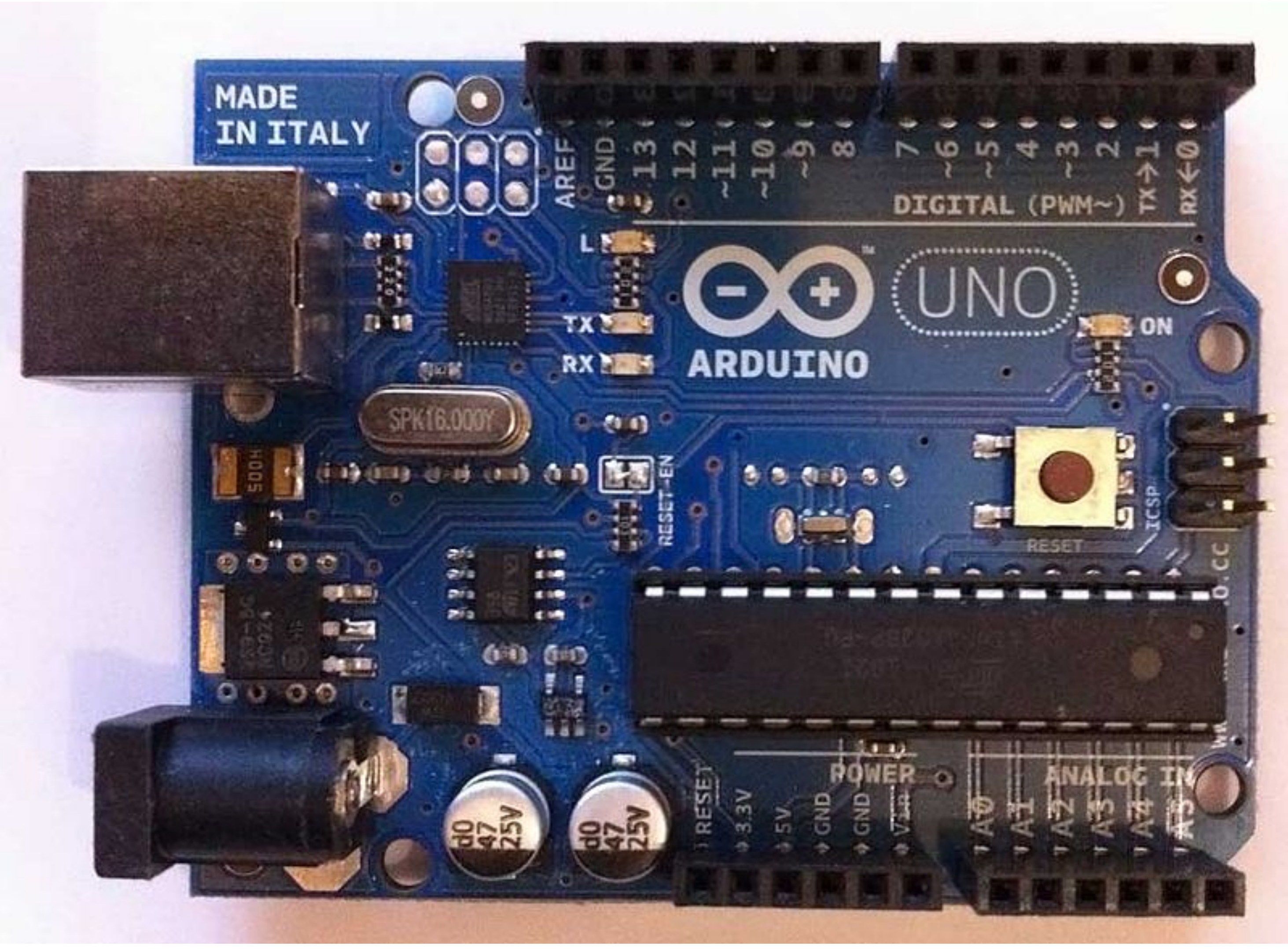


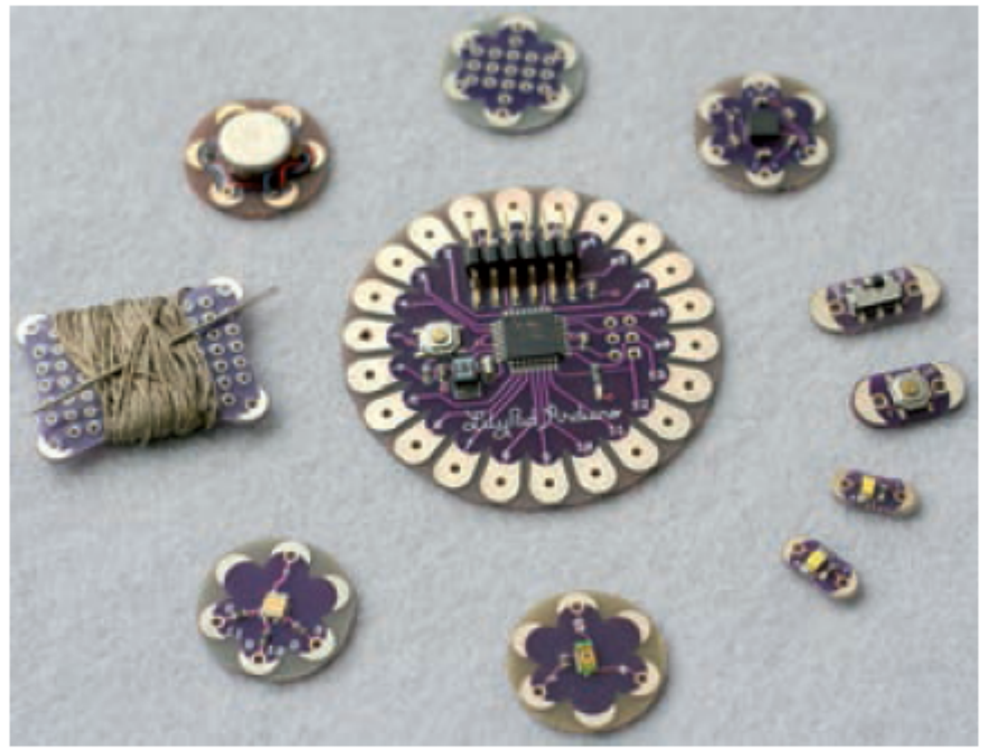
Mobile devices are the main technology for accessing the WEB

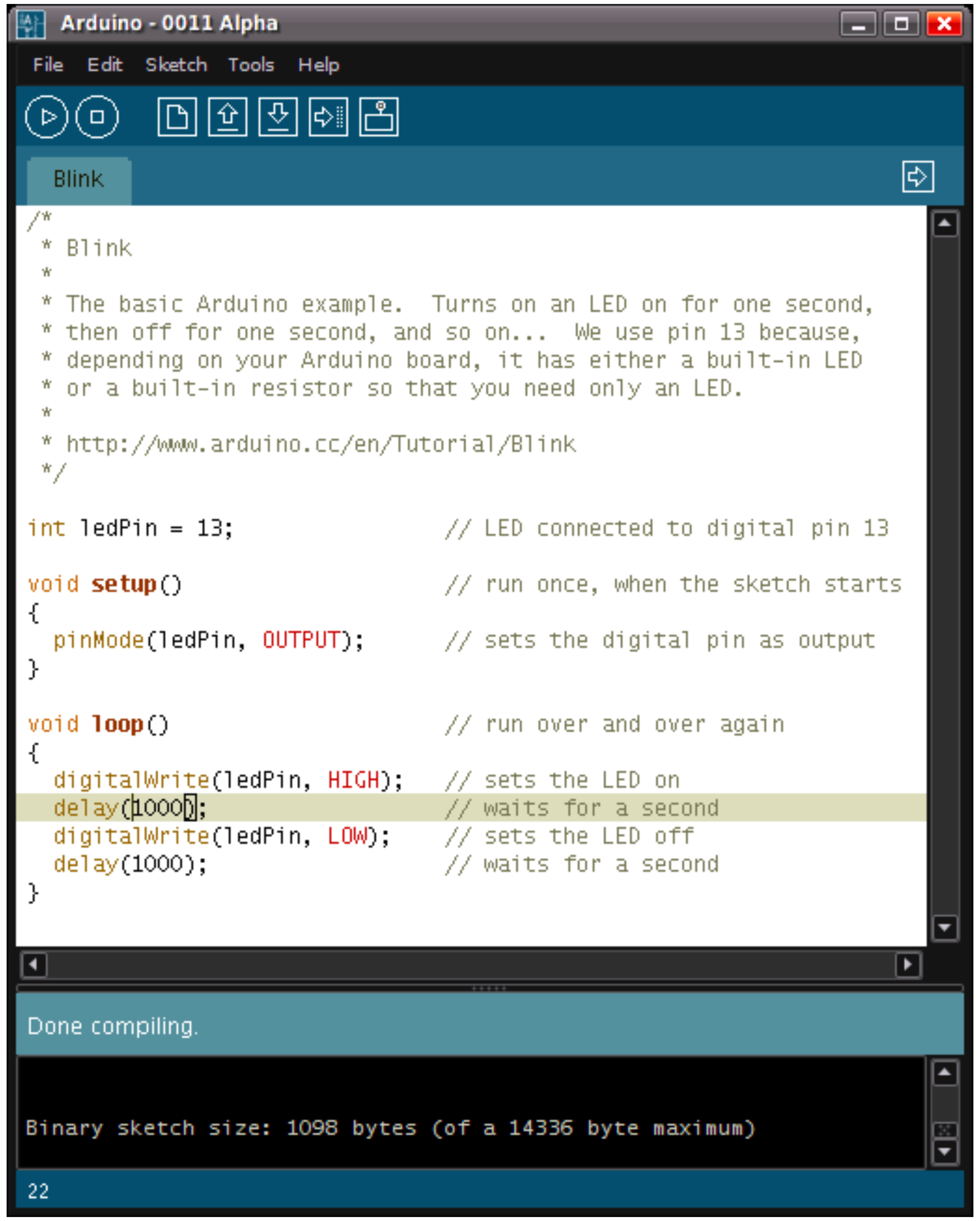
"In theory there is no difference between theory and practice. In practice there is." - Yogi Berra

Pebble Smartwatch

The Hardware Renaissance



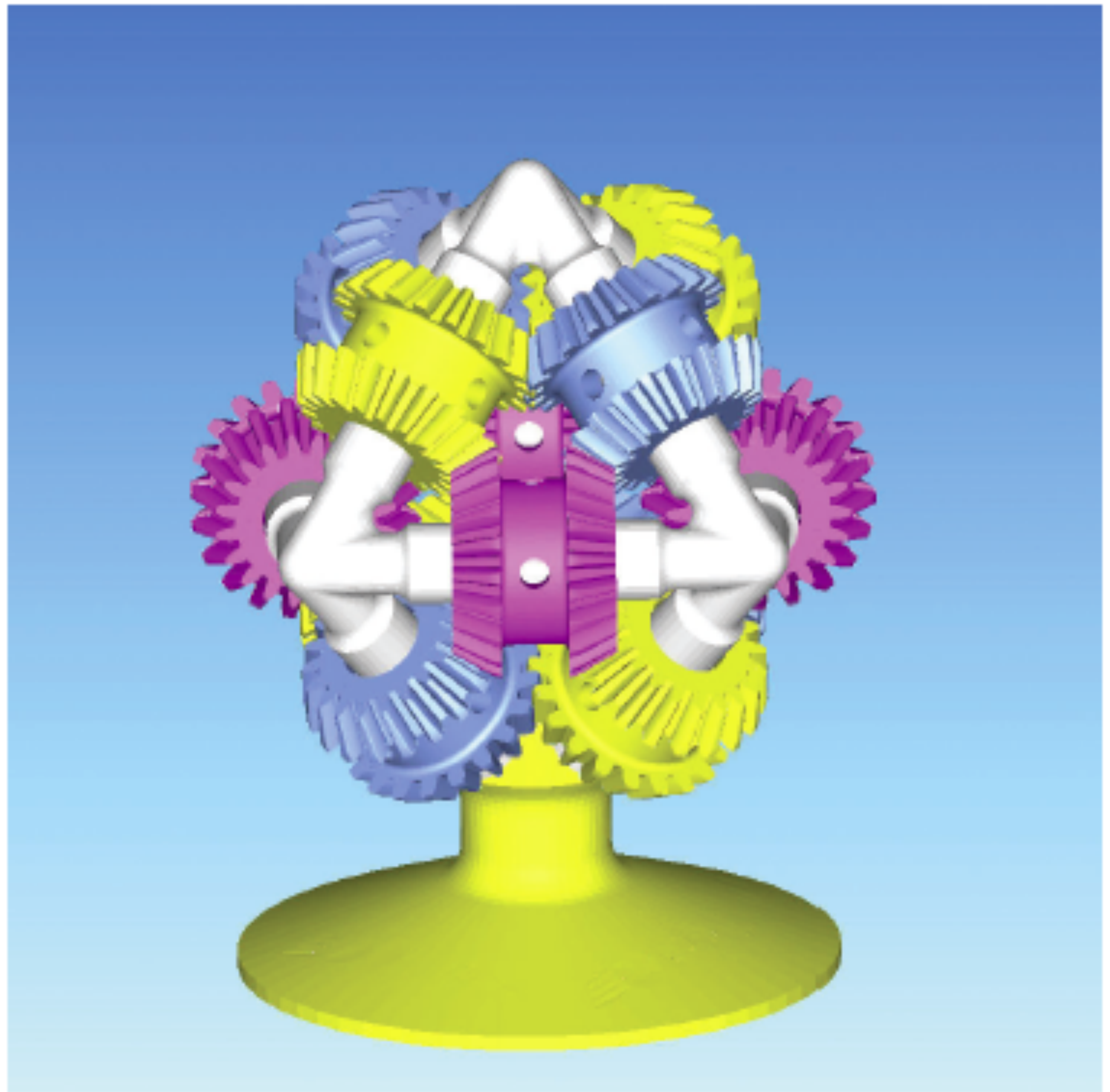




- Rapid Prototyping
- Mass Customisation
- Cheap Deployment

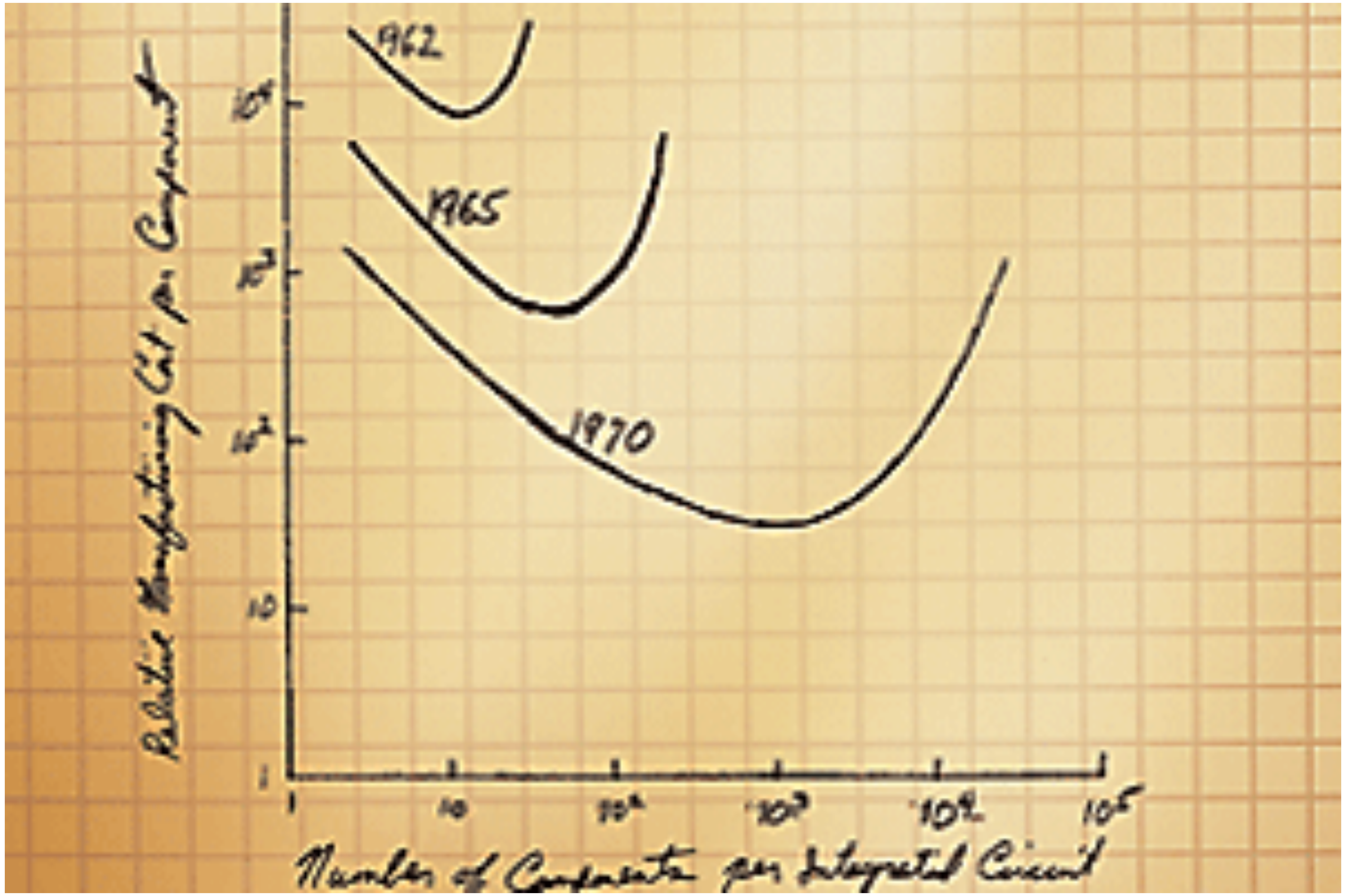
The Hardware Renaissance

- Rapid Prototyping
- Mass Customisation
- Cheap Deployment
- 3D Fabrication

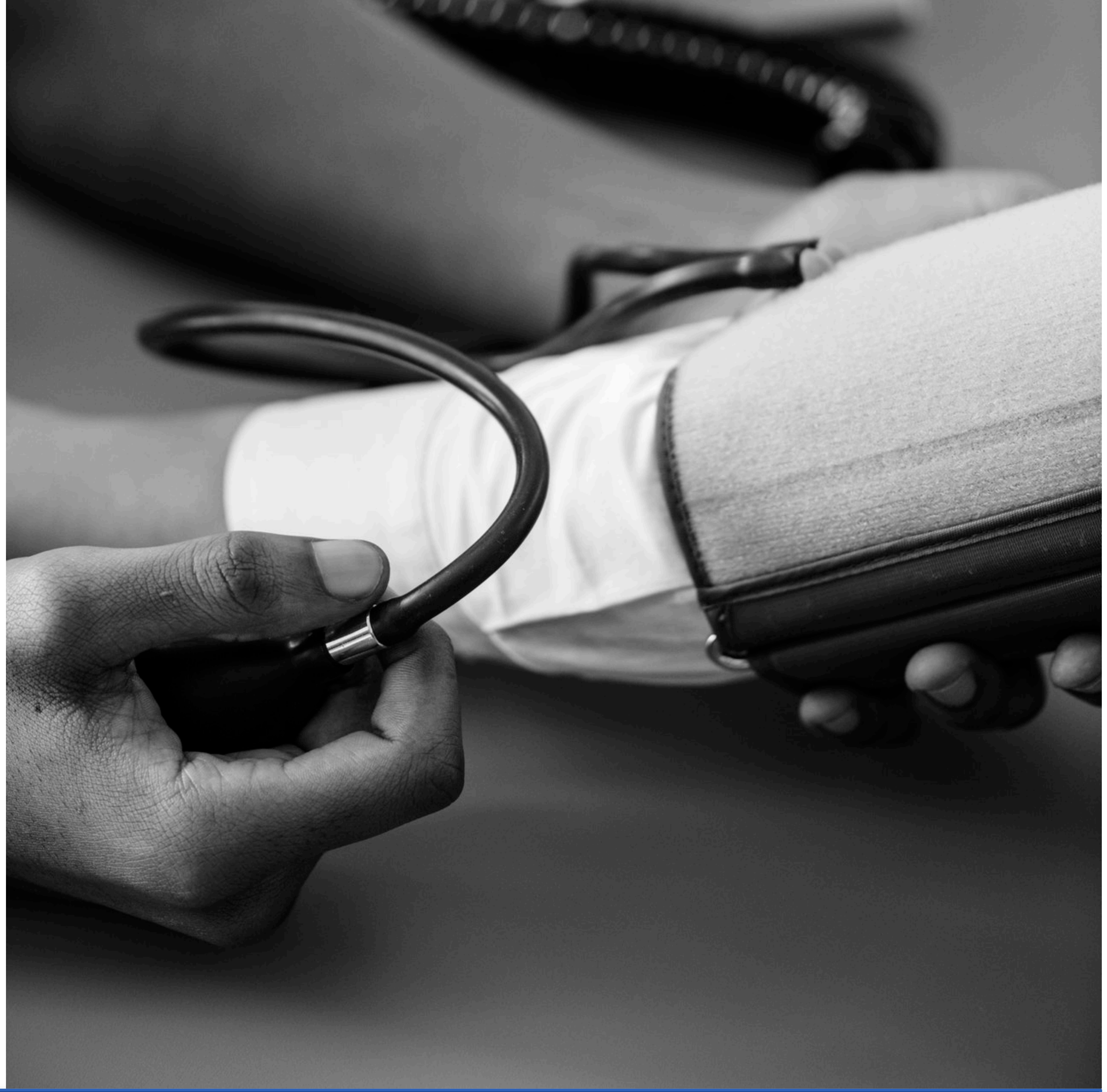


The Hardware Renaissance

In 1965, Gordon Moore noticed that the number of transistors per square inch on integrated circuits had doubled every year since their invention.



Moore’s Law



Sensors

Physical magnitude or phenomenon

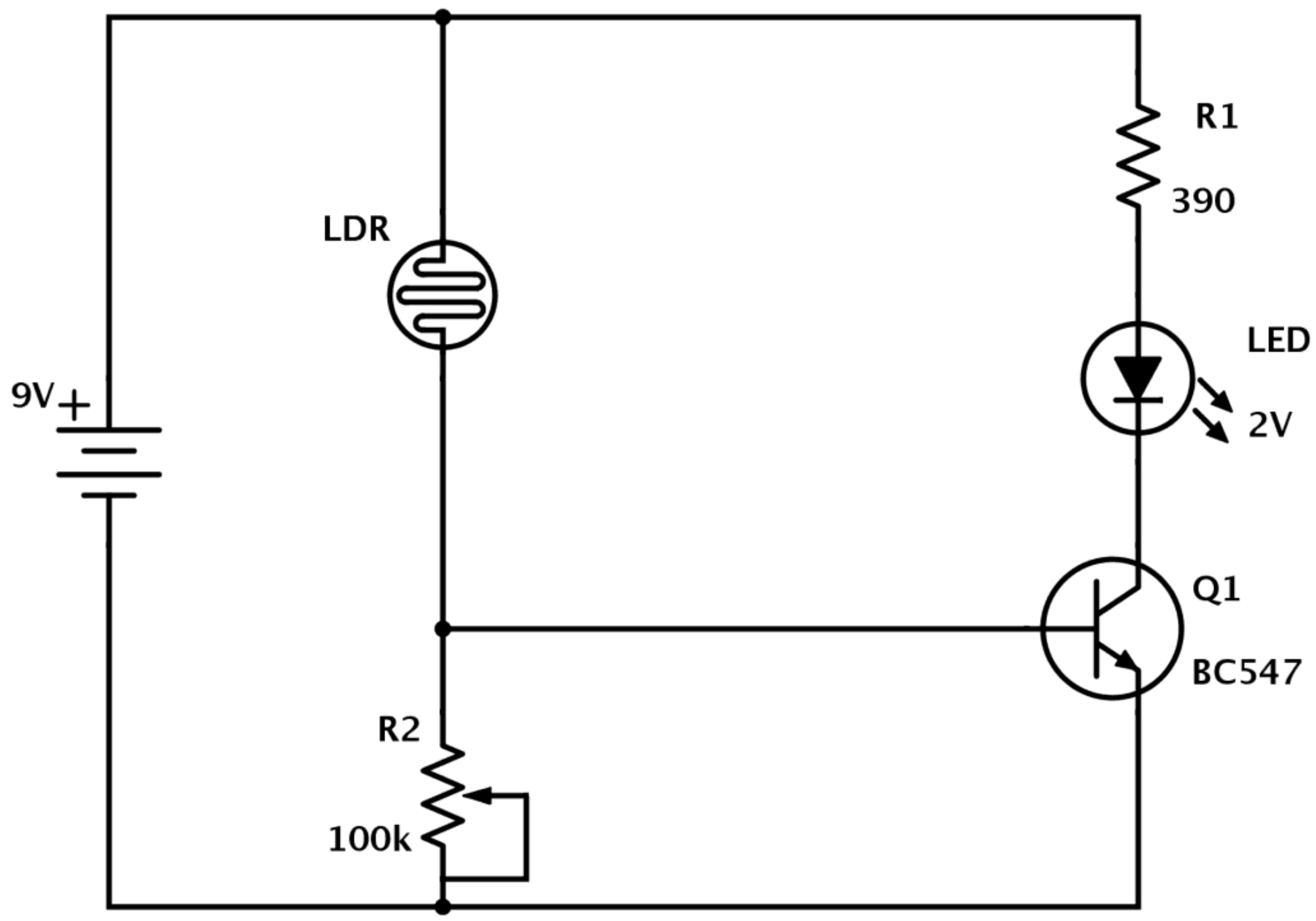
temperature
location
motion
…

Sensor

Data

What is a sensor?

- A **sensor** is a **device**, module, or subsystem
- **Detects events or changes in its environment**
- By translating a physical magnitude into electrical properties
- **Sends the information** to other electronics

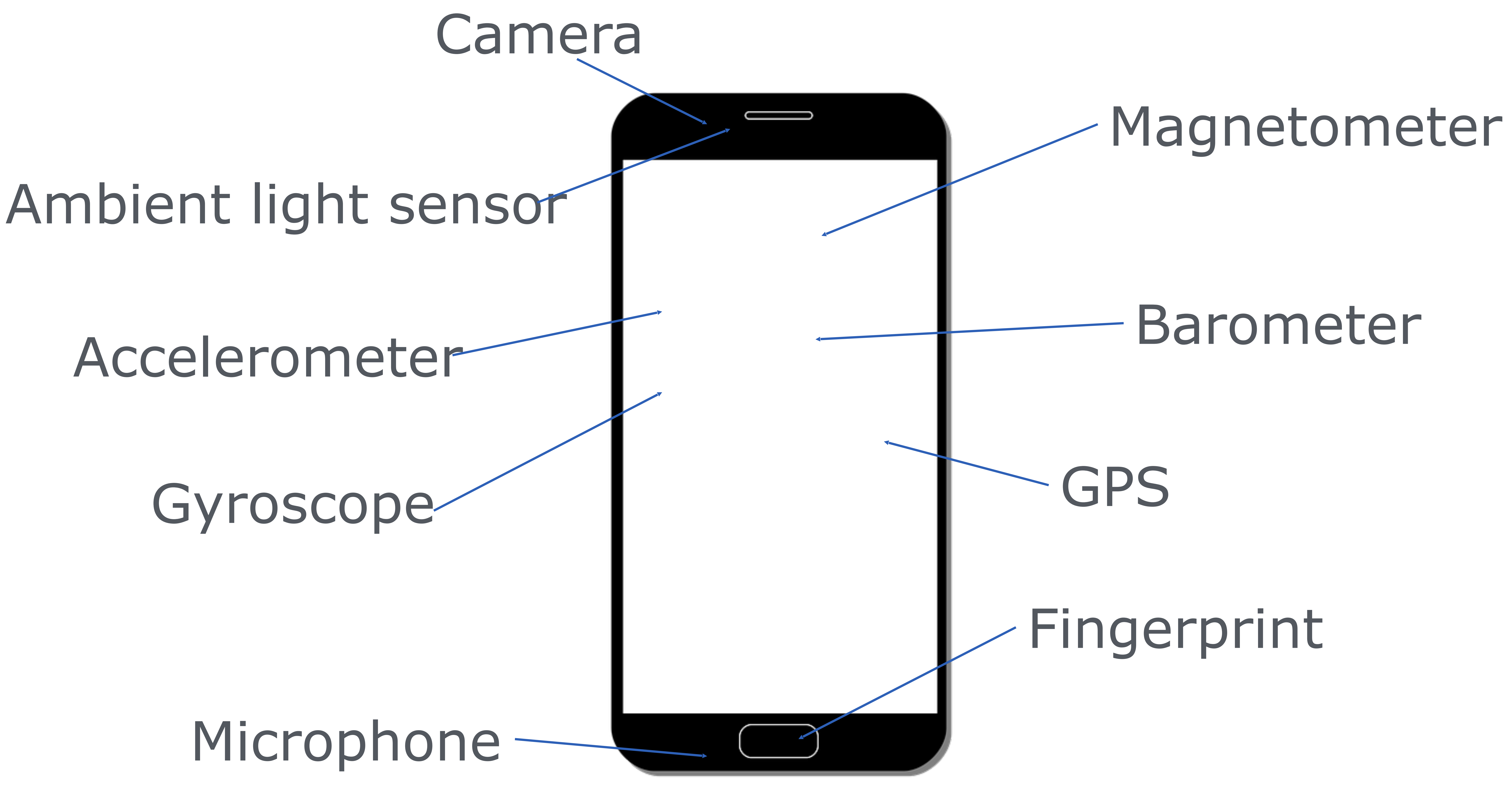


Sensor

https://www.build-electronic-circuits.com/ldr-circuit-diagram/

Back then...

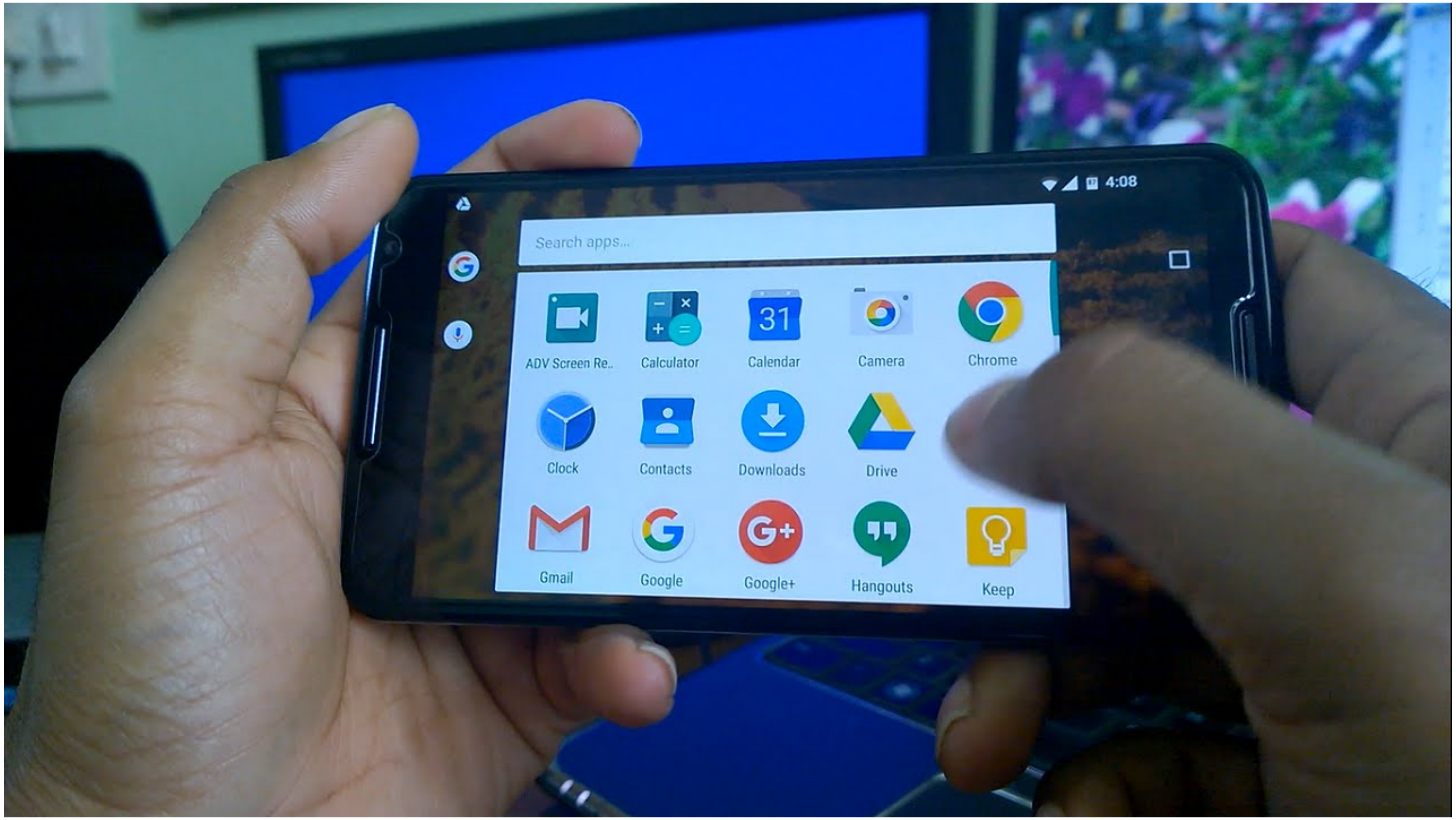
… now.



Sensors

Android sensor overview: https://developer.android.com/guide/topics/sensors/sensors_overview

Sensor?



Screen Rotation

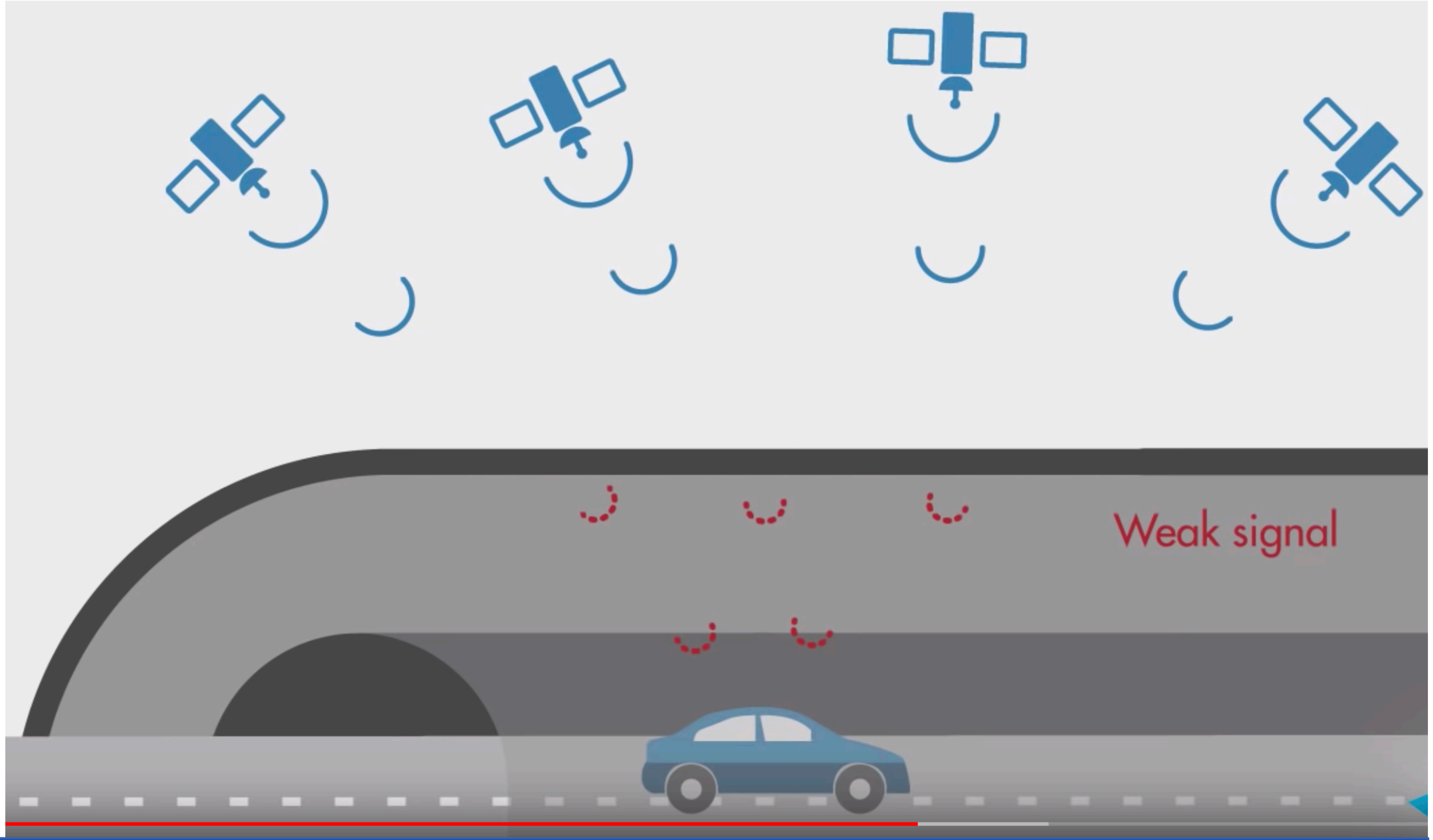
Sensor?

Avoiding Accidental Touches

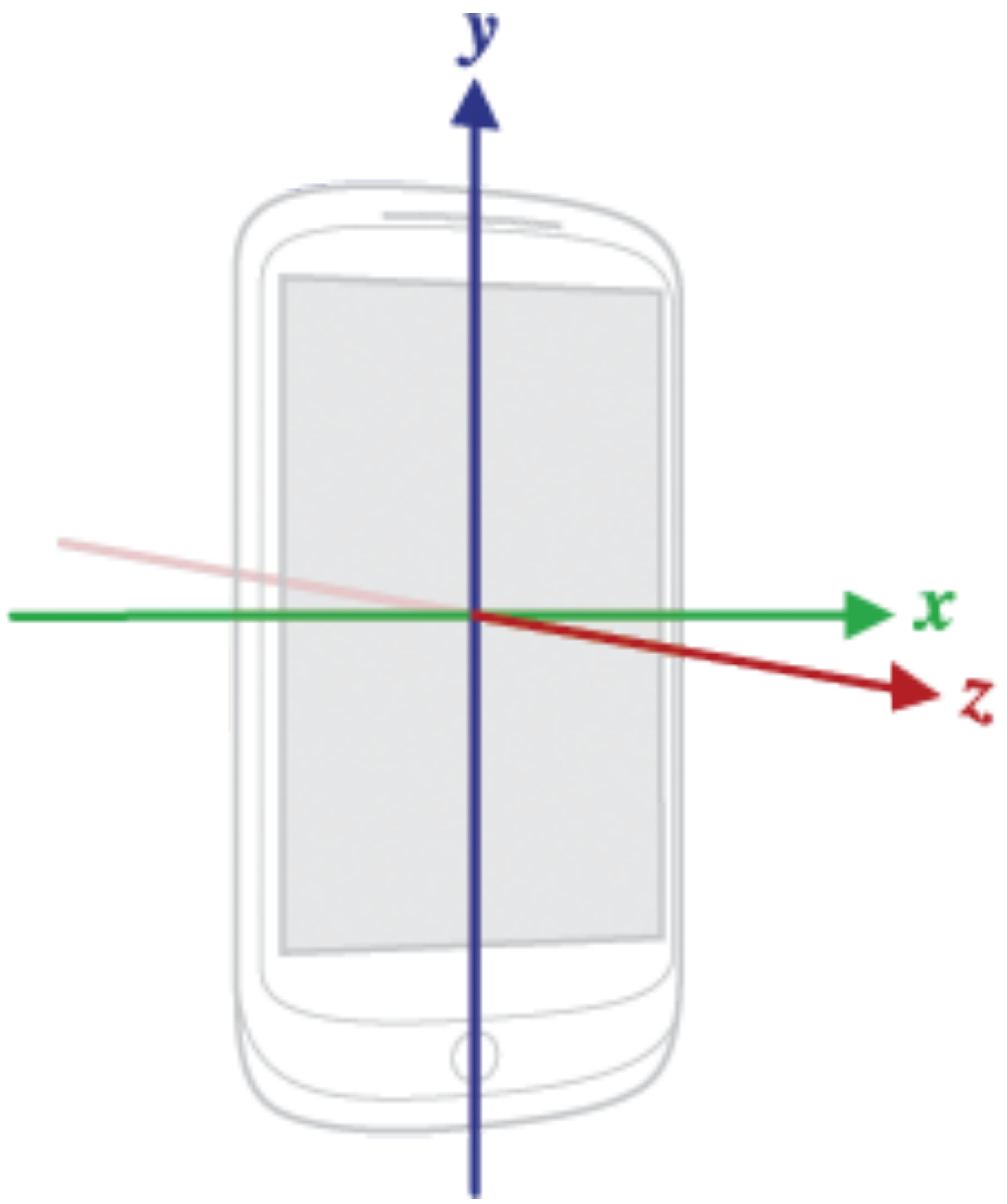
Sensor?

Pokémon GO?

Sensor?

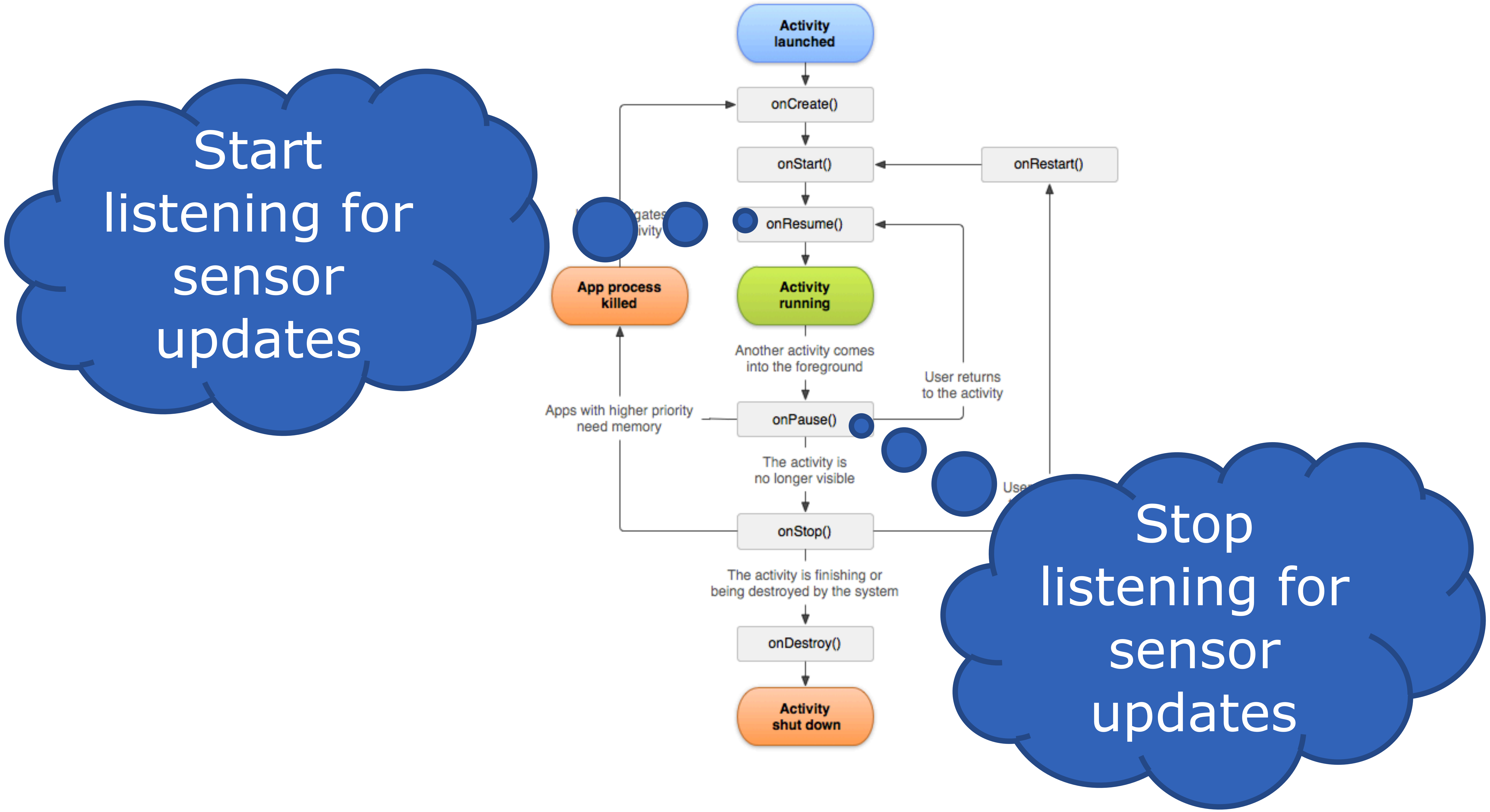


Driving through a Tunnel

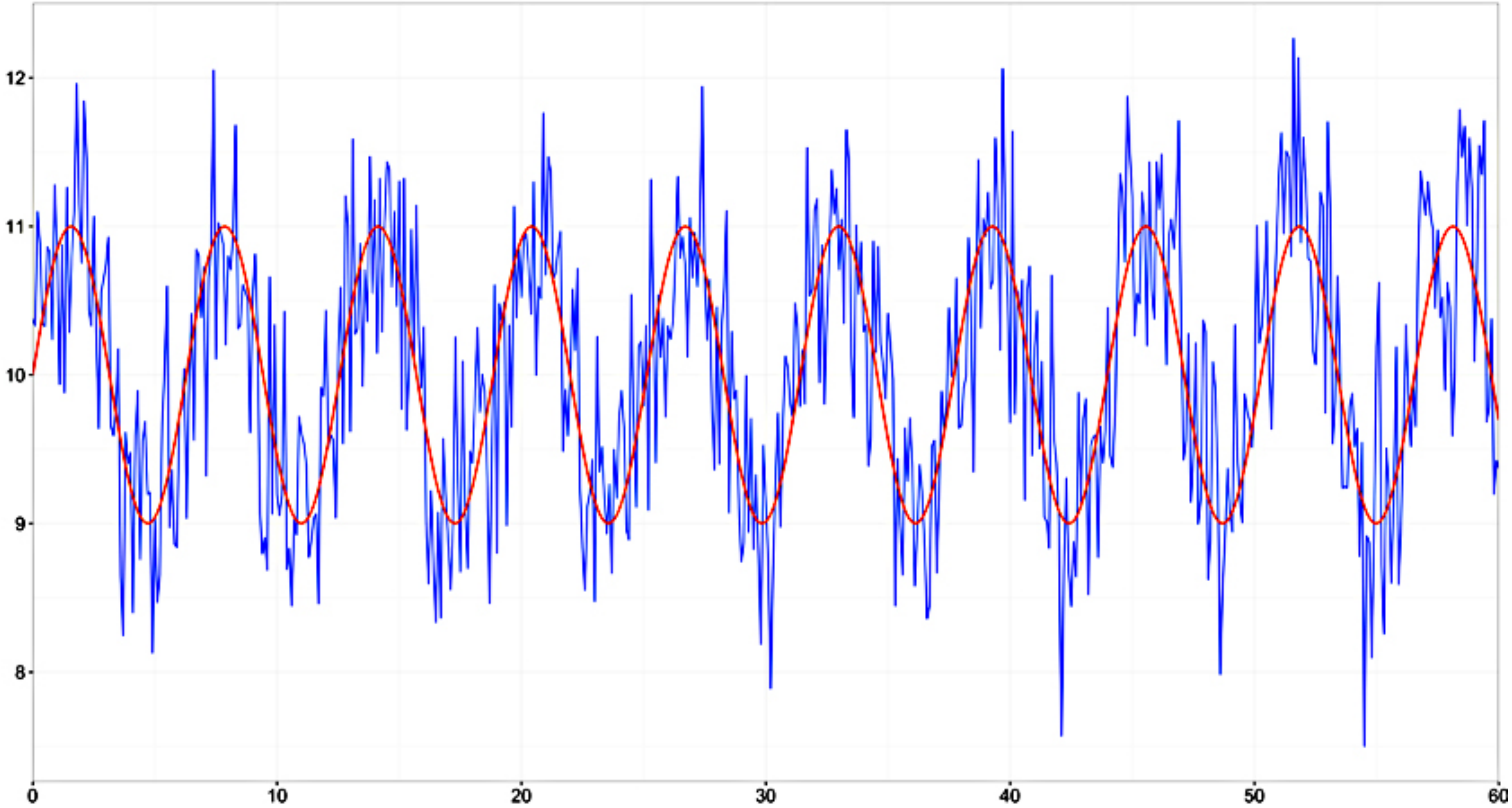


- Raw sensor data
- Higher abstraction (e.g. step counter)
- Events and Callbacks
- Device independent (as long as present!)

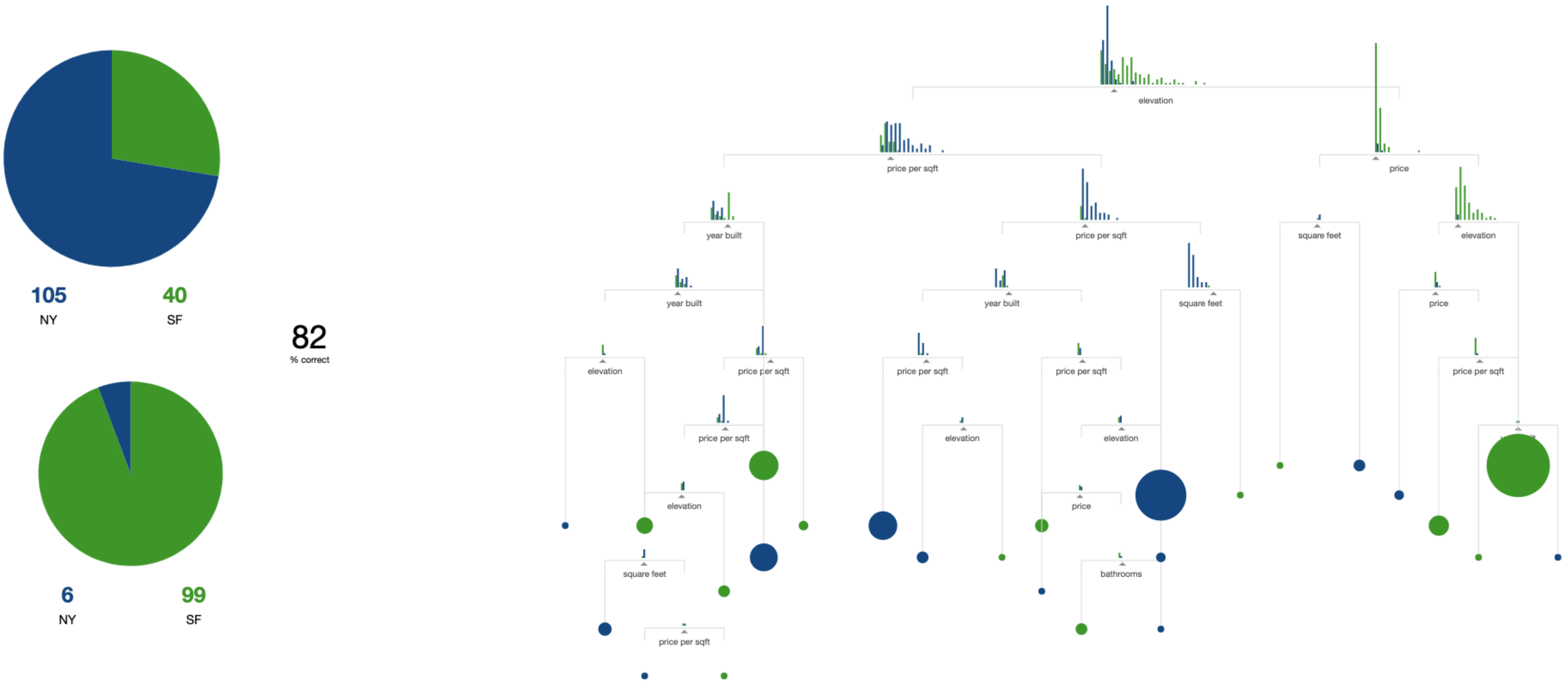
Sensors in Android / iOS



Respect the Activity Lifecycle

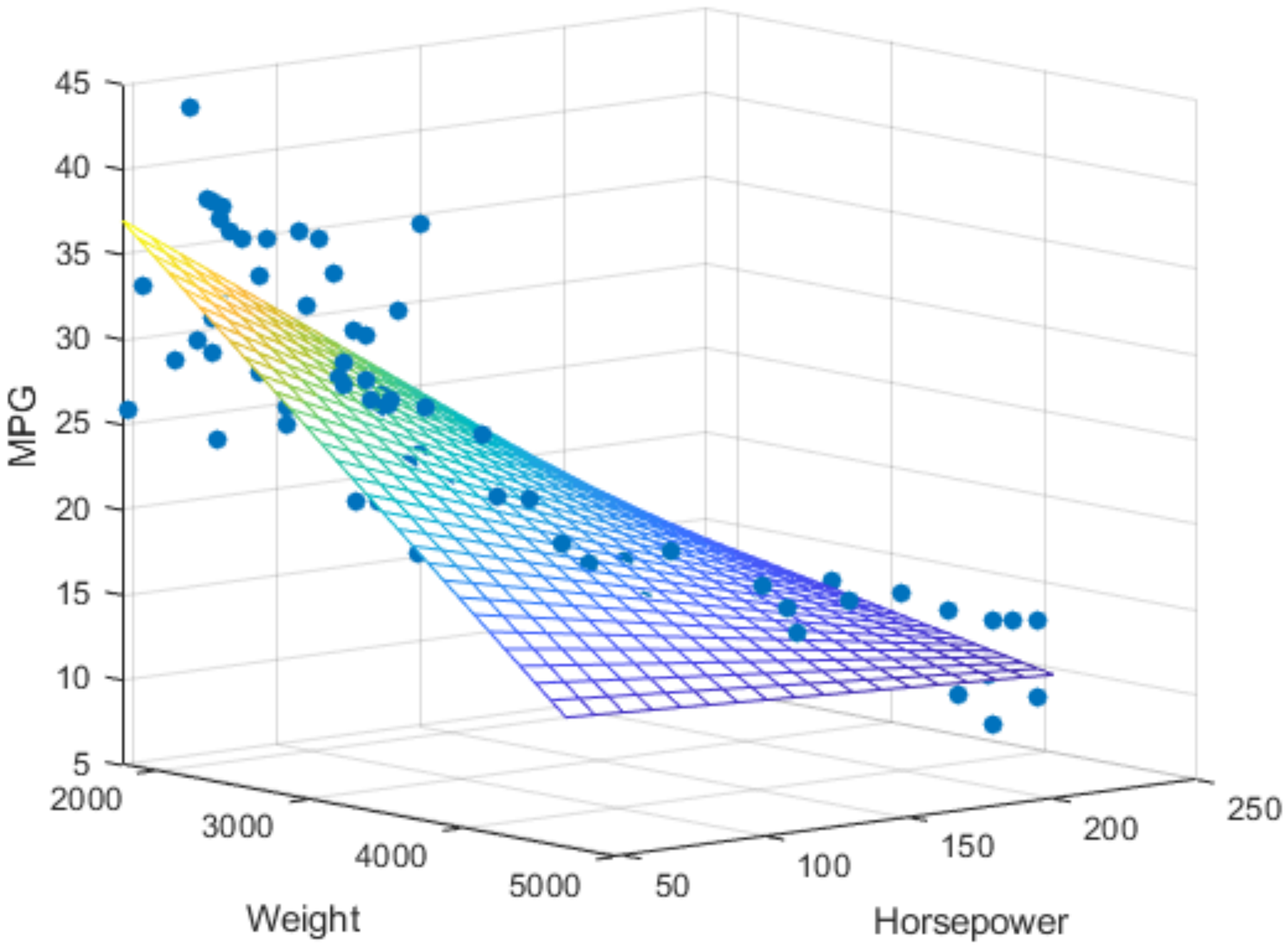


Signal Processing



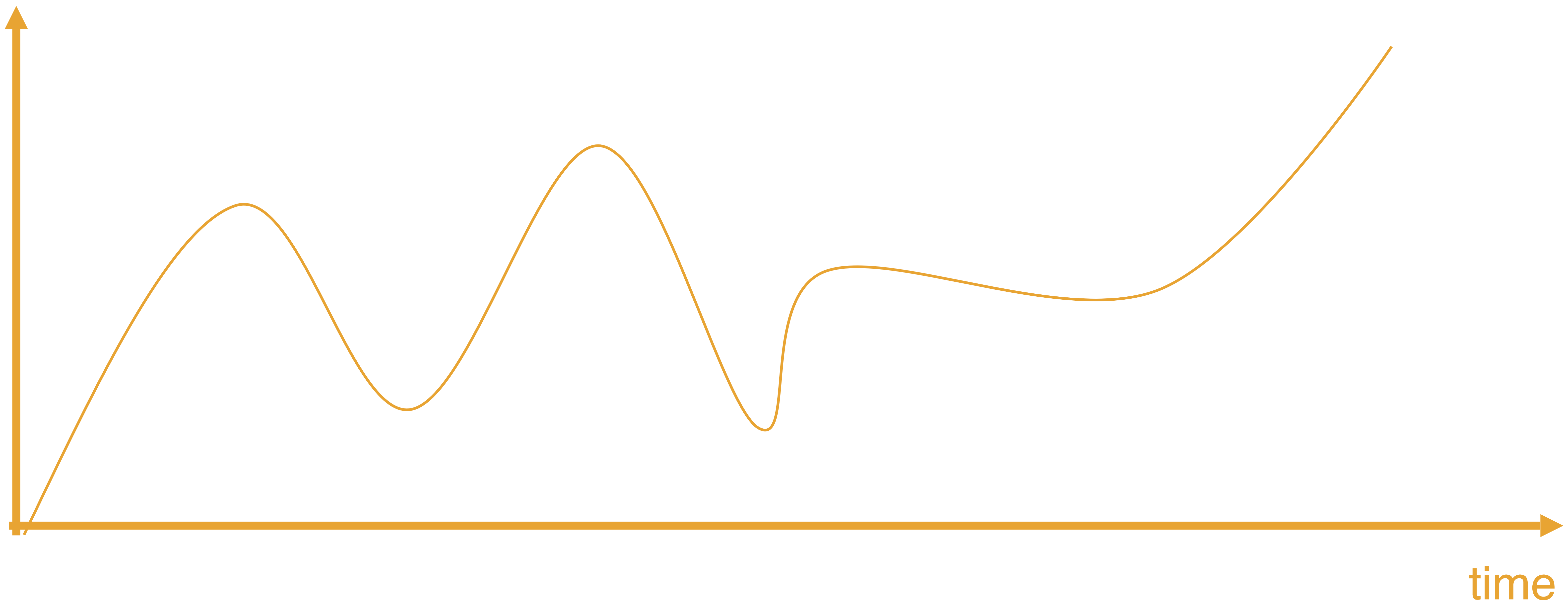
Machine Learning

http://www.r2d3.us/visual-intro-to-machine-learning-part-1/

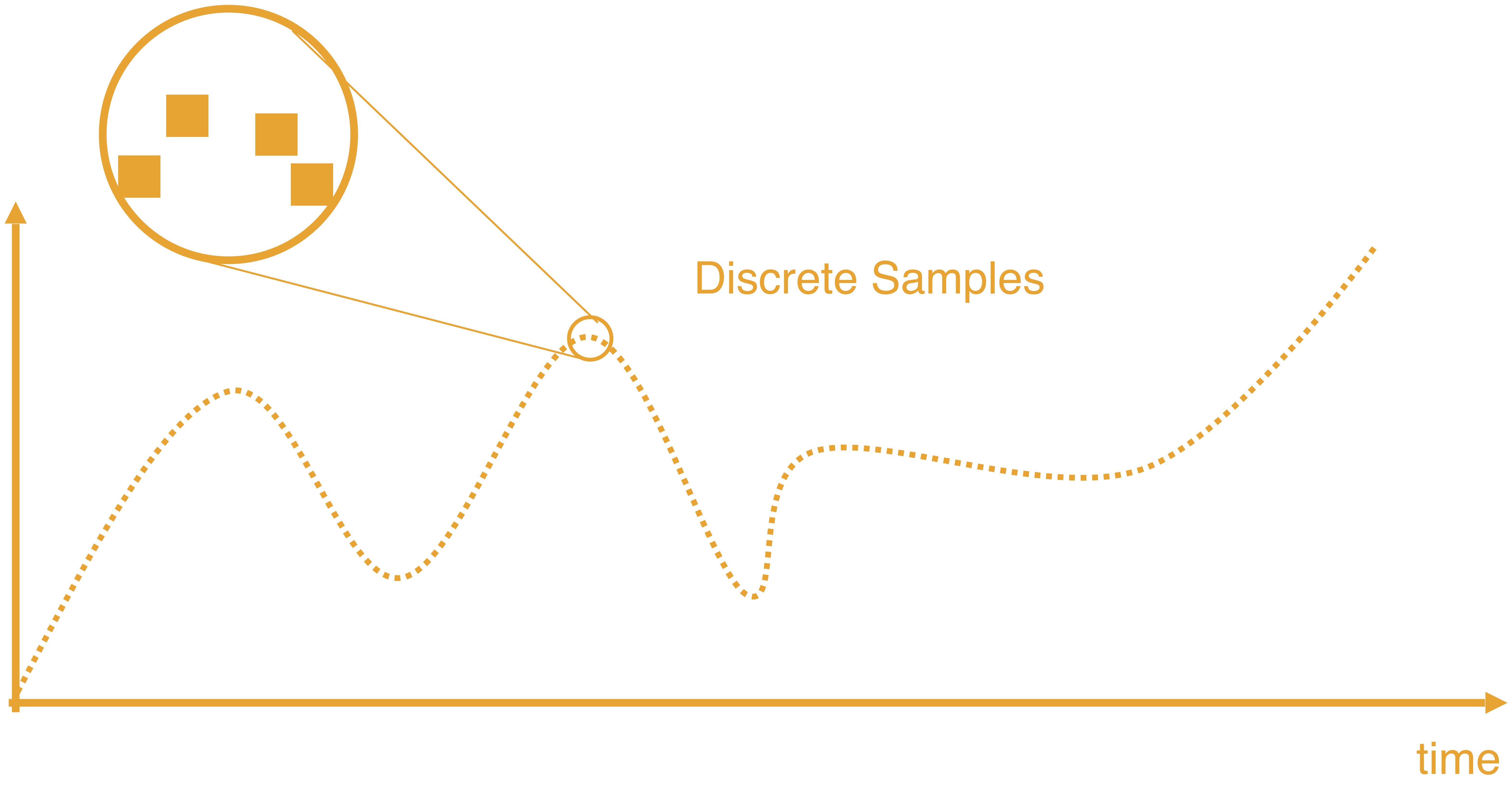


Linear Regressions

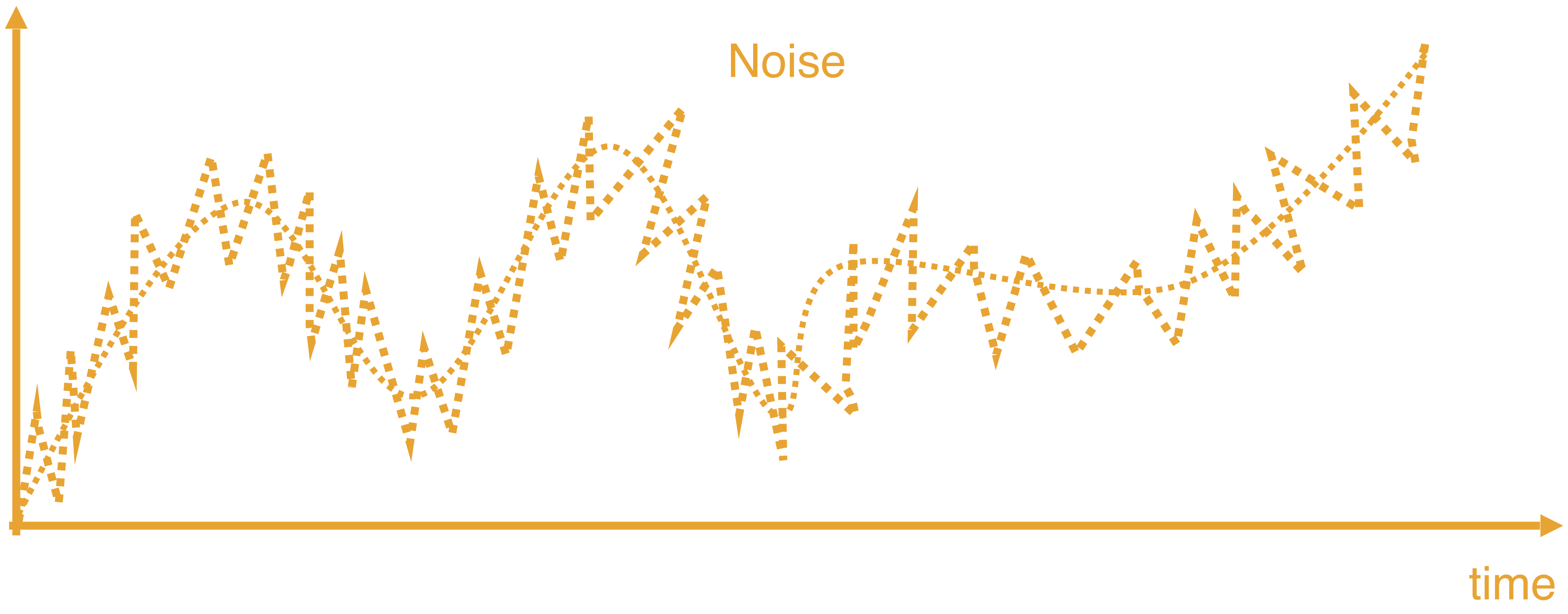
https://www.mathworks.com/help/stats/regress.html



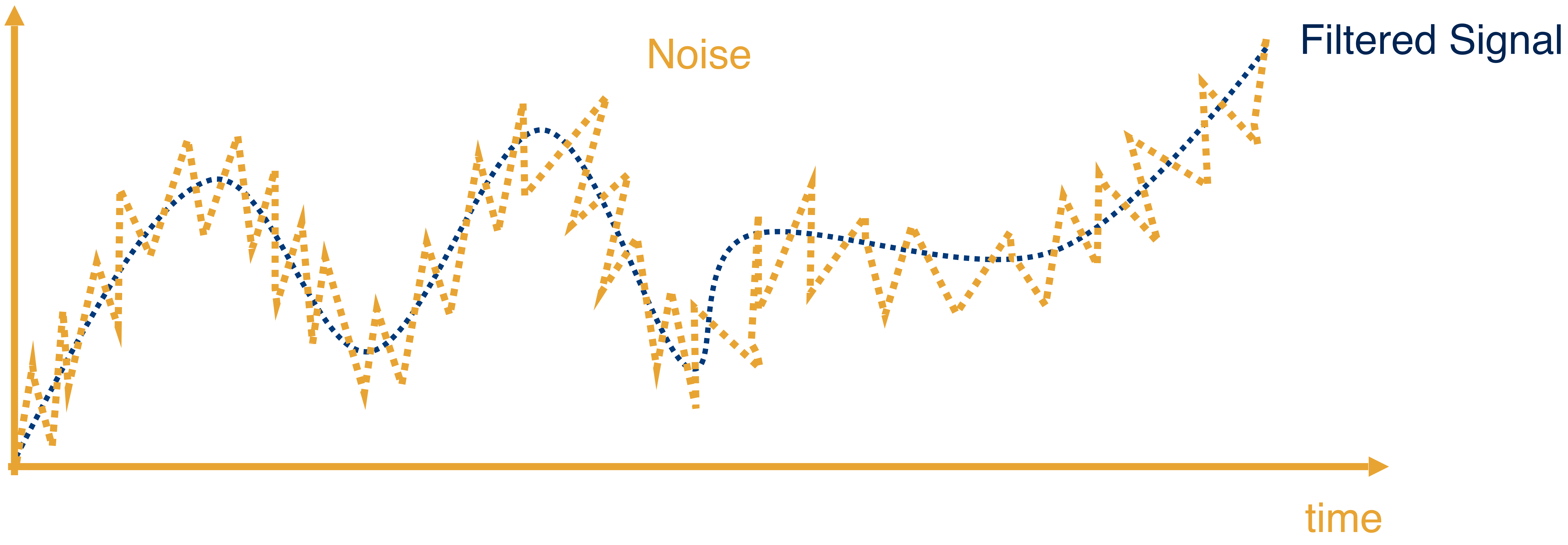
Sensor Data



Sensor Data



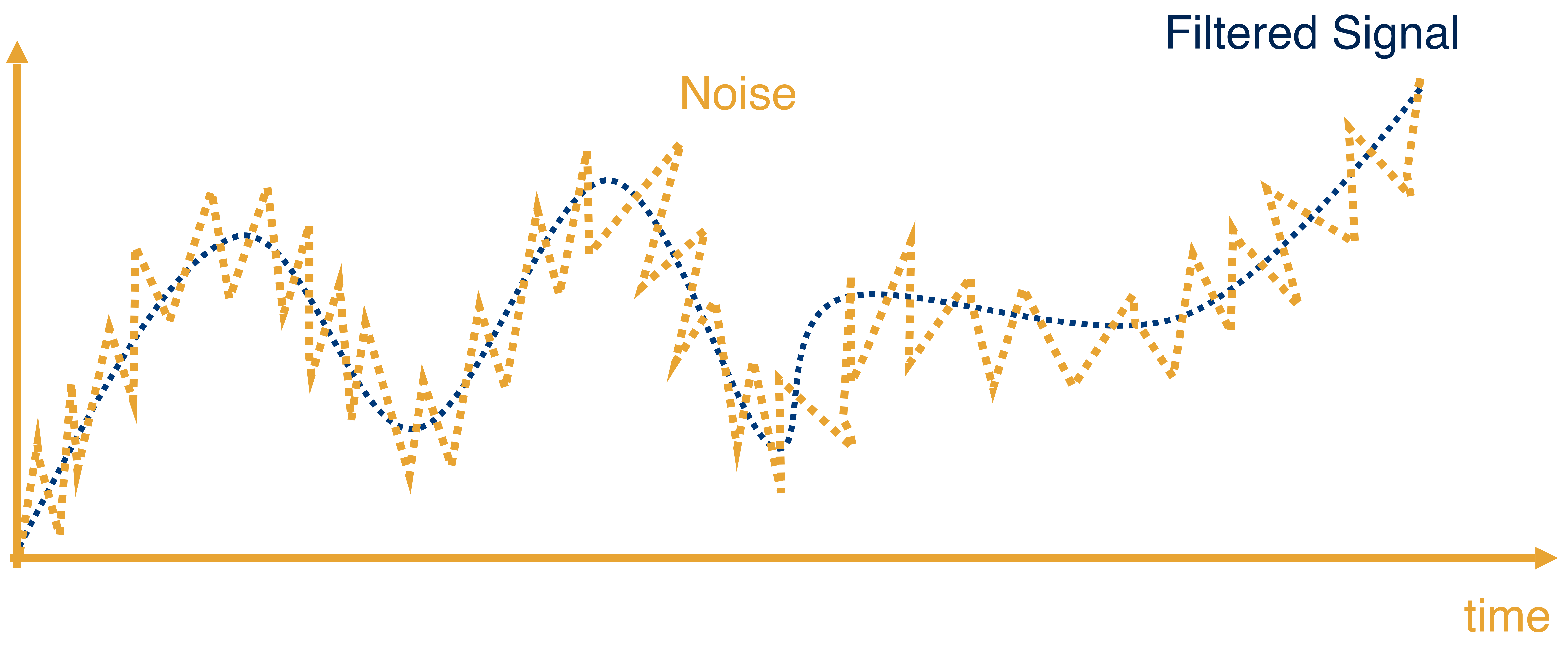
Sensor Data

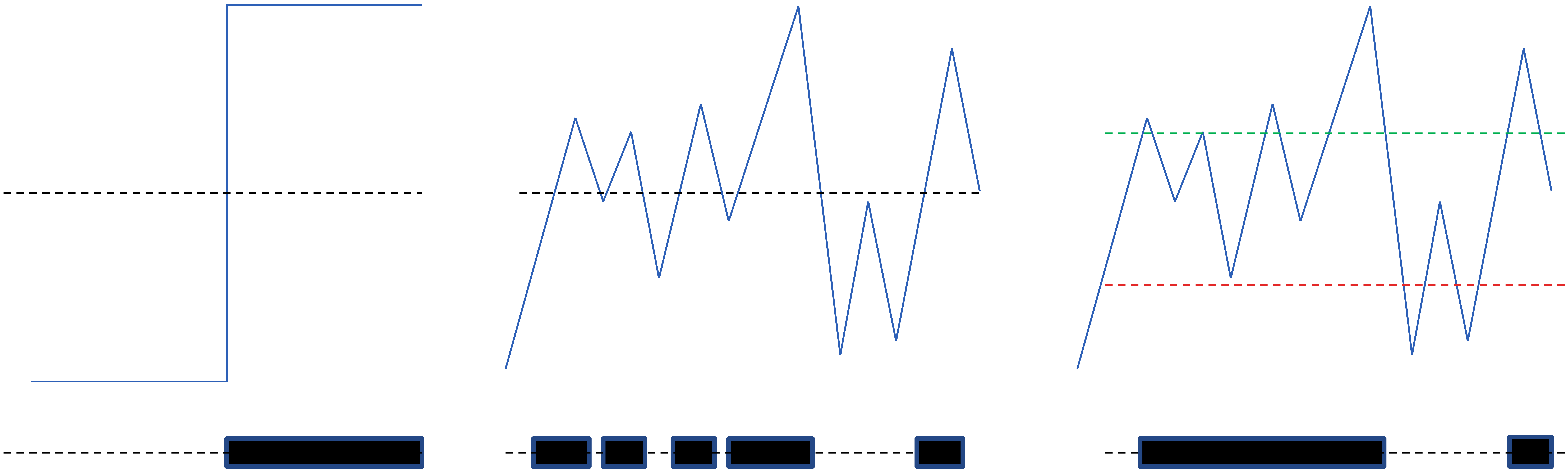


Signal to Noise Ratio: SNR

Sensor Data Processing

1. Thresholds
2. Mean Filters
3. Median Filters
4. Kalman Filters
5. Particle Filters





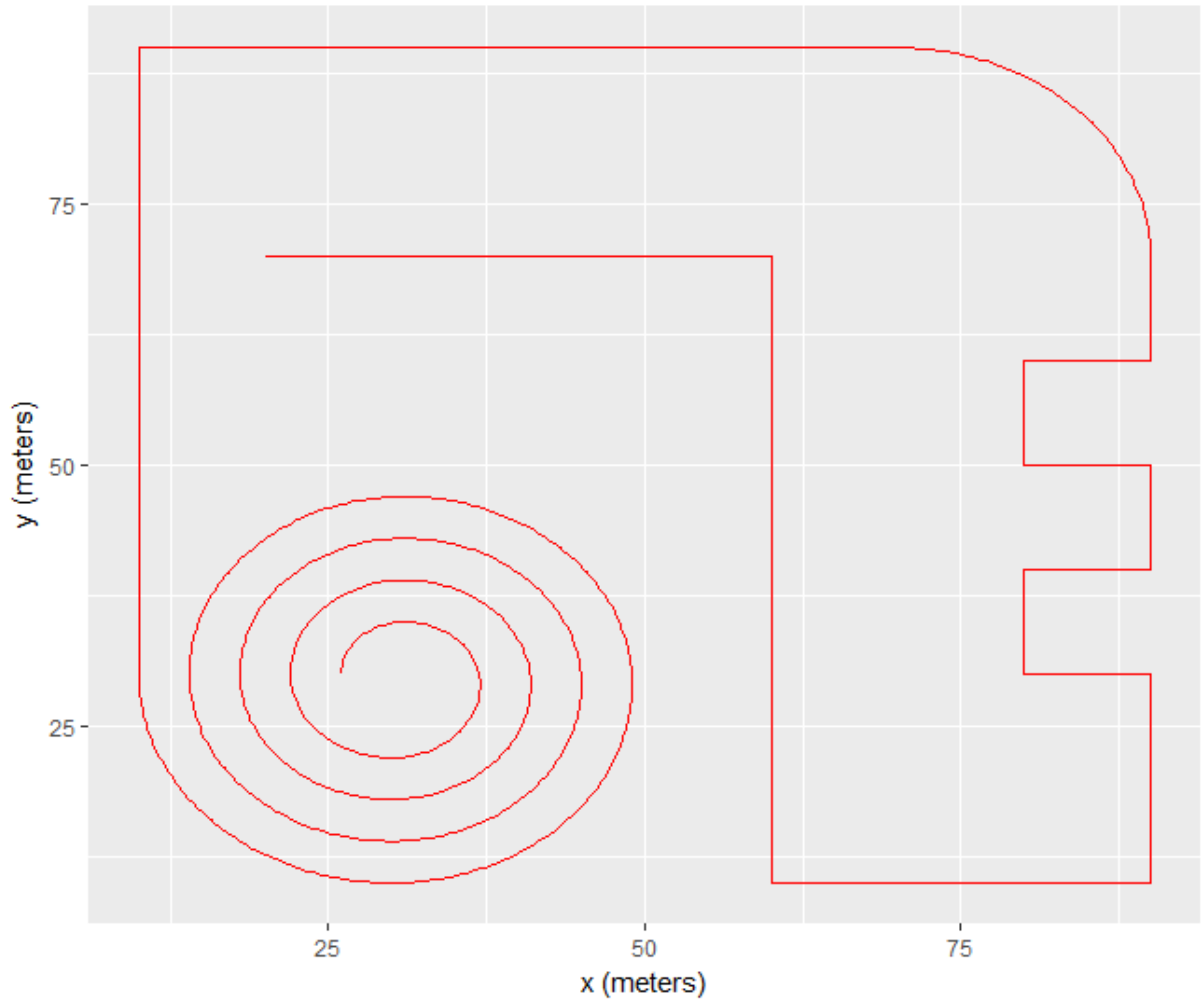
Thresholds

$$z_i = x_i$$

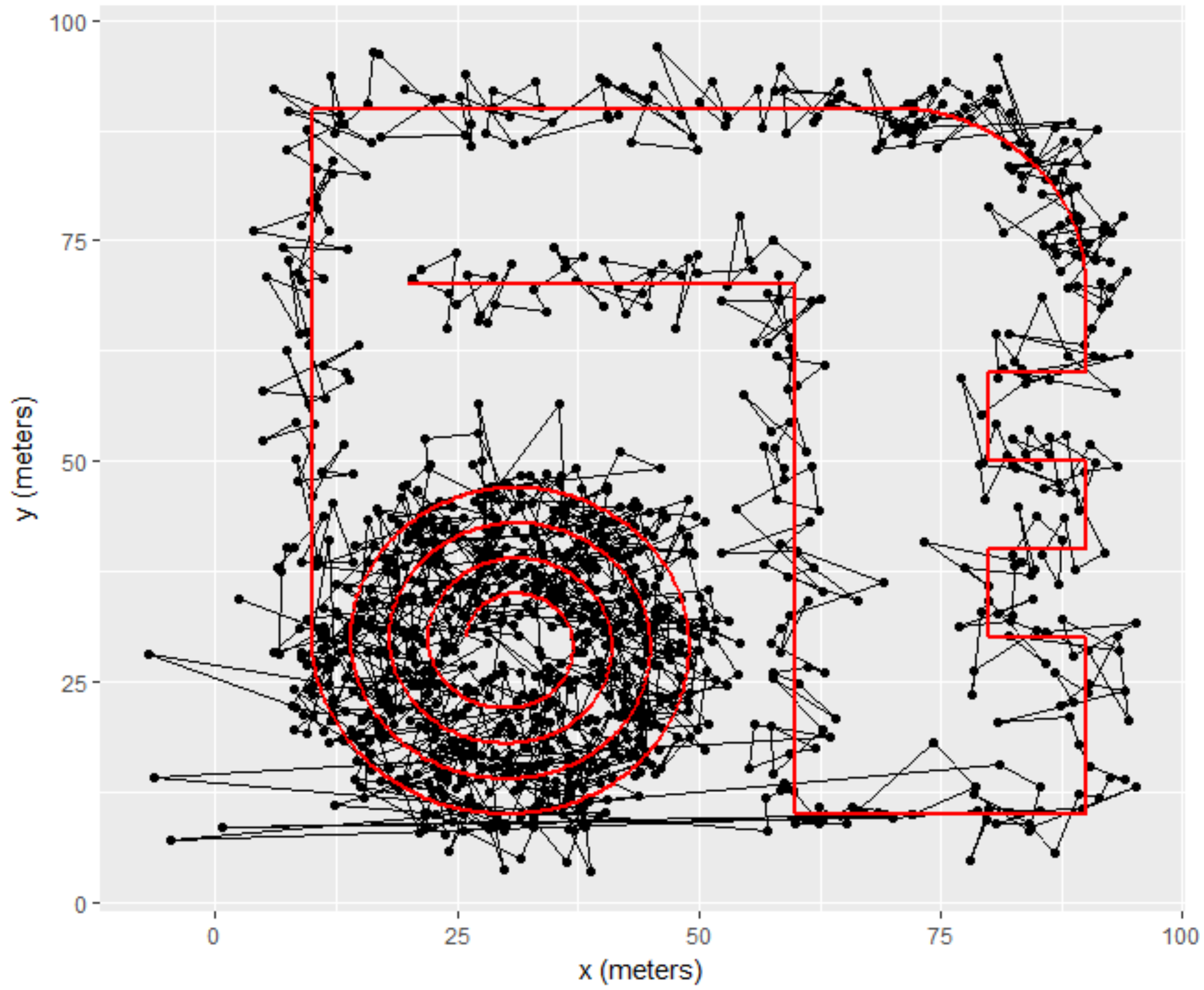
Measurement from sensor

Actual Value or Ground Truth

Measurement vs. State



Measurement vs. State



Measurement vs. State

Measurement vs. State

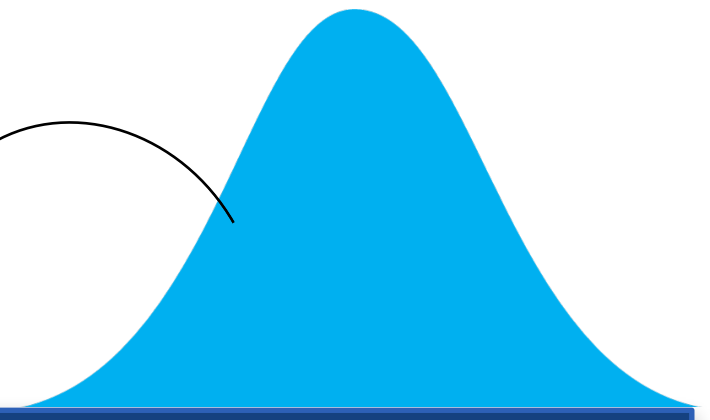
$$z_i = x_i + v_i$$

Measurement from sensor

Actual Value or Ground Truth

Sensor noise

$v_i \sim N(0, \sigma)$



Measurement vs. State

Measurement $zi = \begin{pmatrix} z_i^{(x)} \\ z_i^{(y)} \end{pmatrix}$

State $xi = \begin{pmatrix} xi \\ yi \end{pmatrix}$

Noise $vi = \begin{pmatrix} v_i^{(x)} \\ v_i^{(y)} \end{pmatrix}$

$\sim \begin{pmatrix} N(0,\sigma) \\ N(0,\sigma) \end{pmatrix}$

$$\underbrace{z_i}_{\text{Measurement from sensor}} = \underbrace{x_i}_{\text{Actual Value or Ground Truth (State)}} + \underbrace{v_i}_{\text{Sensor noise}}$$

●●●●●●●●●●●●

Actual Value

Measurements

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$

Mean Filter

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$

Mean Filter

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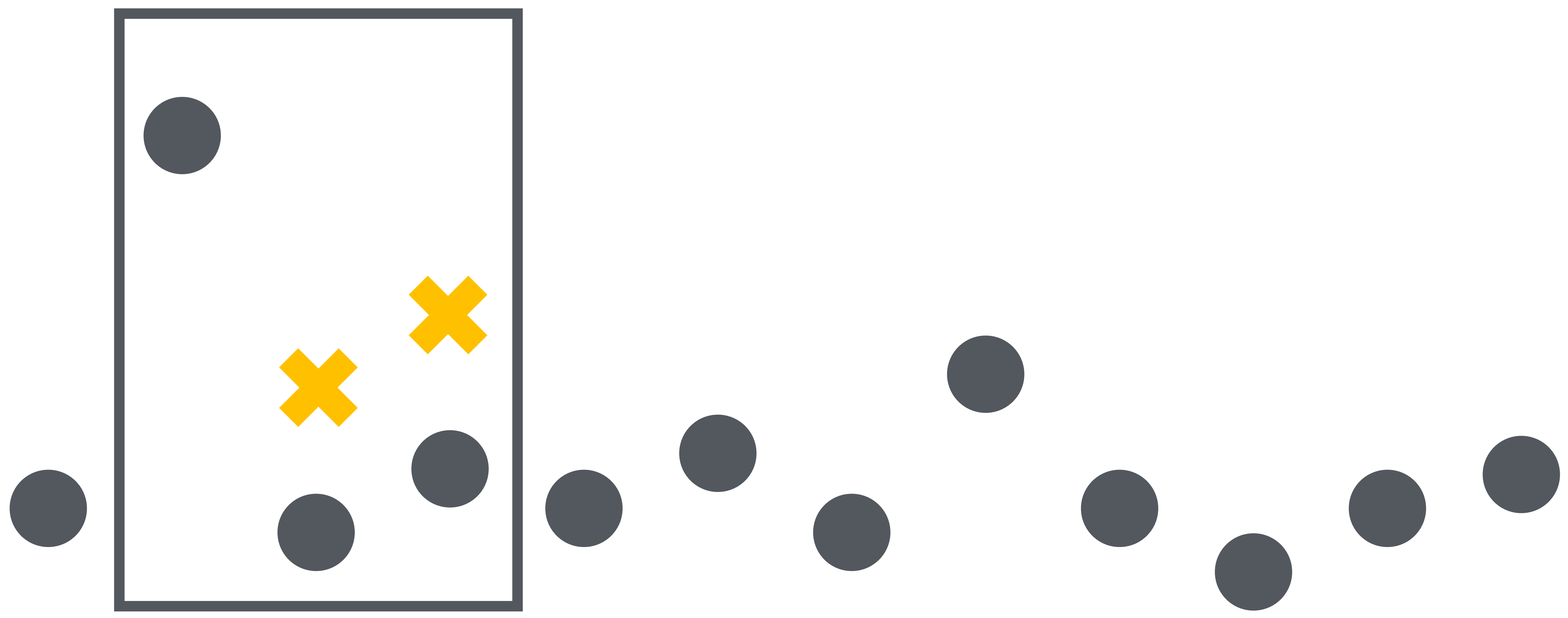

Mean Filter

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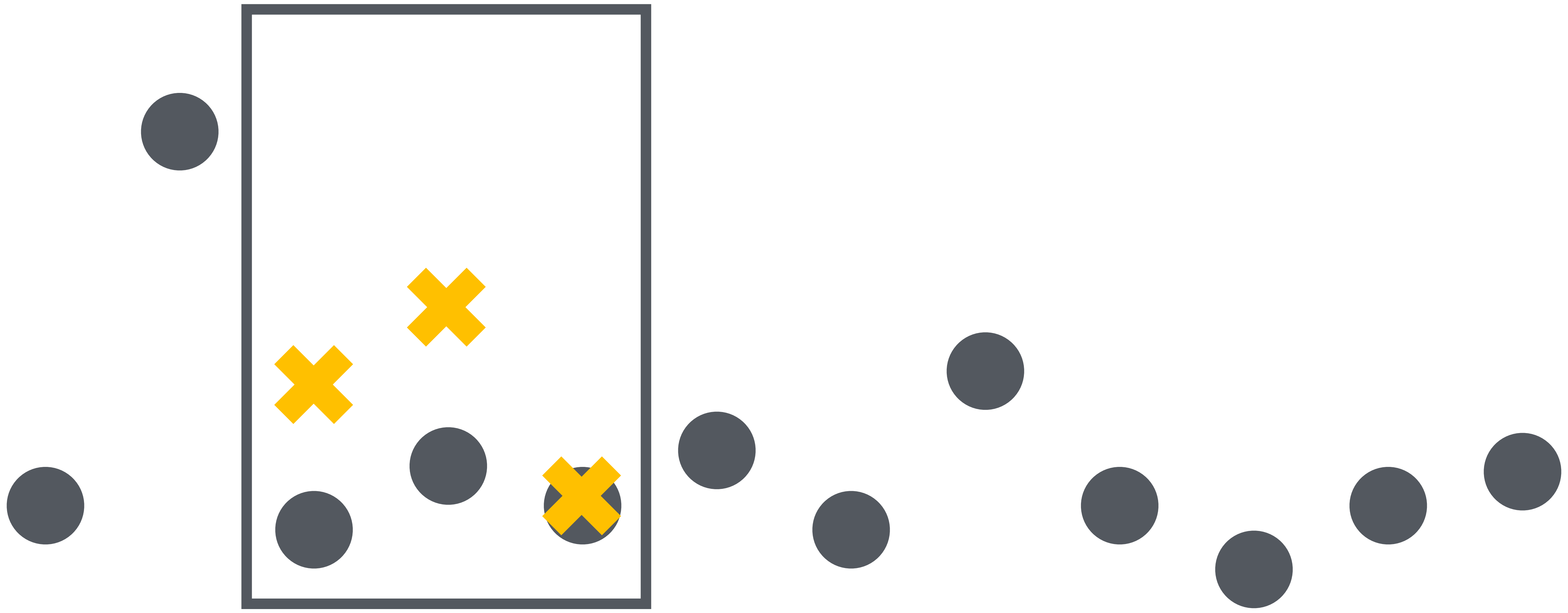
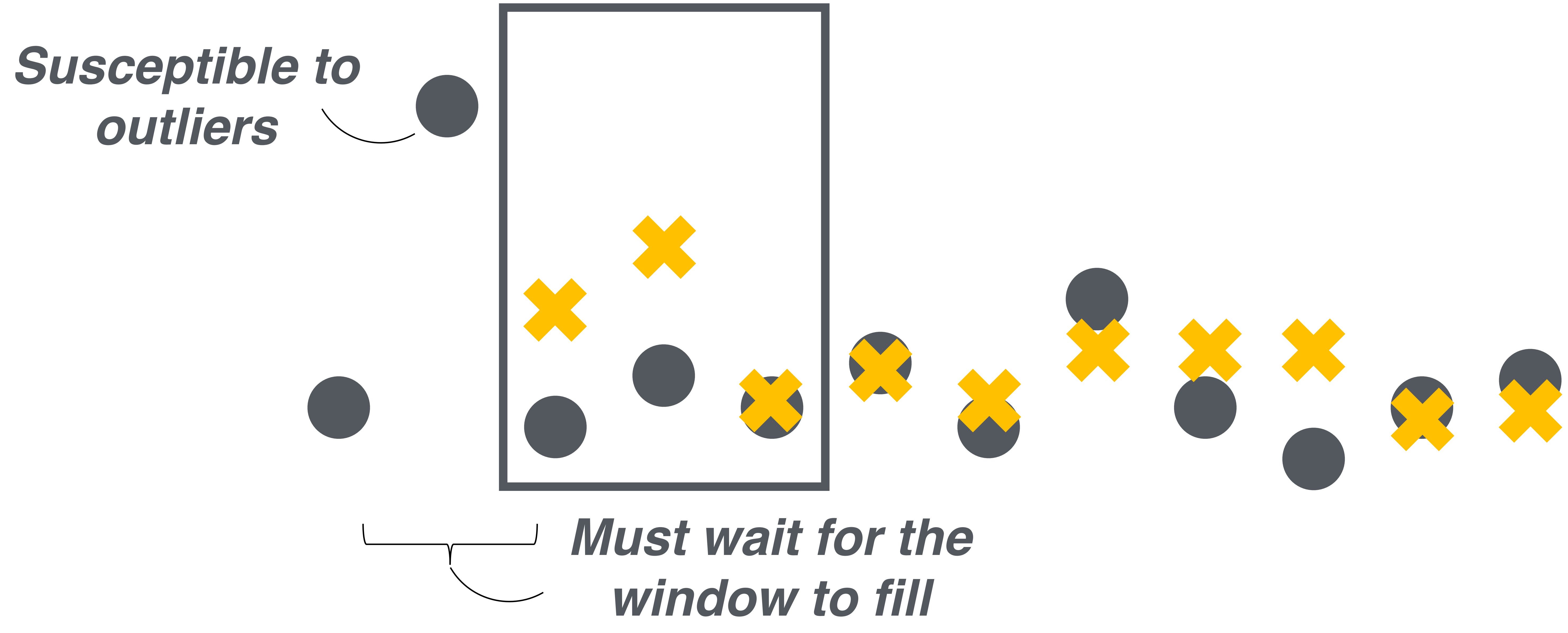


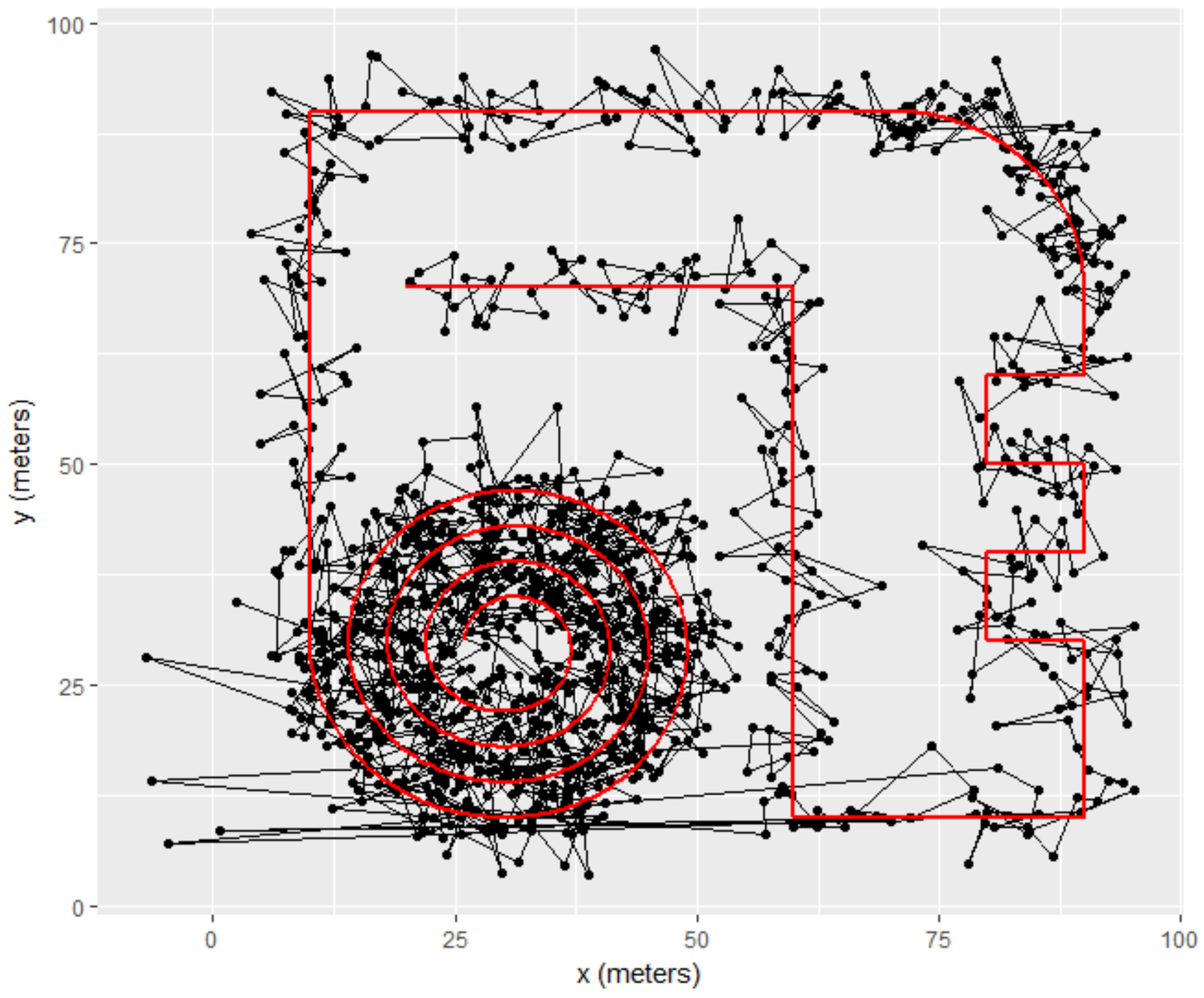
Mean Filter

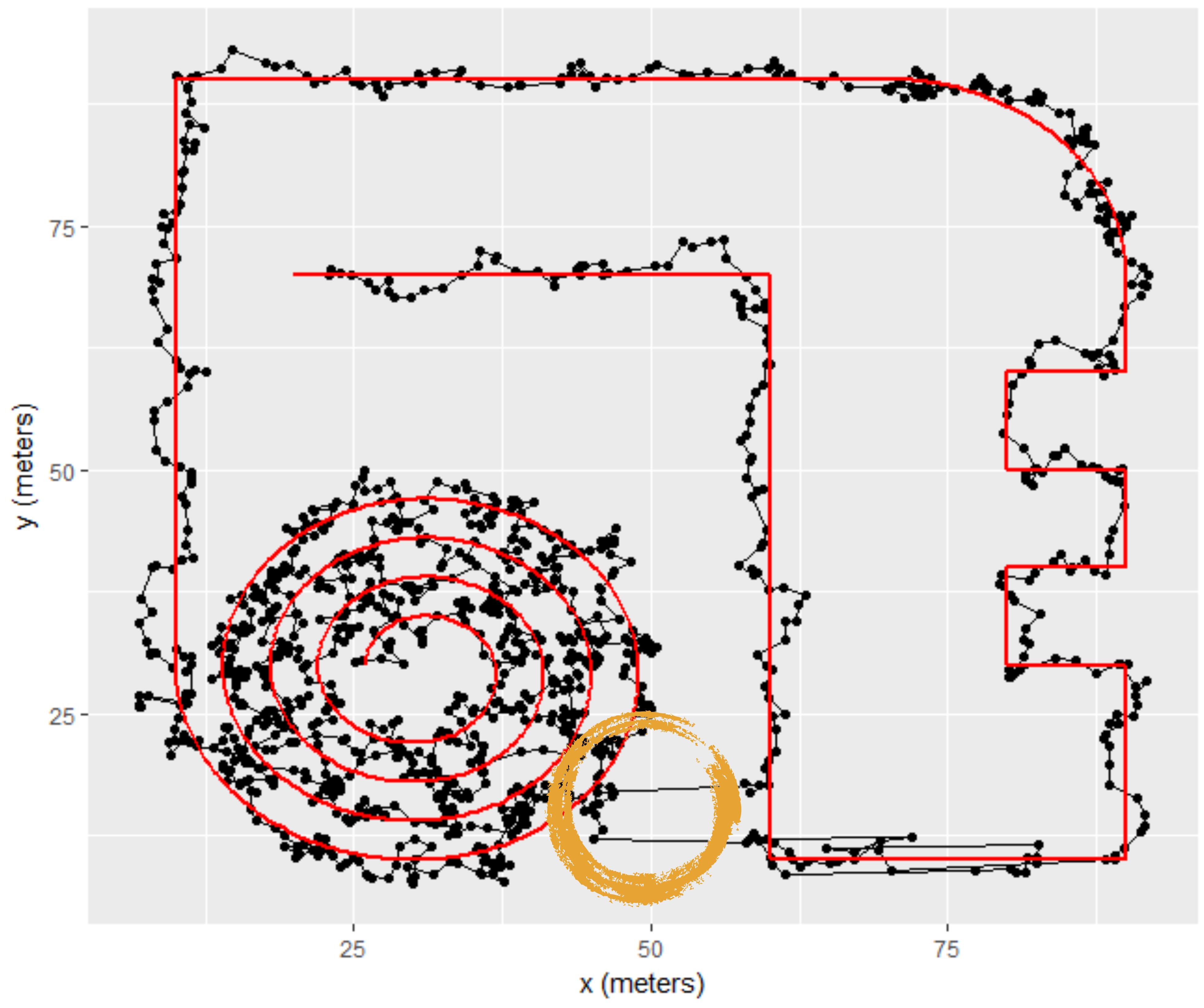
$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$



Mean Filter

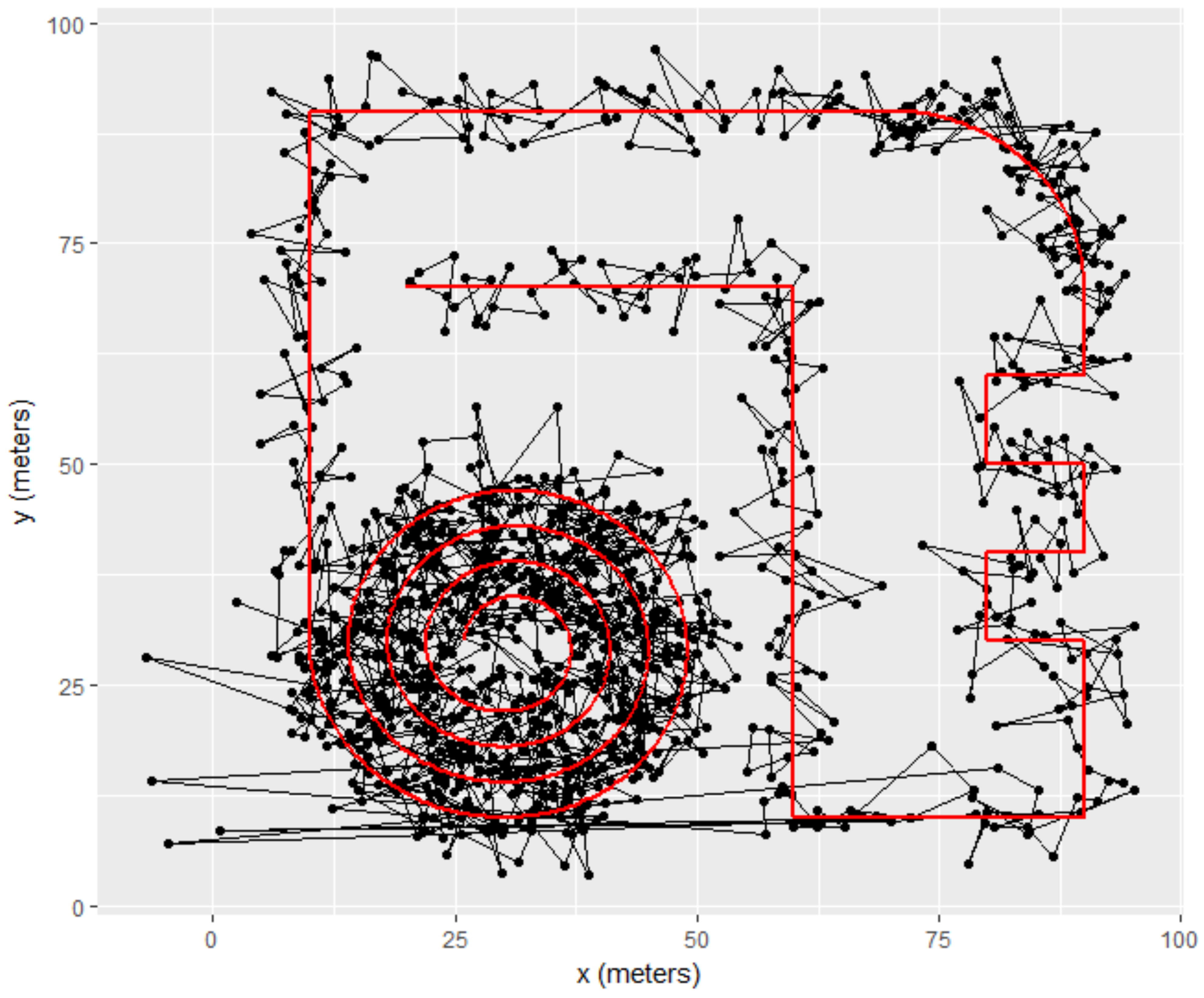
window = 5

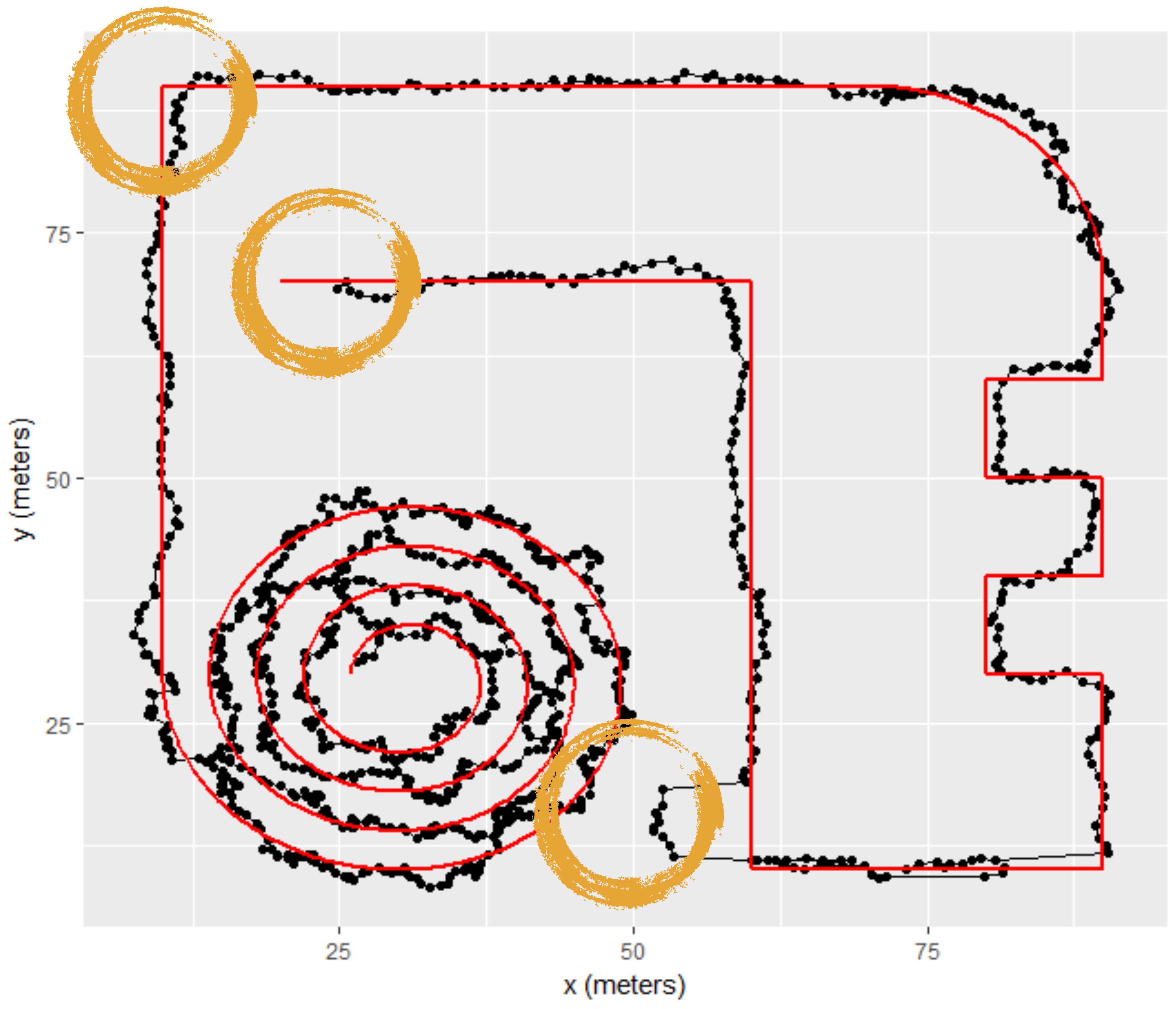




Mean Filter

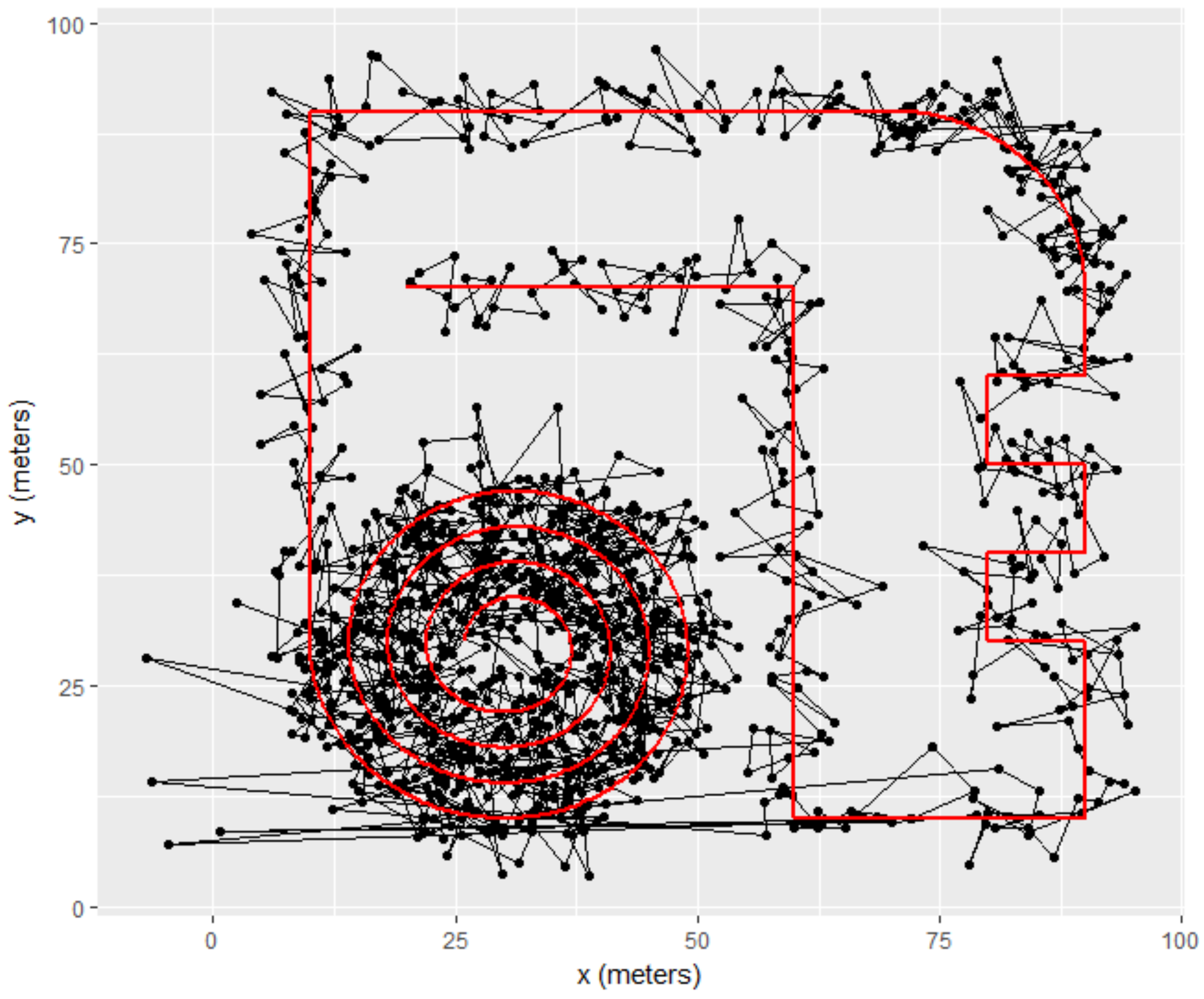
window = 10

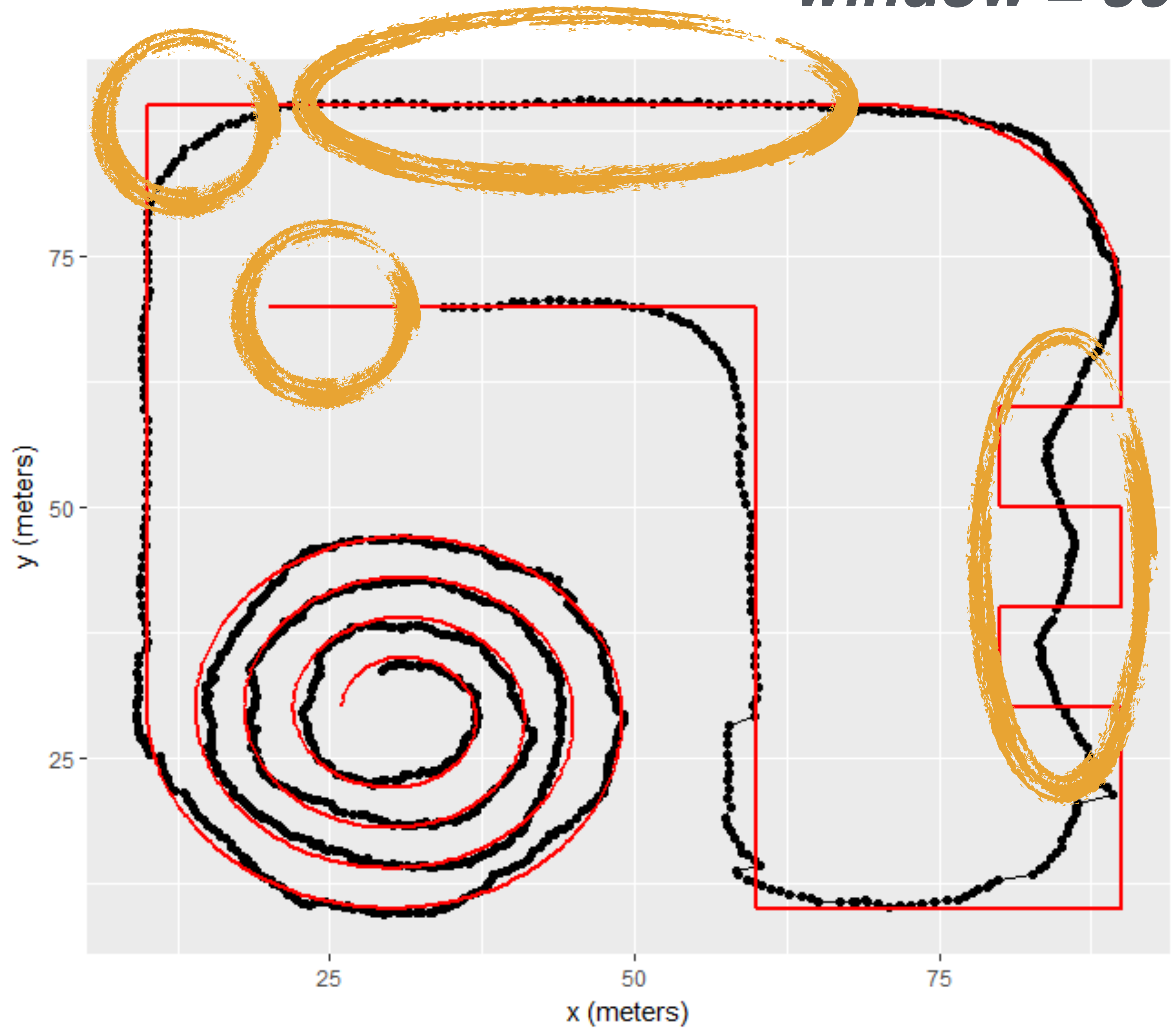




Mean Filter

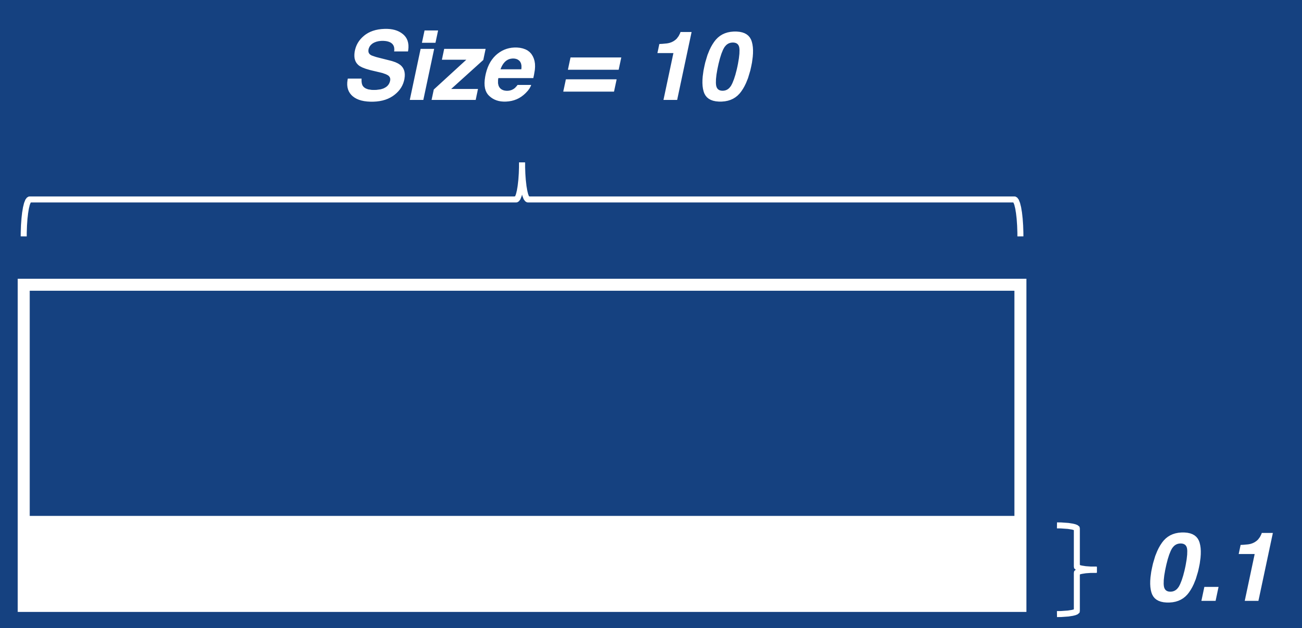
window = 30





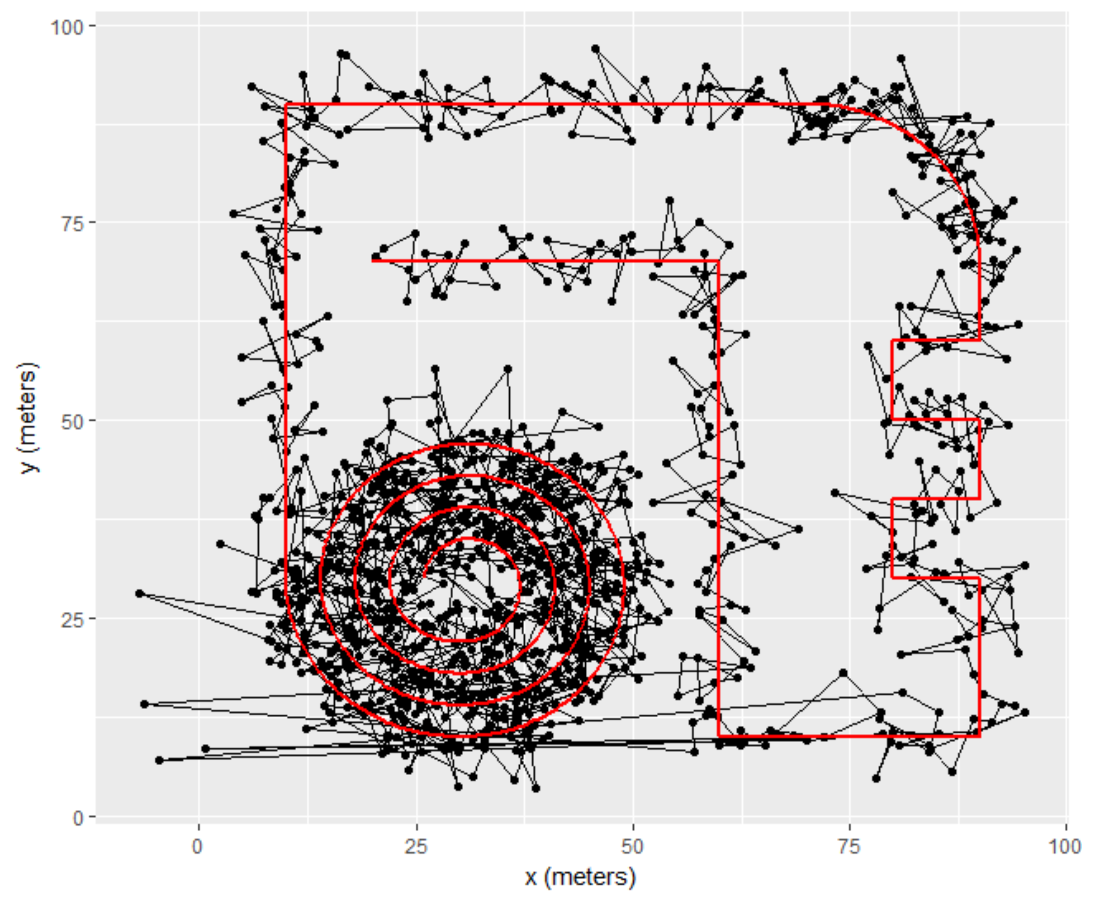
Mean Filter

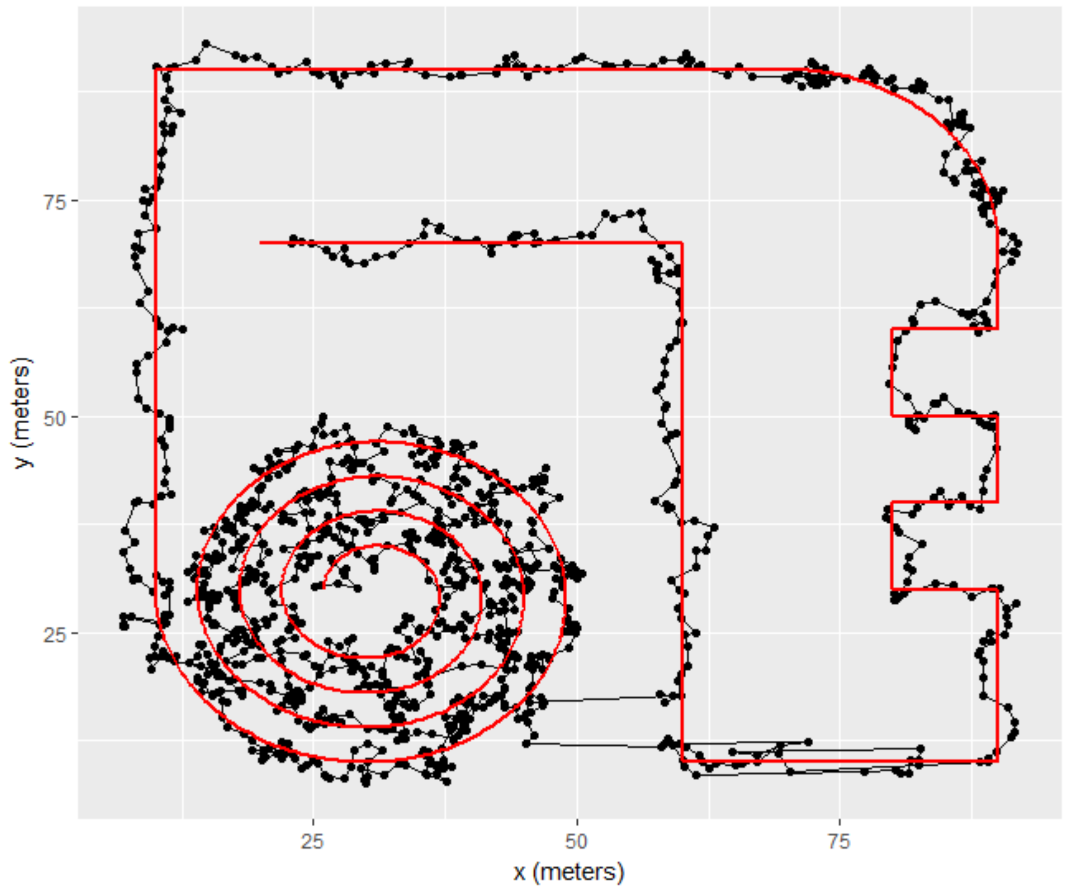
Mean Filter

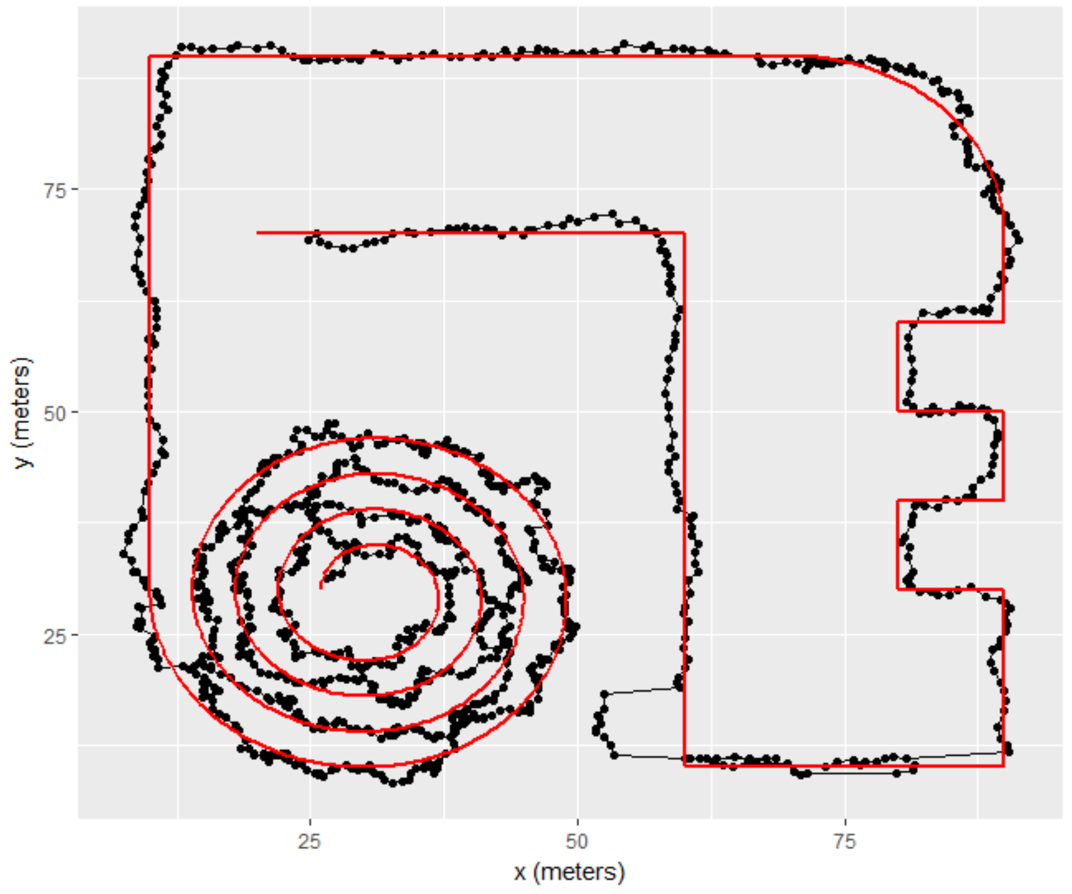


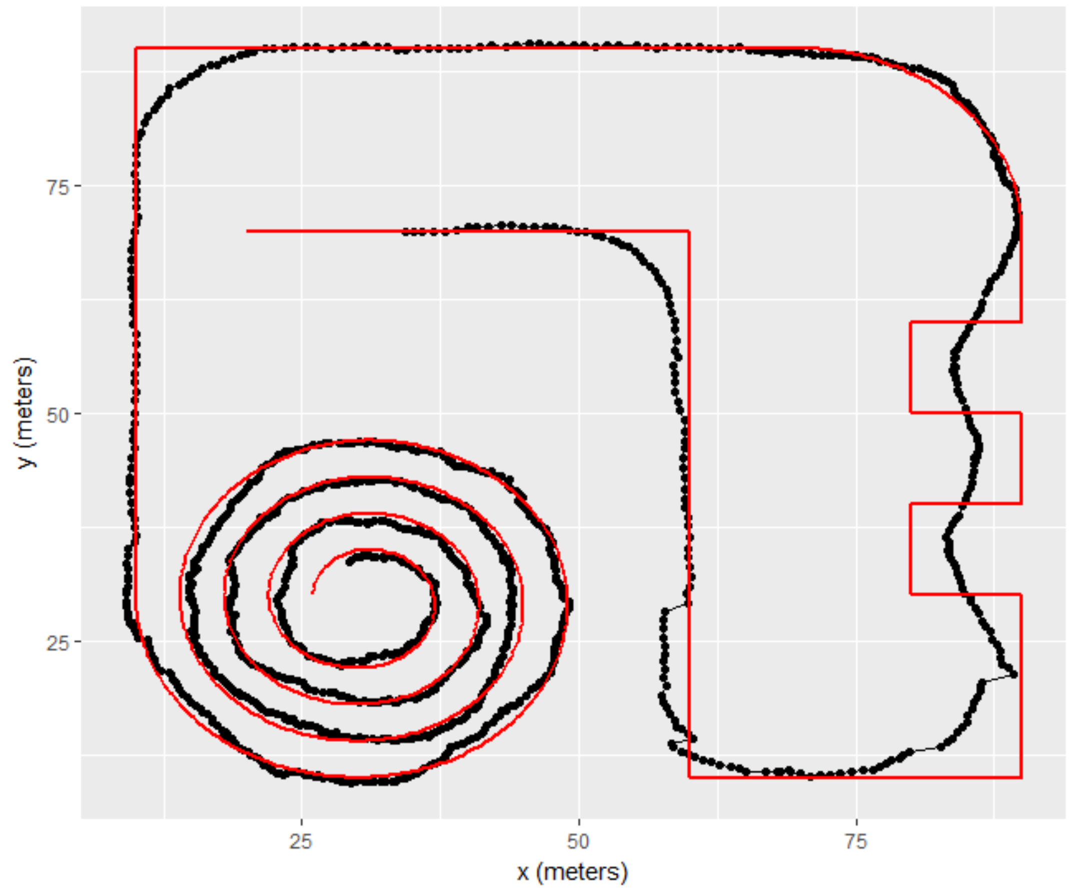
Uniform mean

Weighted mean



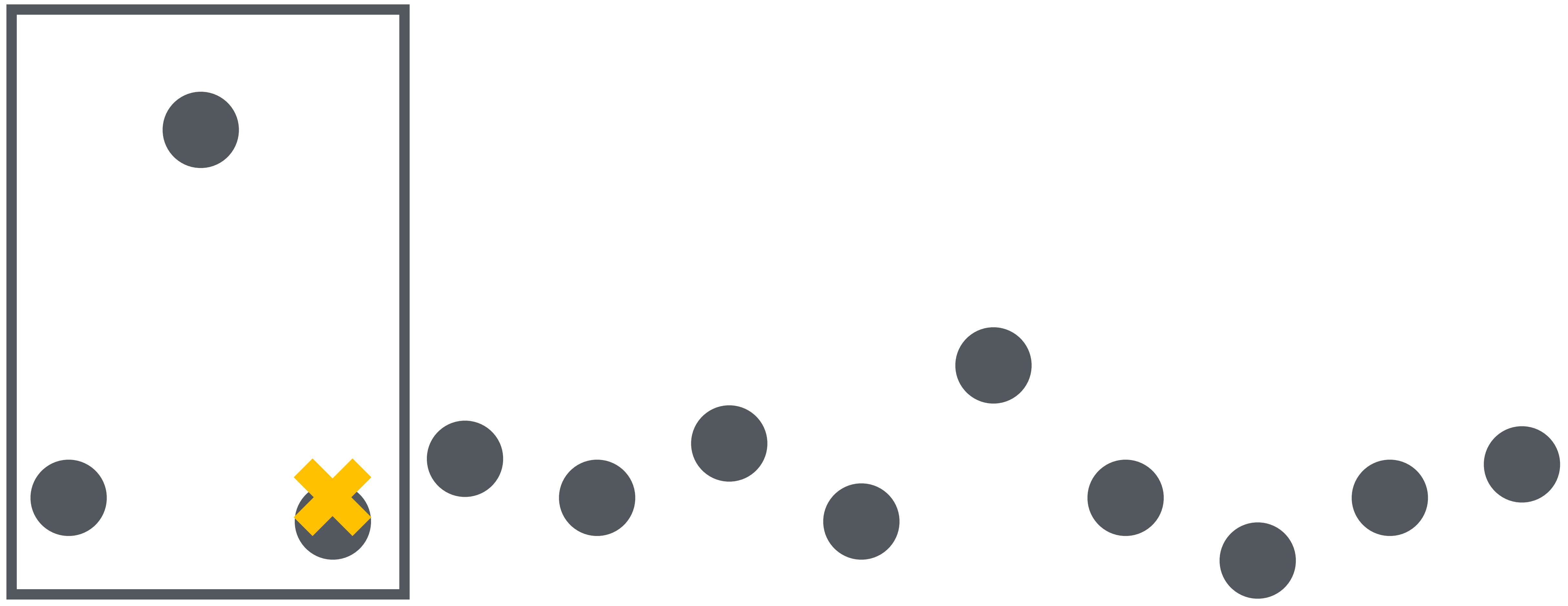




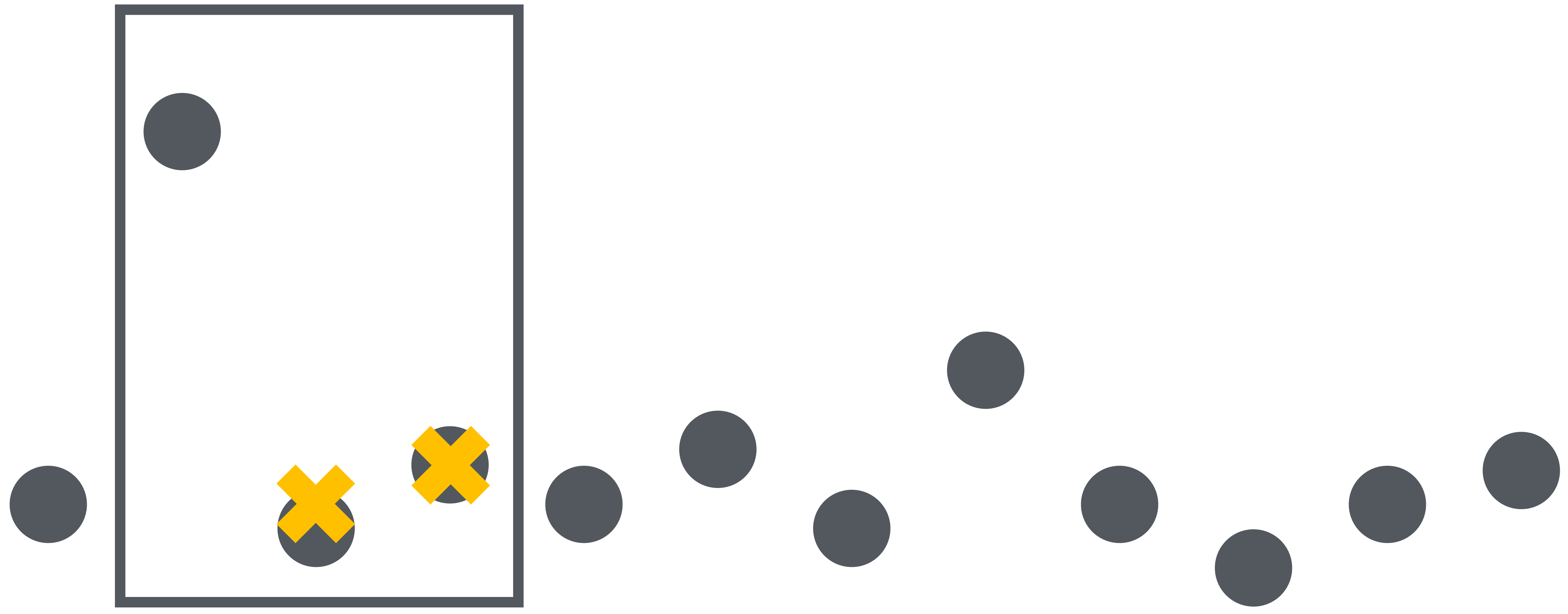


Median Filter

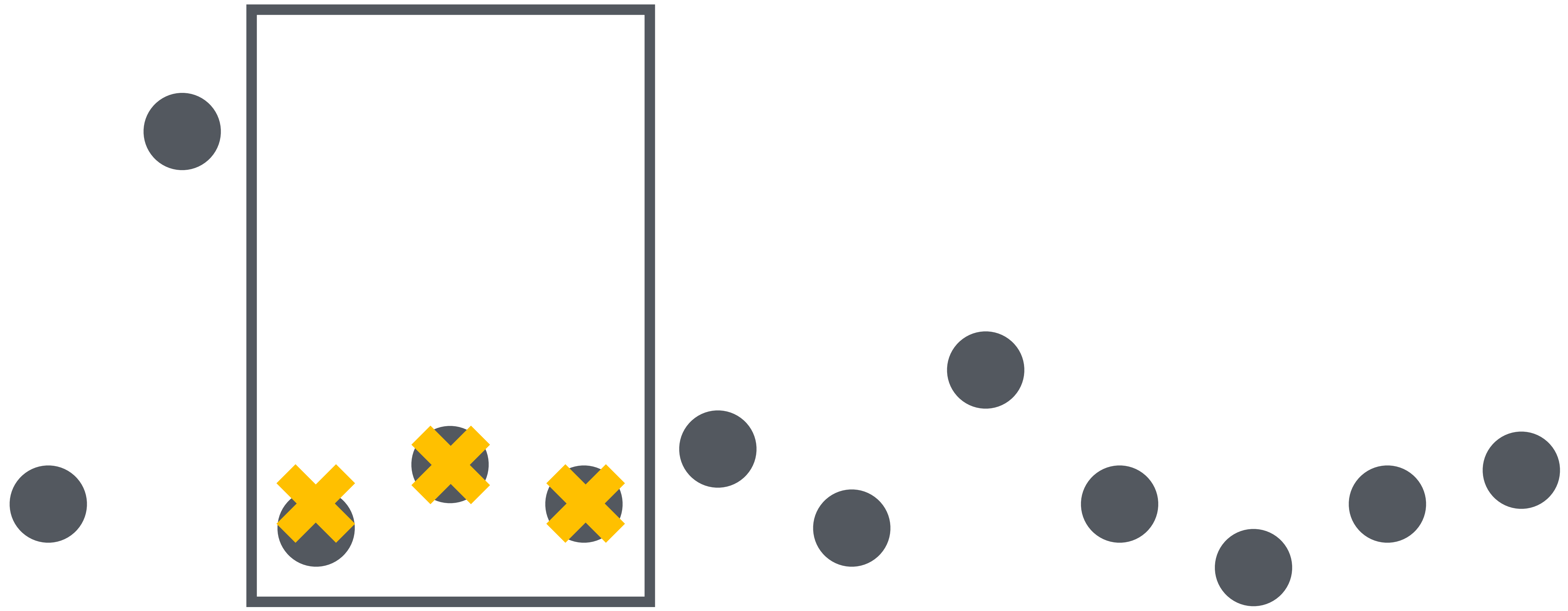
Median Filter



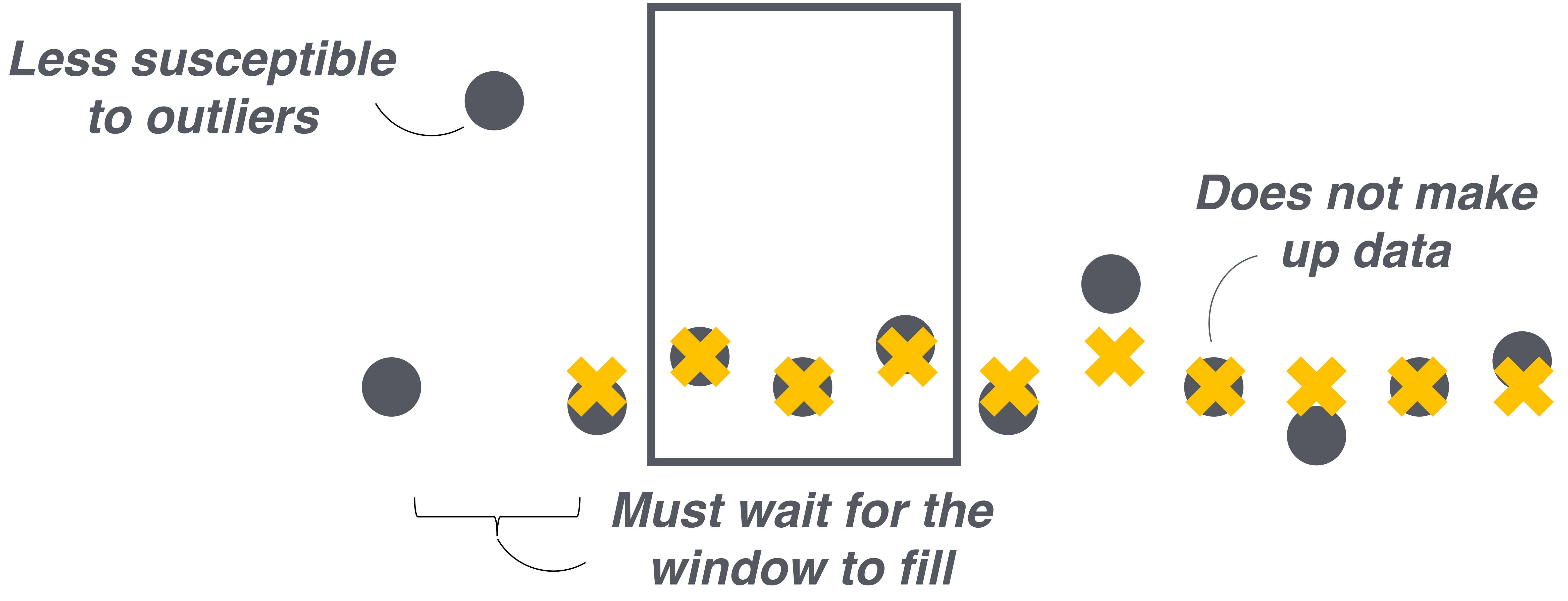
Median Filter



Median Filter

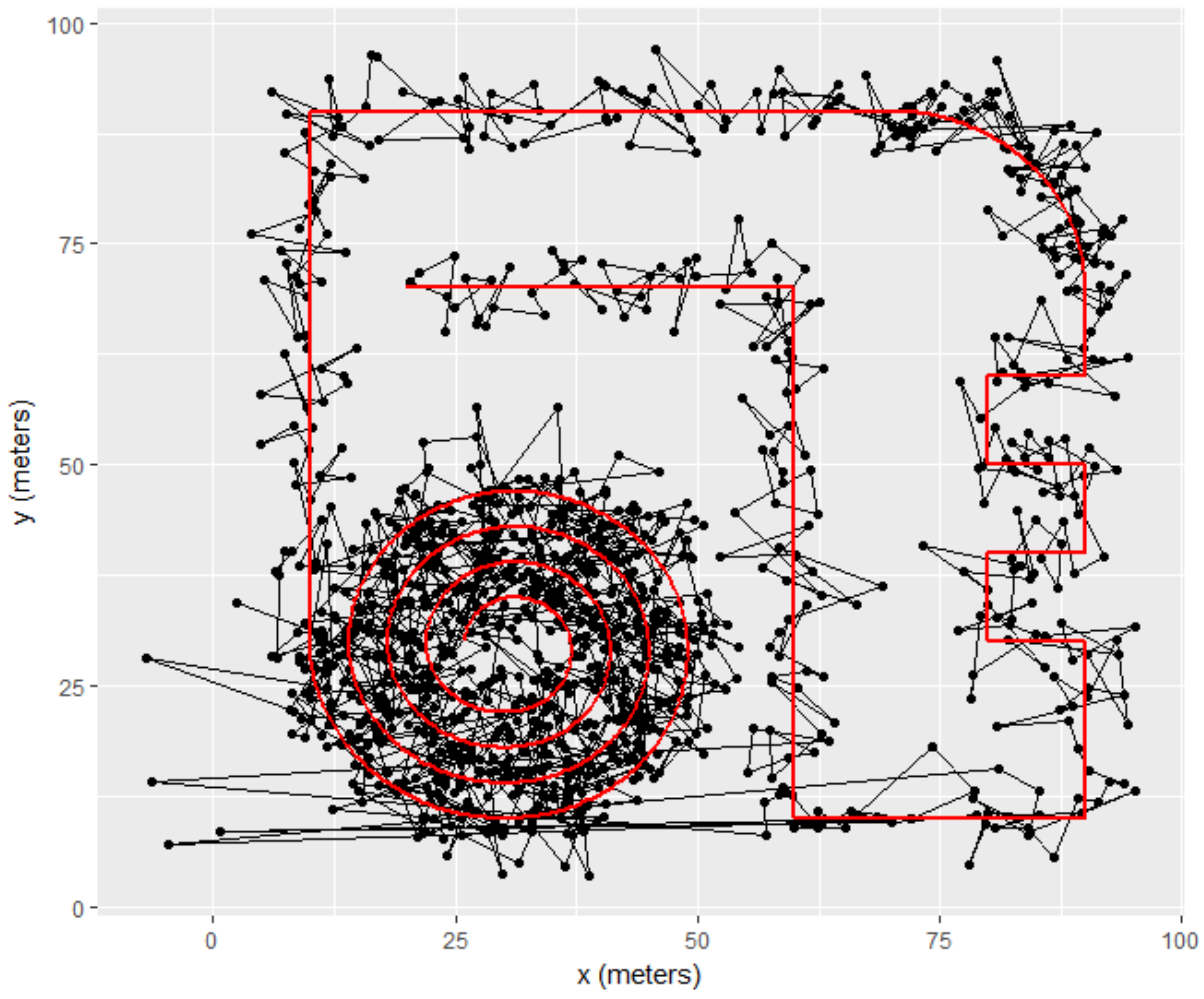


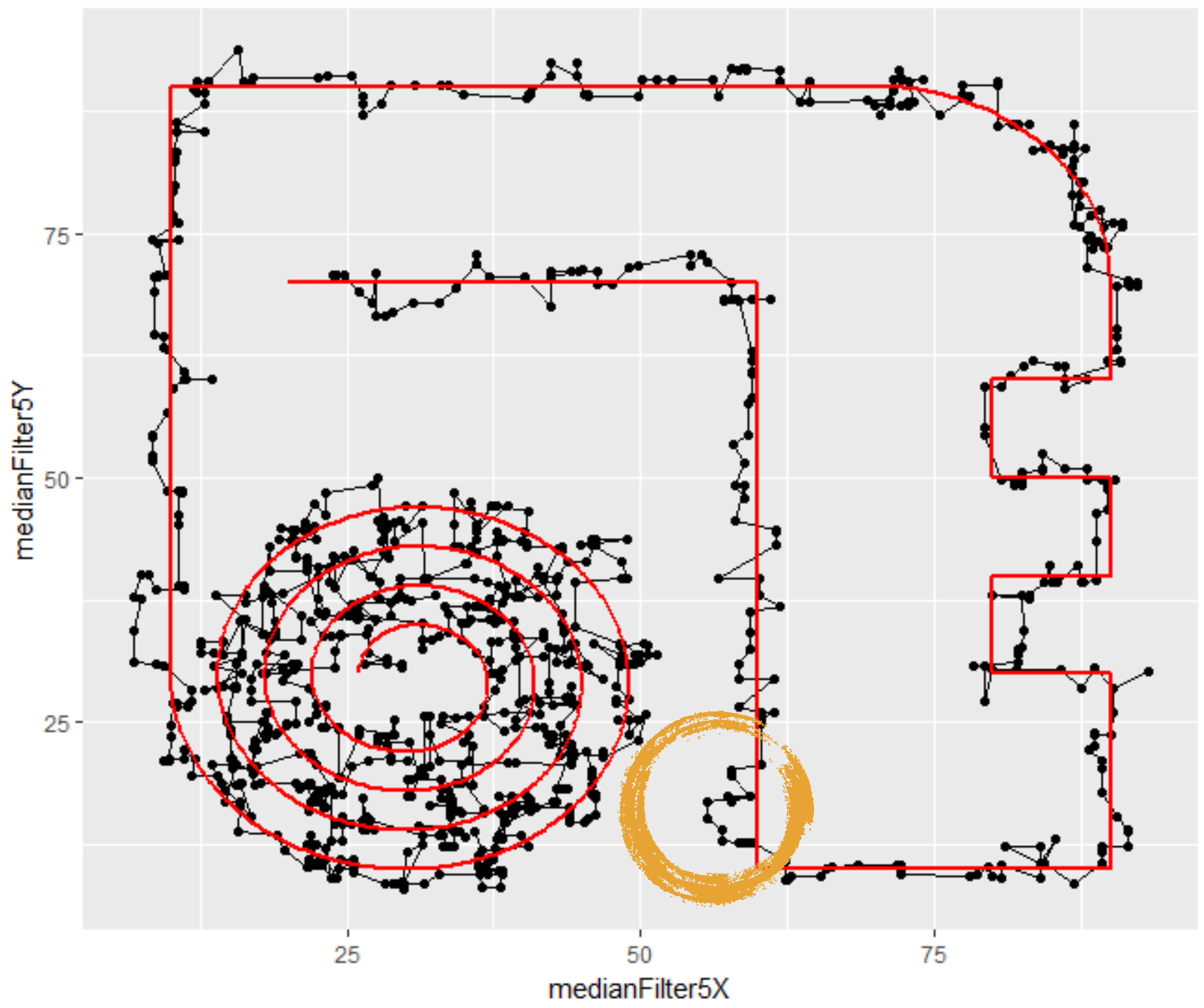
Median Filter



Median Filter

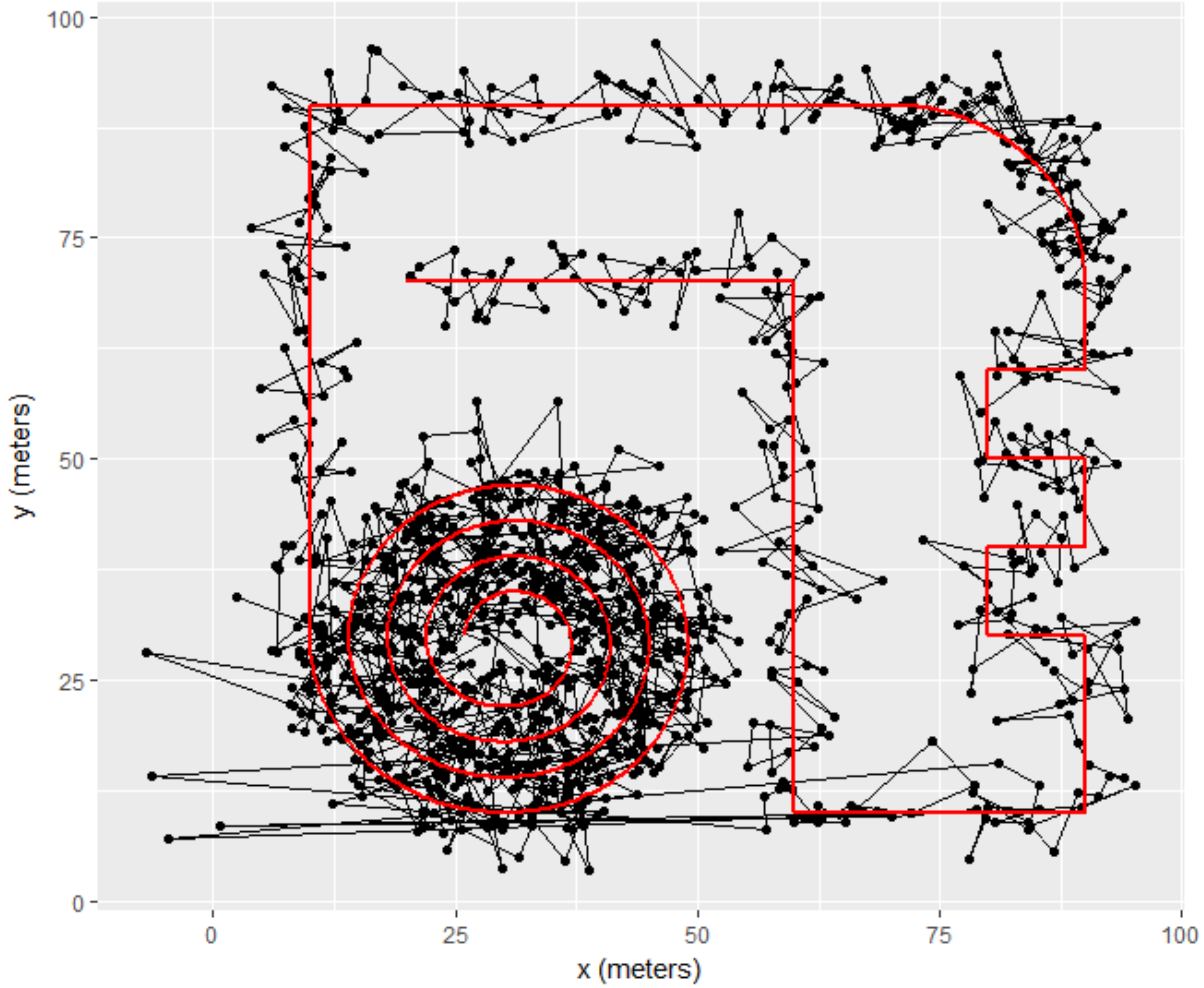
window = 5

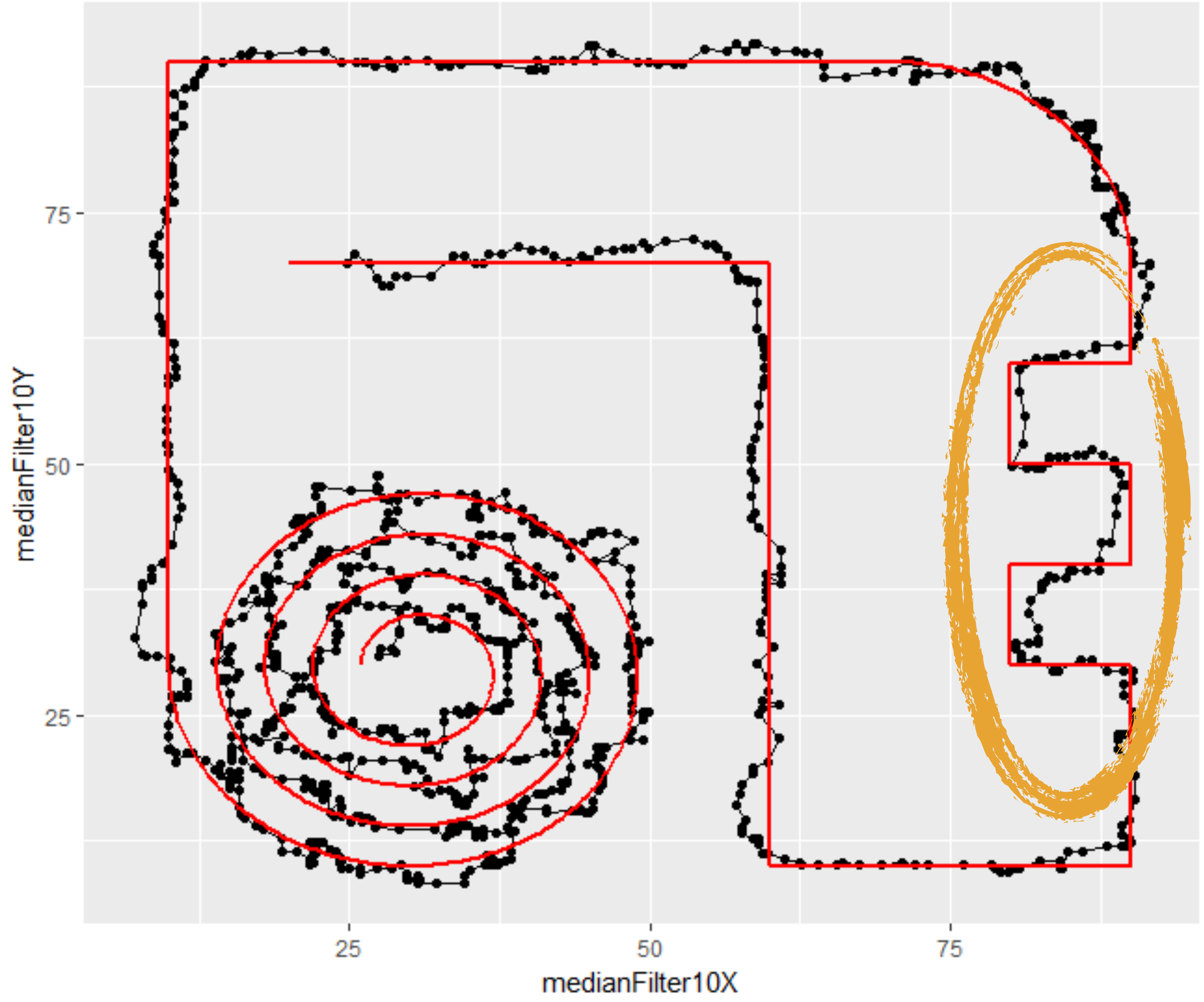




Median Filter

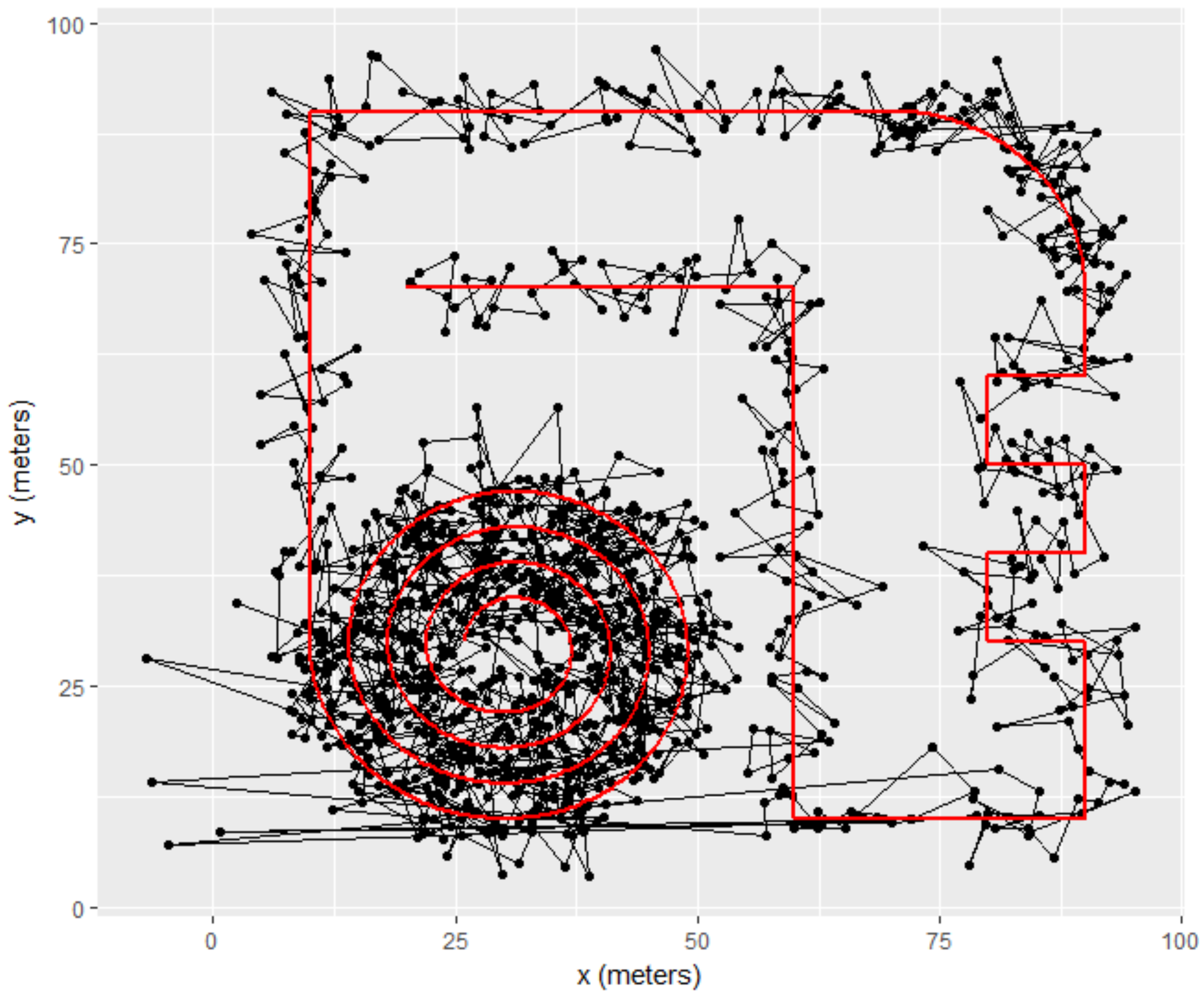
window = 10





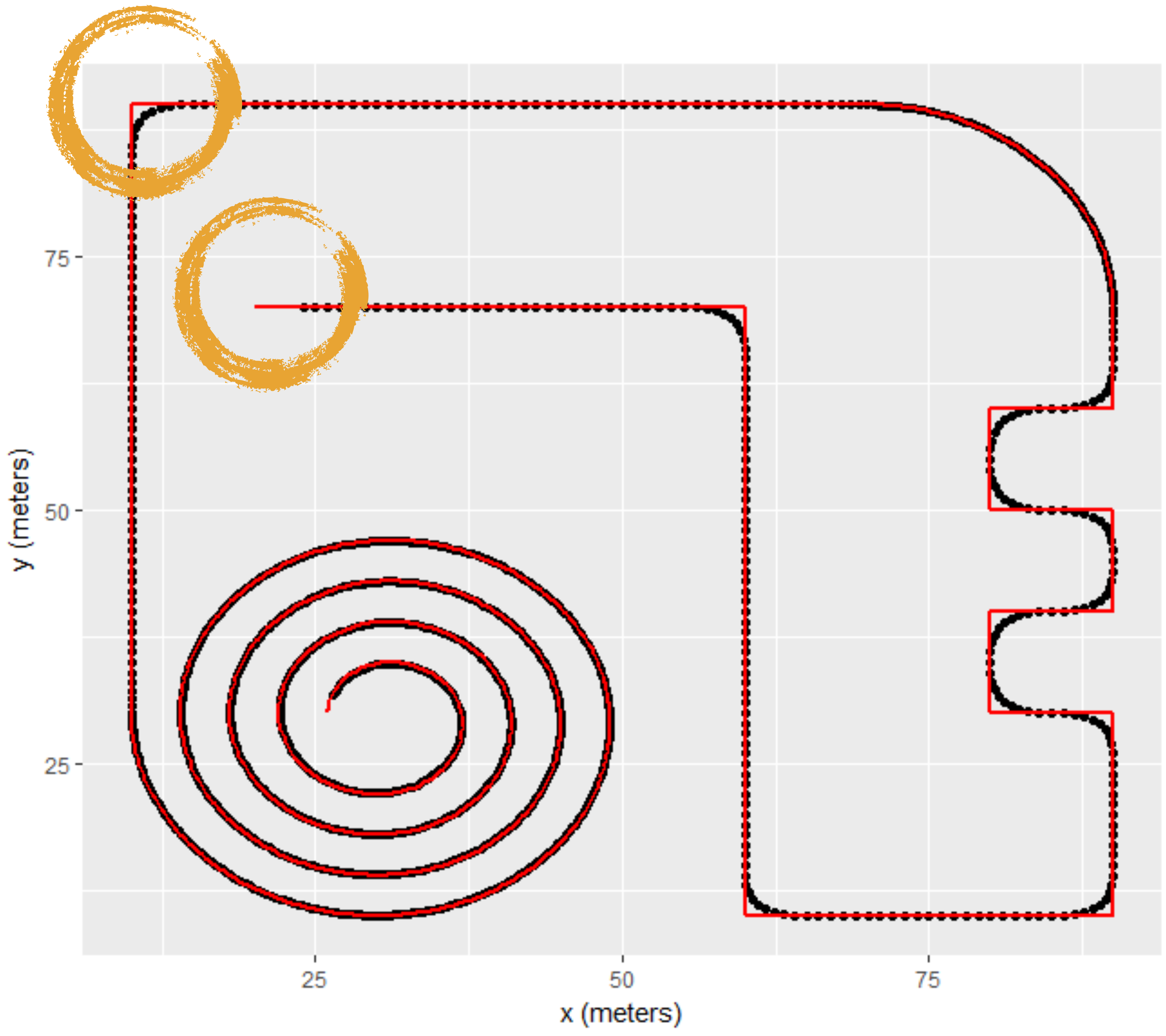
Median Filter

window = 30

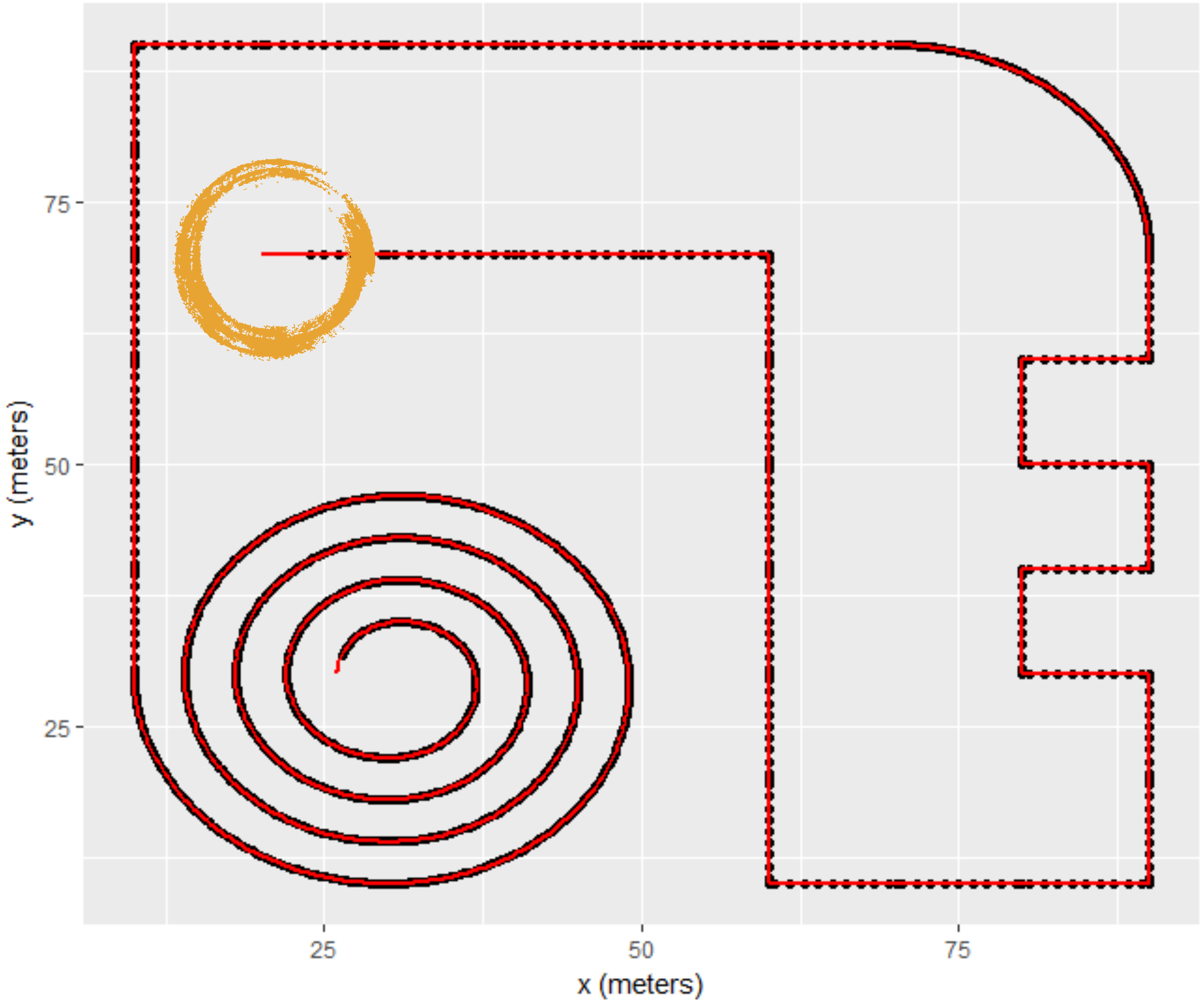


Median Filter

Mean



Median



Comparison on Ground Truth Data

Mean/Median Filter

+ easy to implement

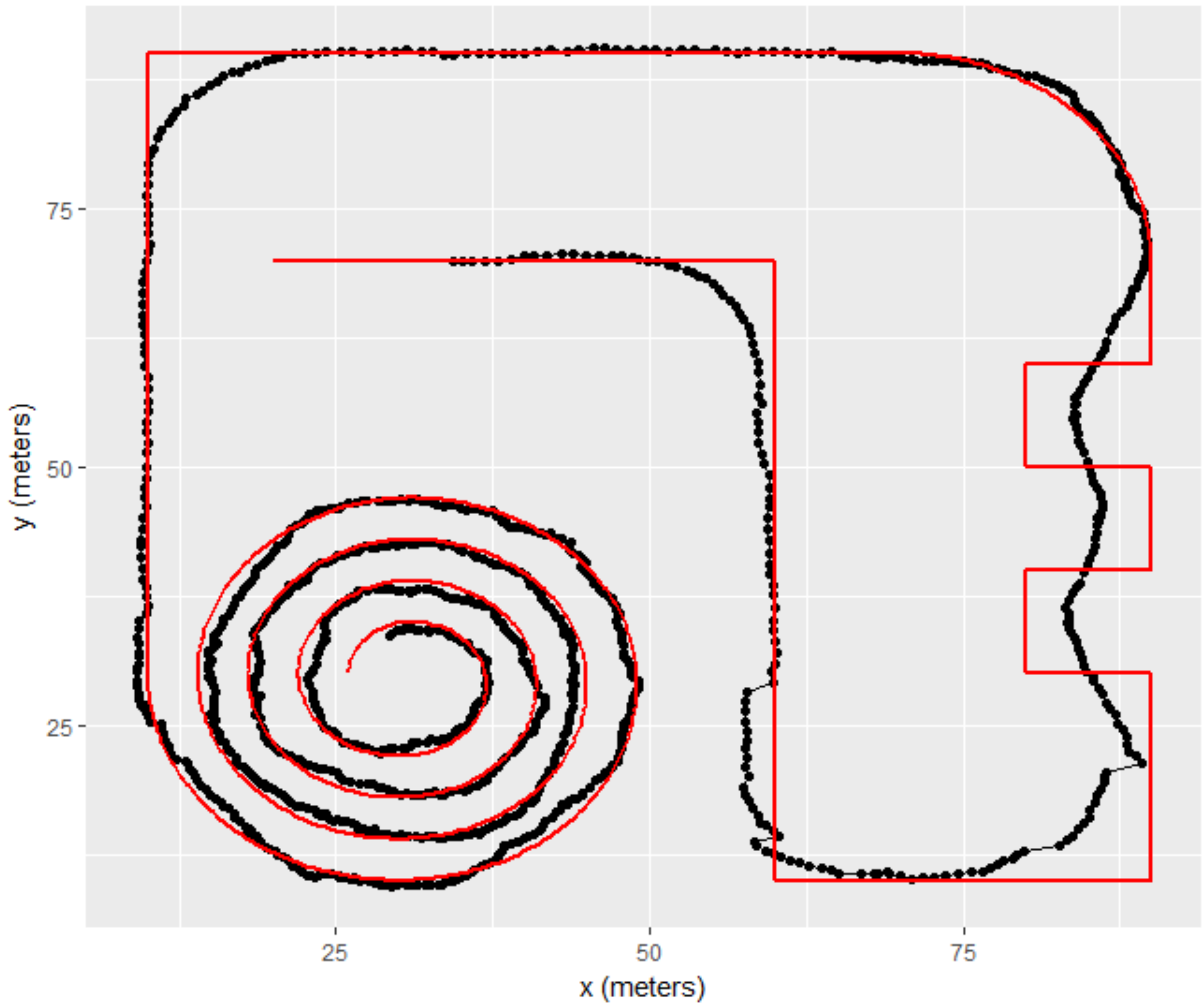
+ efficient

+ great cost-benefit

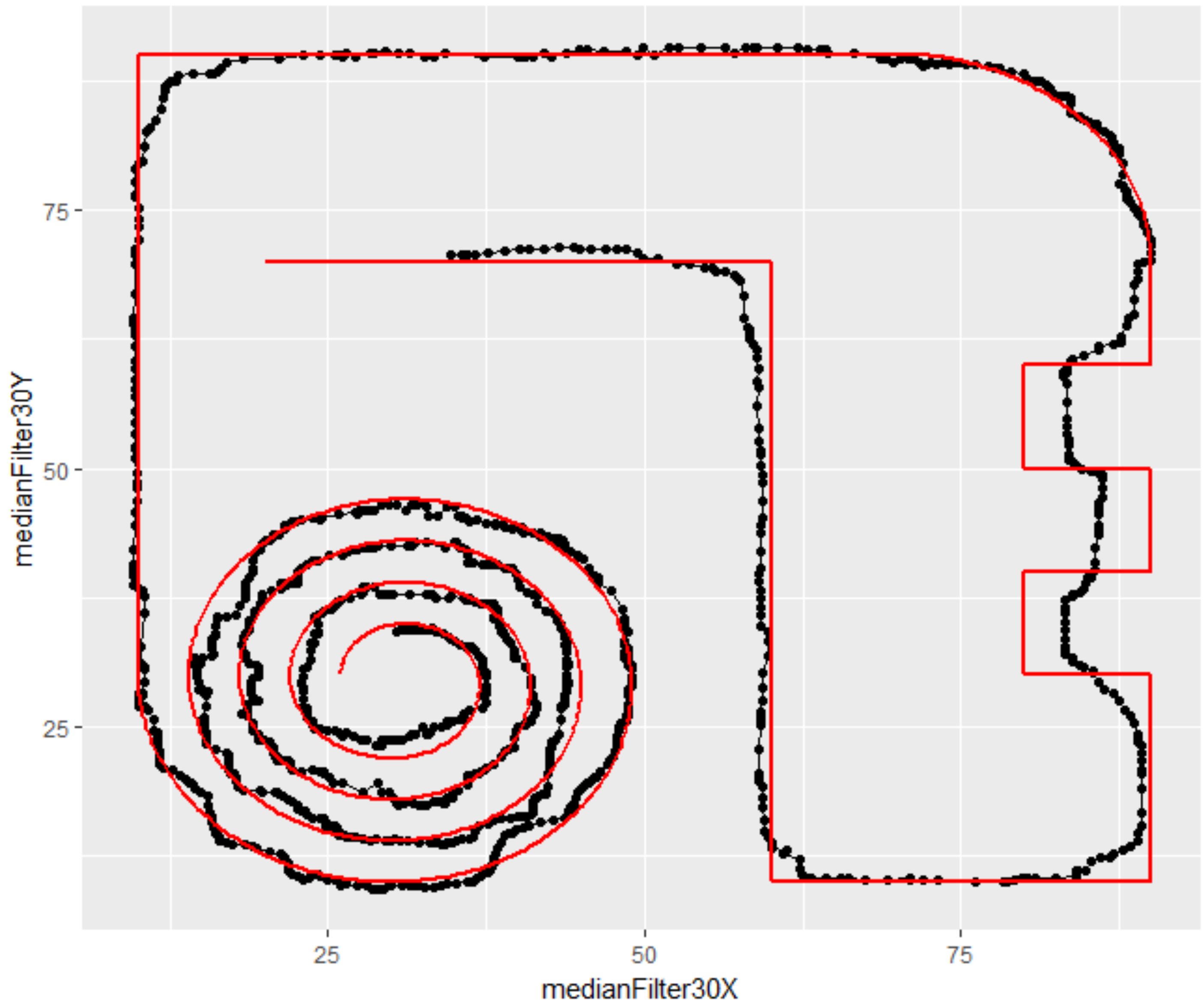
- laggy

- no dynamic model

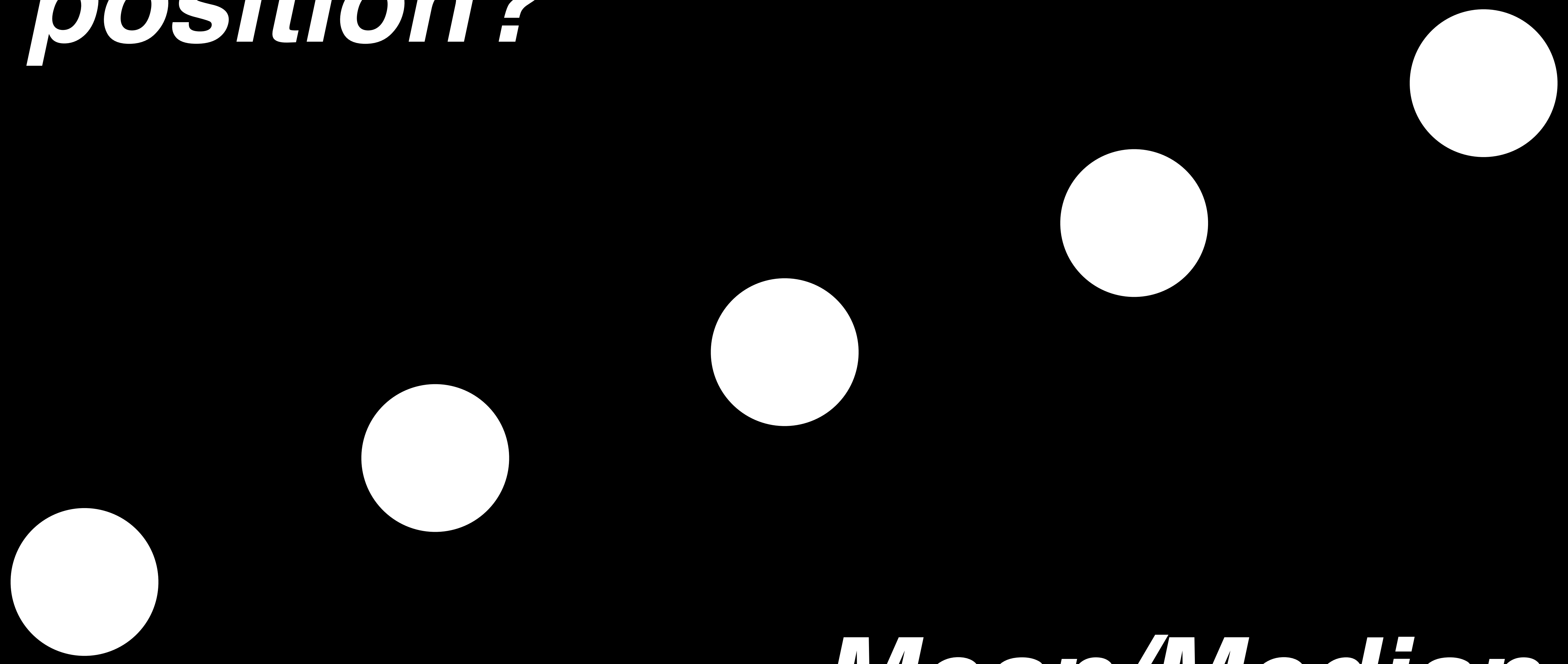
Mean



Median



Where is the next position?



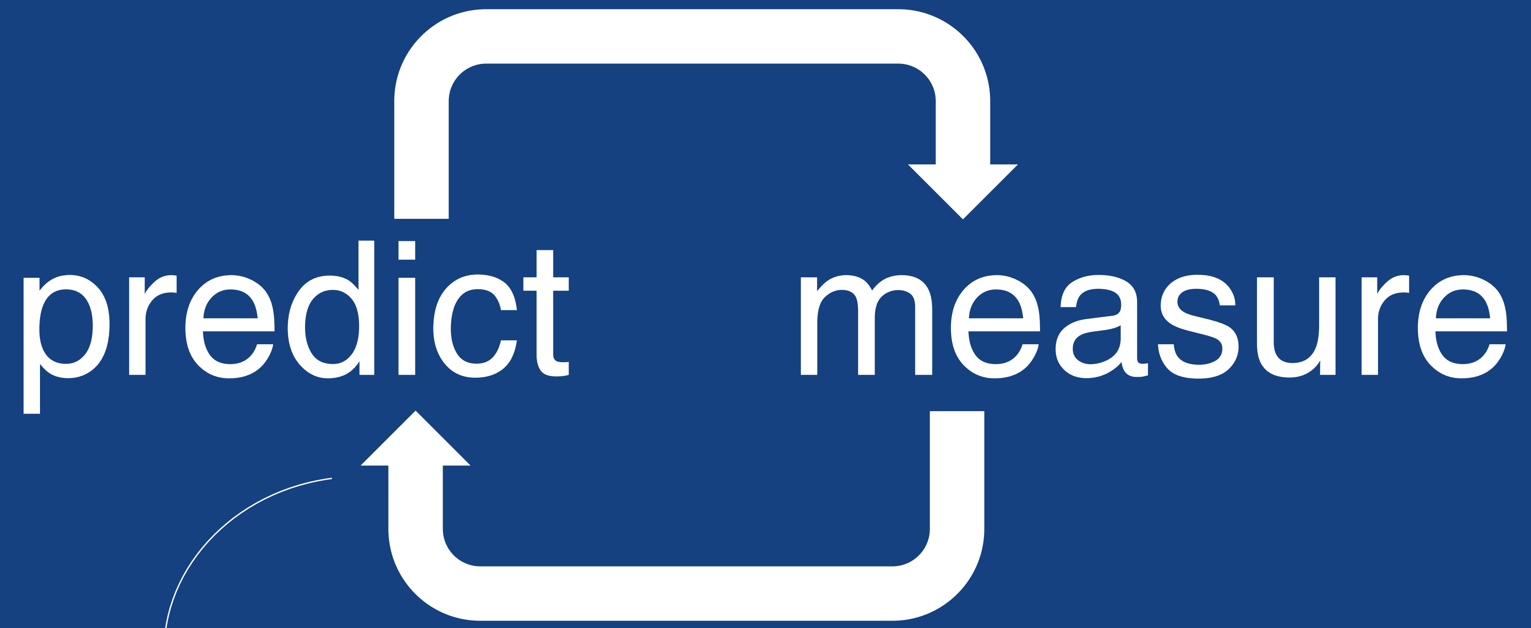
○ A
○ B
○ C
○ D

Mean/Median Filters' assumption:

Trajectory is smooth

Kalman Filter

Rudolf Emil Kálmán
(1930 - 2016)



Assumptions about behaviour!

https://en.wikipedia.org/wiki/Rudolf_E._Kálmán

Kalman Filter

Measurement

$$zi = \begin{pmatrix} z_i^{(x)} \\ z_i^{(y)} \end{pmatrix}$$

State

$$x_i = \begin{pmatrix} x_i \\ y_i \\ v_i^{(x)} \\ v_i^{(y)} \end{pmatrix} \begin{array}{l} \left.\vphantom{\begin{matrix} x \\ y \end{matrix}}\right\} \textit{positions} \\ \left.\vphantom{\begin{matrix} x \\ y \end{matrix}}\right\} \textit{velocities} \end{array}$$

Variables that are not measured directly

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\boldsymbol{H}$$

$$\boldsymbol{z_i = x_i + v_i}$$

Kalman Filter

Measurement $zi = \begin{pmatrix} z_i^{(x)} \\ z_i^{(y)} \end{pmatrix}$

State

$$x_i = \begin{pmatrix} x_i \\ y_i \\ v_i^{(x)} \\ v_i^{(y)} \end{pmatrix} \begin{matrix} \left.\begin{matrix} \\ \\ \end{matrix}\right\} \text{positions} \\ \left.\begin{matrix} \\ \\ \end{matrix}\right\} \text{velocities} \end{matrix}$$

Variables that are not measured directly

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Noise $vi \sim N(0,\mathrm{Ri})$ $\quad Ri = \begin{bmatrix} \sigma 2 & 0 \\ 0 & \sigma 2 \end{bmatrix}$

$$z_i = Hx_i + v_i$$

Modelling the Dynamics

$$\begin{pmatrix} x_i \\ y_i \\ v_i^{(x)} \\ v_i^{(y)} \end{pmatrix} \Leftarrow \begin{pmatrix} x_{i-1} \\ y_{i-1} \\ v_{i-1}^{(x)} \\ v_{i-1}^{(y)} \end{pmatrix}$$

$$\mathbf{x}_i \Leftarrow \mathbf{x}_{i-1}$$

Modelling the Dynamics

$$\begin{pmatrix} x_i \\ y_i \\ v_i^{(x)} \\ v_i^{(y)} \end{pmatrix} \Leftarrow \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} x_{i-1} \\ y_{i-1} \\ v_{i-1}^{(x)} \\ v_{i-1}^{(y)} \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ N(0, \sigma_s) \\ N(0, \sigma_s) \end{pmatrix}$$

$$x_i = x_{i-1} + v_{i-1}\Delta t$$
$$v_i = v_{i-1}$$

Newtonian Velocity

$$\mathbf{x}_i \Leftarrow \mathbf{x}_{i-1}$$

Modelling the Dynamics

$$\begin{pmatrix} x_i \\ y_i \\ v_i^{(x)} \\ v_i^{(y)} \end{pmatrix} \Leftarrow \underbrace{\begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\phi_{i-1}} \begin{pmatrix} x_{i-1} \\ y_{i-1} \\ v_{i-1}^{(x)} \\ v_{i-1}^{(y)} \end{pmatrix} + \underbrace{\begin{pmatrix} 0 \\ 0 \\ N(0,\sigma_s) \\ N(0,\sigma_s) \end{pmatrix}}_{w_{i-1}}$$

$$w_{i-1} \sim N(0, Qi) \qquad Qi = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_s^2 & 0 \\ 0 & 0 & 0 & \sigma_s^2 \end{bmatrix}$$

$$\mathbf{x}_i \Leftarrow \mathbf{x}_{i-1}$$

Modelling the Dynamics

Putting it all together…

Measurement matrix

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Dynamics of states

$$\phi_{i-1} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Measurement noise

$$vi \sim N(0,\mathrm{Ri})$$

Dynamic noise

$$w_{i-1} \sim N(0,Qi)$$

$$\boldsymbol{x_i} \leftarrow \boldsymbol{x_{i-1}}$$

Modelling the Dynamics

Putting it all together…

Initial state estimate

$$x_0 = \begin{pmatrix} x_0 \\ y_0 \\ v_0^{(x)} \\ v_0^{(y)} \end{pmatrix} = \underbrace{\begin{pmatrix} z_0^{(x)} \\ z_0^{(y)} \\ 0 \\ 0 \end{pmatrix}}$$

e.g. First measurement of position

and zero velocity

Initial estimate of state error covariance

$$P_0 = \begin{bmatrix} \sigma^2 & 0 & 0 & 0 \\ 0 & \sigma^2 & 0 & 0 \\ 0 & 0 & \sigma_s^2 & 0 \\ 0 & 0 & 0 & \sigma_s^2 \end{bmatrix}$$

$$\mathbf{x}_i \Leftarrow \mathbf{x}_{i-1}$$

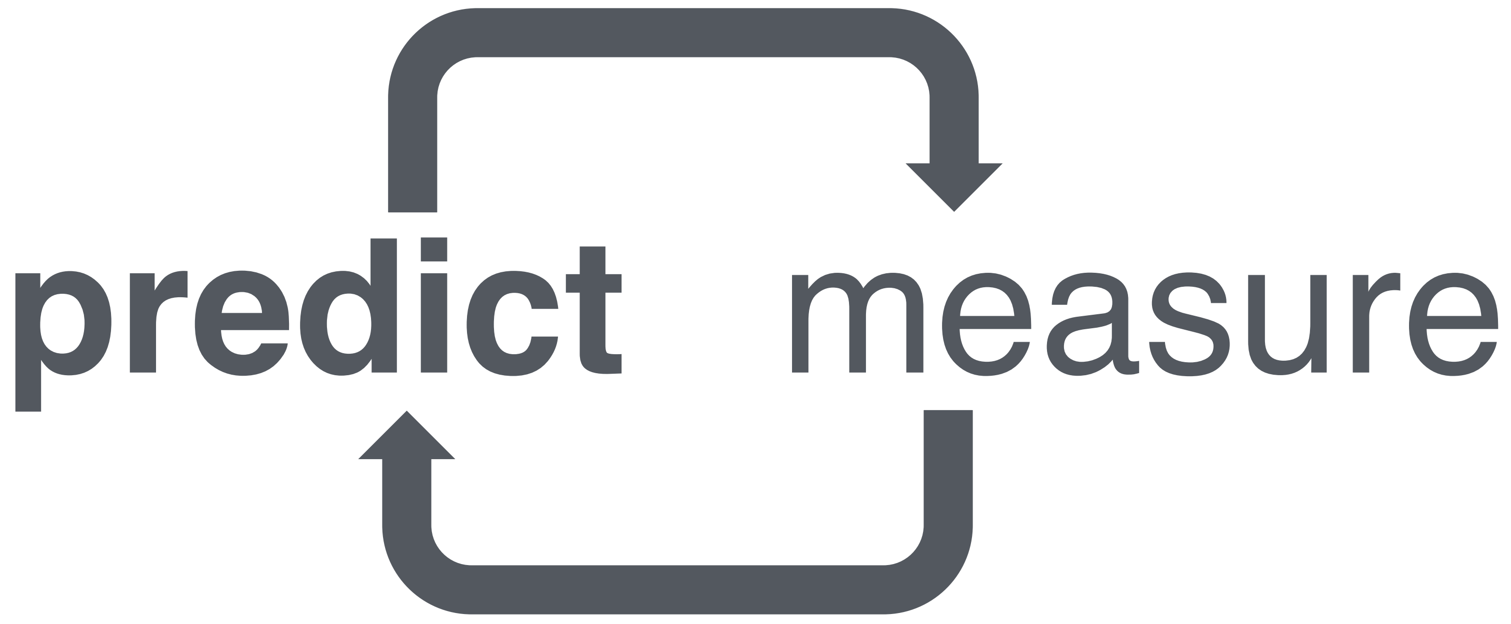
Step 1: Predicting States

1. Extrapolate the state:

$$x_i^{predicted} = \phi_{i-1}\, x_{i-1}^{corrected}$$

2. Extrapolate the state error covariance:

$$P_i^{predicted} = \phi_{i-1}\, P_{i-1}^{corrected}\, \phi_{i-1}^{T} + Q_{i-1}$$



Step 2: Measure

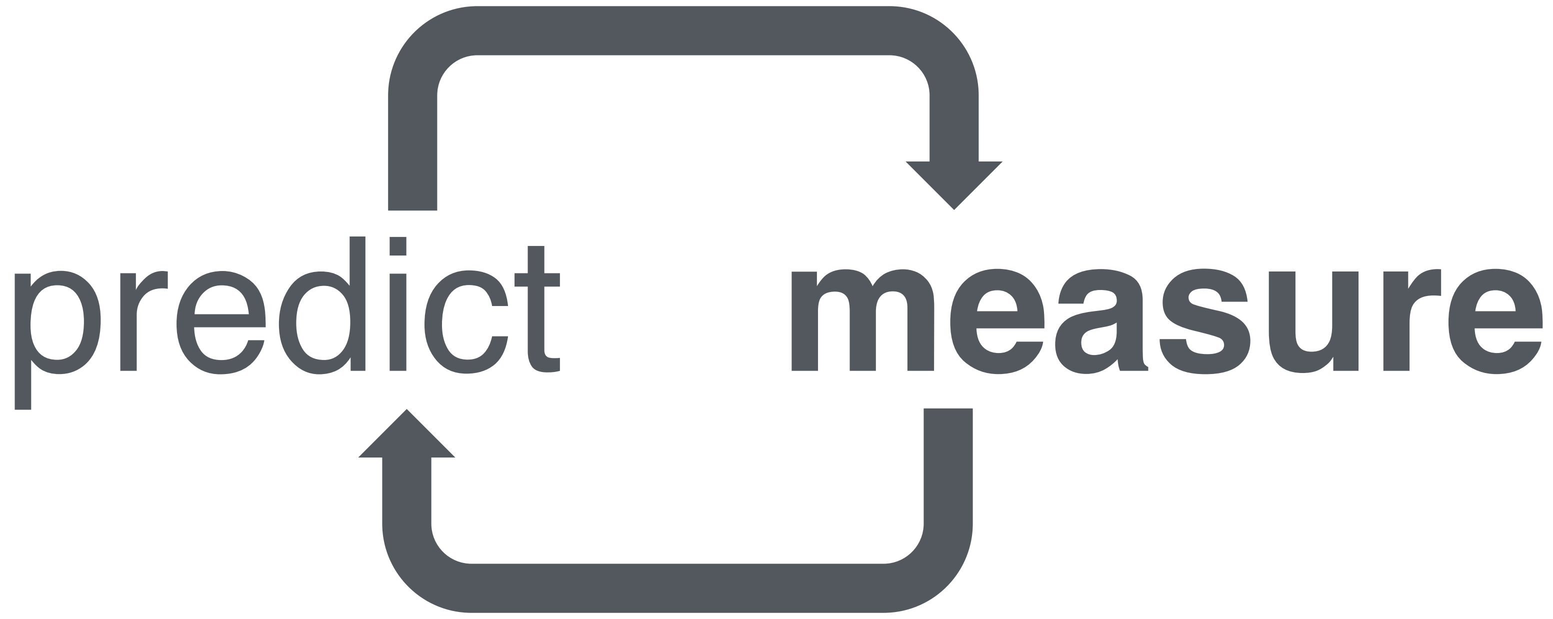
3. Compute the Kalman gain:

$$K_i = \frac{P_i^{predicted} H_i^T}{H_i P_i^{predicted} H_i^T + R_i}$$

Uncertainty propagated by the model

$$= H_i^{-1} \frac{H_i P_i^{predicted} H_i^T}{H_i P_i^{predicted} H_i^T + R_i}$$

Uncertainty from the measurement



Step 2: Measure

3. Compute the Kalman gain:

$$K_i = \frac{P_i^{predicted} H_i^T}{H_i P_i^{predicted} H_i^T + R_i}$$

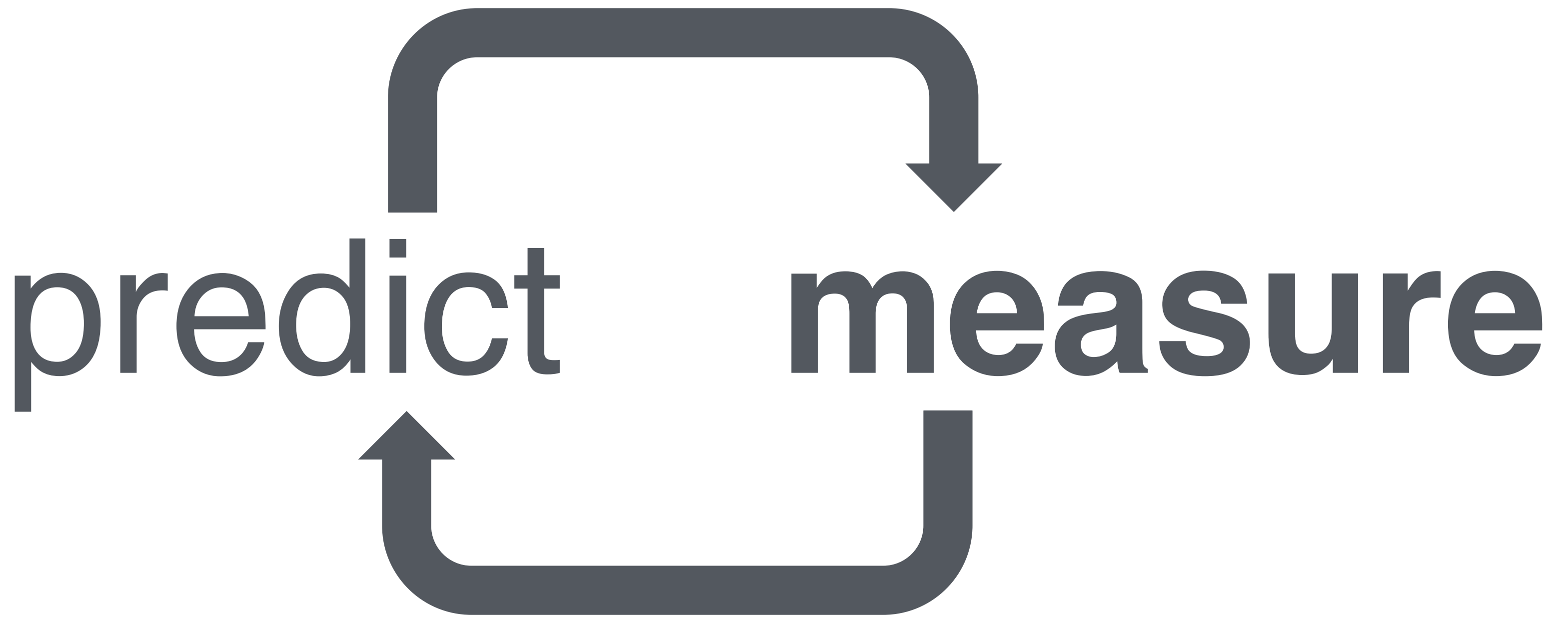
$$= H_i^{-1} \frac{H_i P_i^{predicted} H_i^T}{H_i P_i^{predicted} H_i^T + R_i}$$

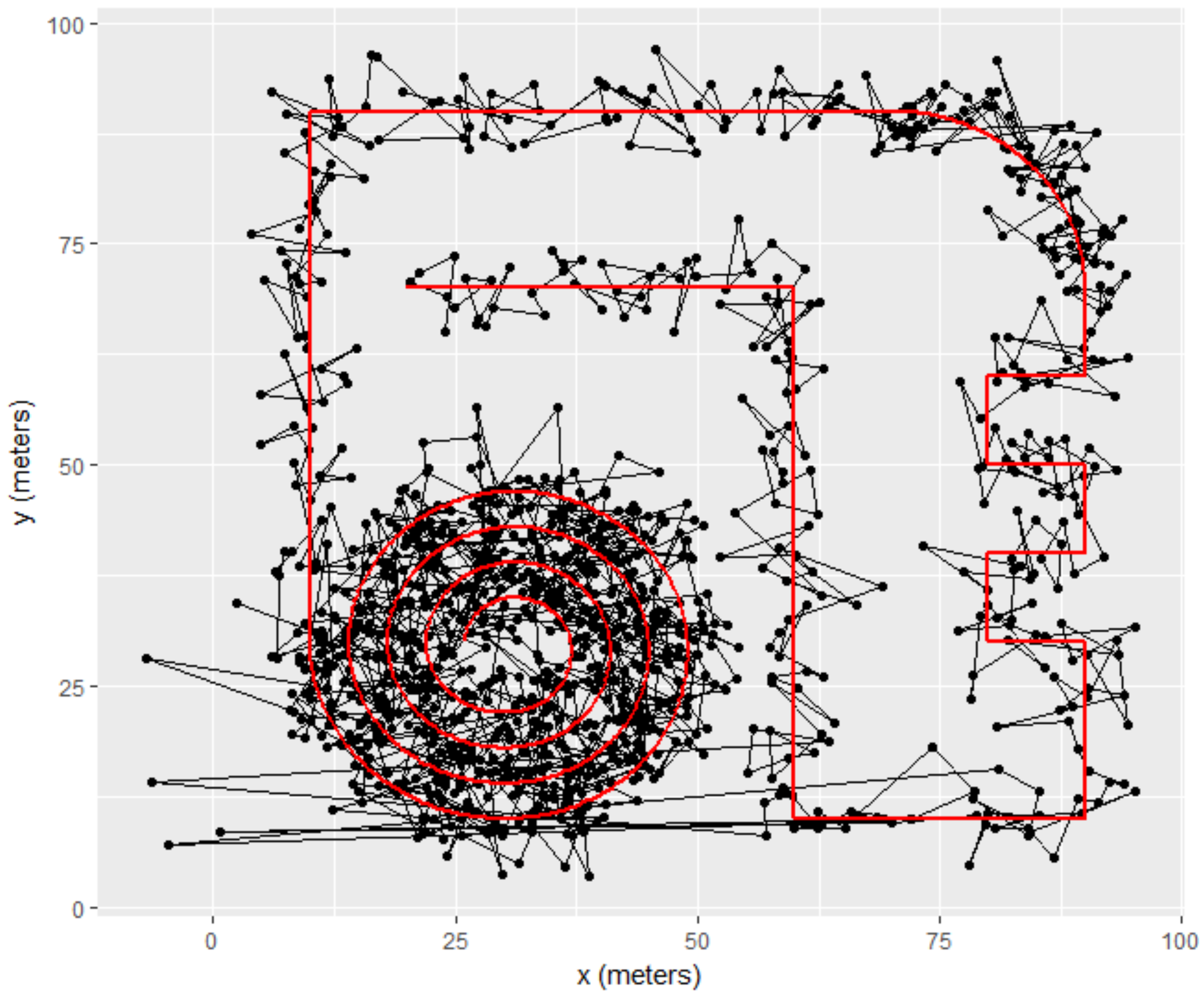
4. Update extrapolations with new measurements:

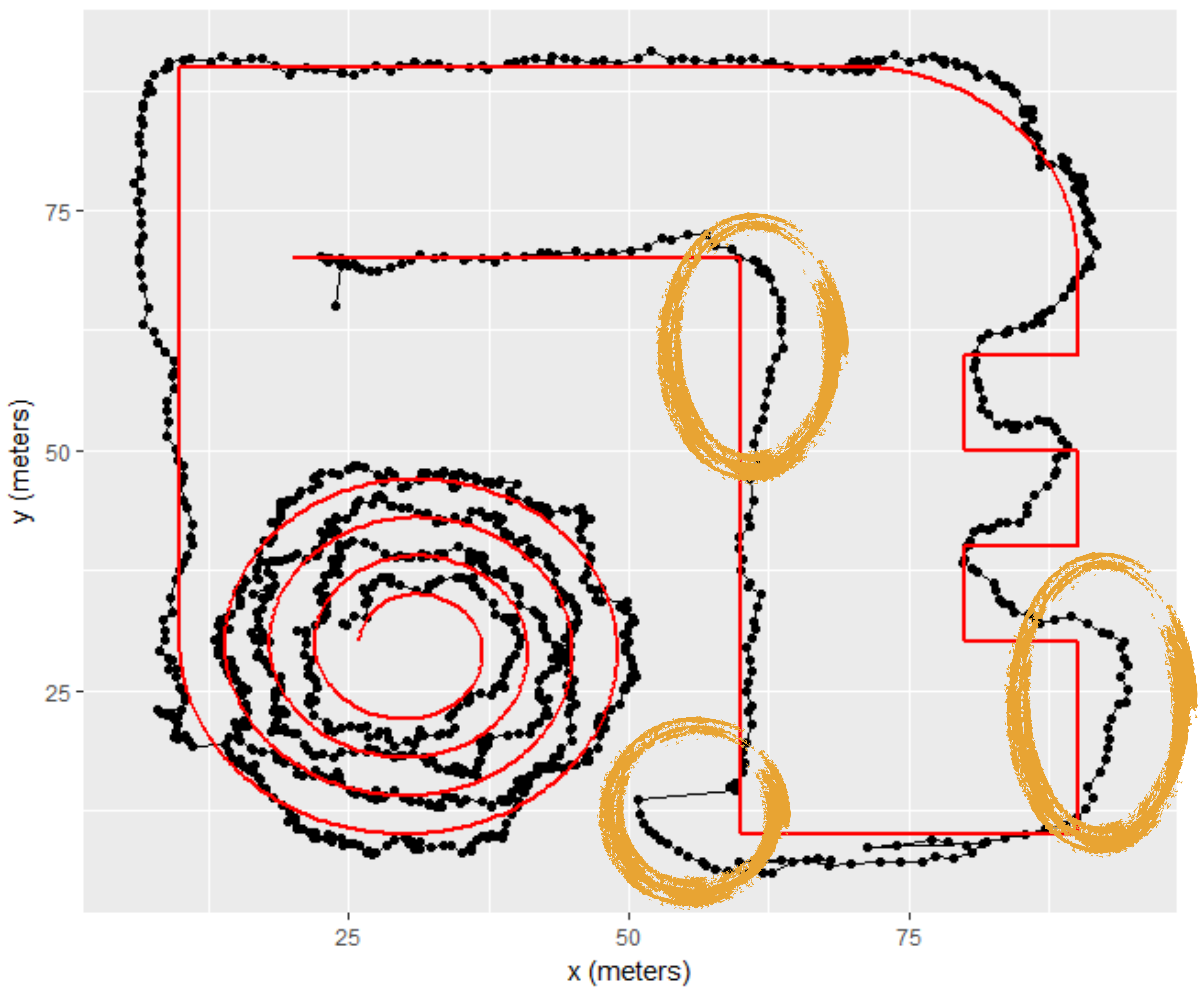
$$x_i^{corrected} = x_i^{predicted} + K_i \left(z_i - H_i x_i^{predicted} \right)$$

$$P_i^{corrected} = \left(I - K_i H_i \right) P_i^{predicted}$$

Identity







Kalman Filter

Kalman Filter

+ dynamic model of the system

+ no lag

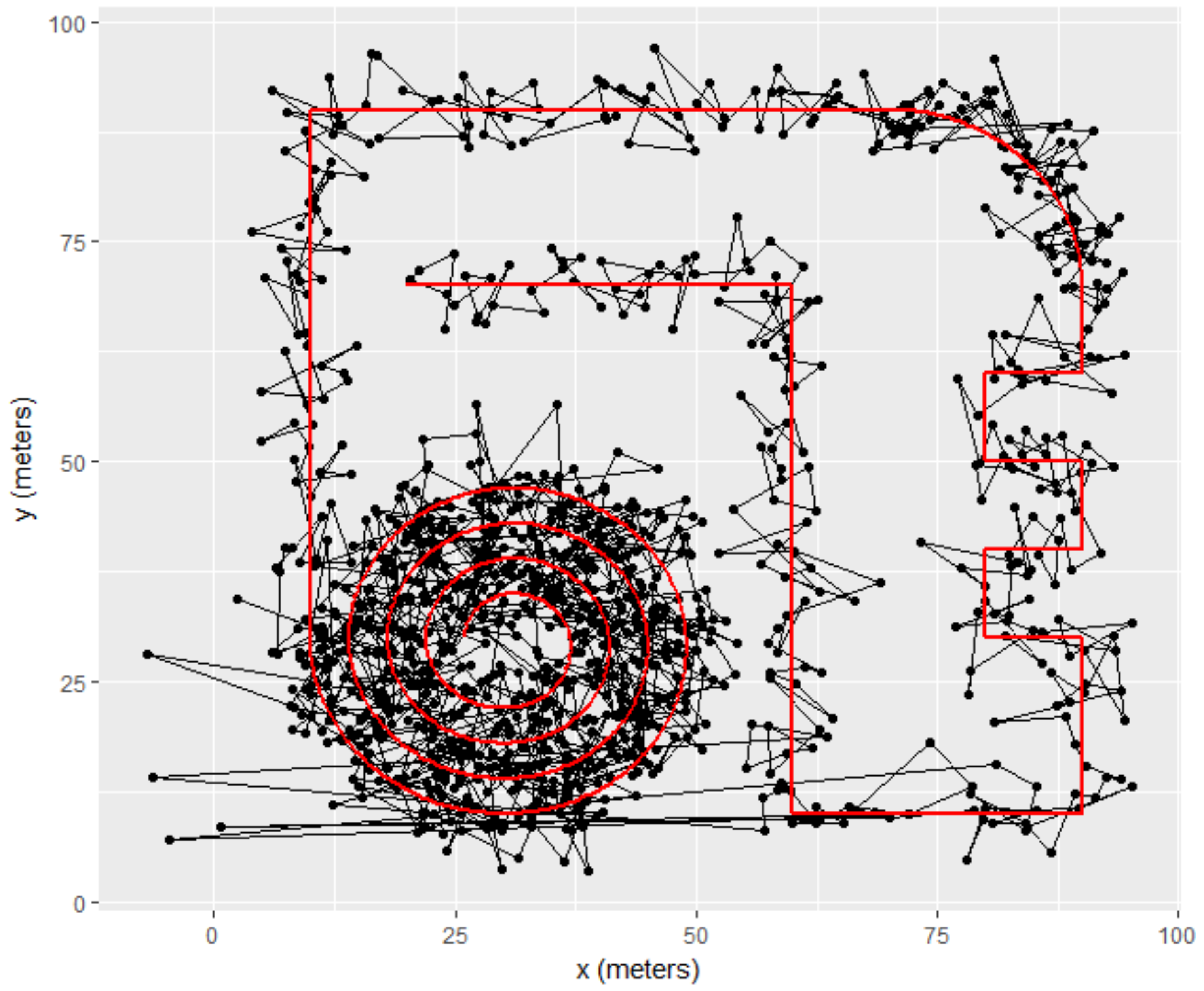
+ tunable tade-off between model and measurement

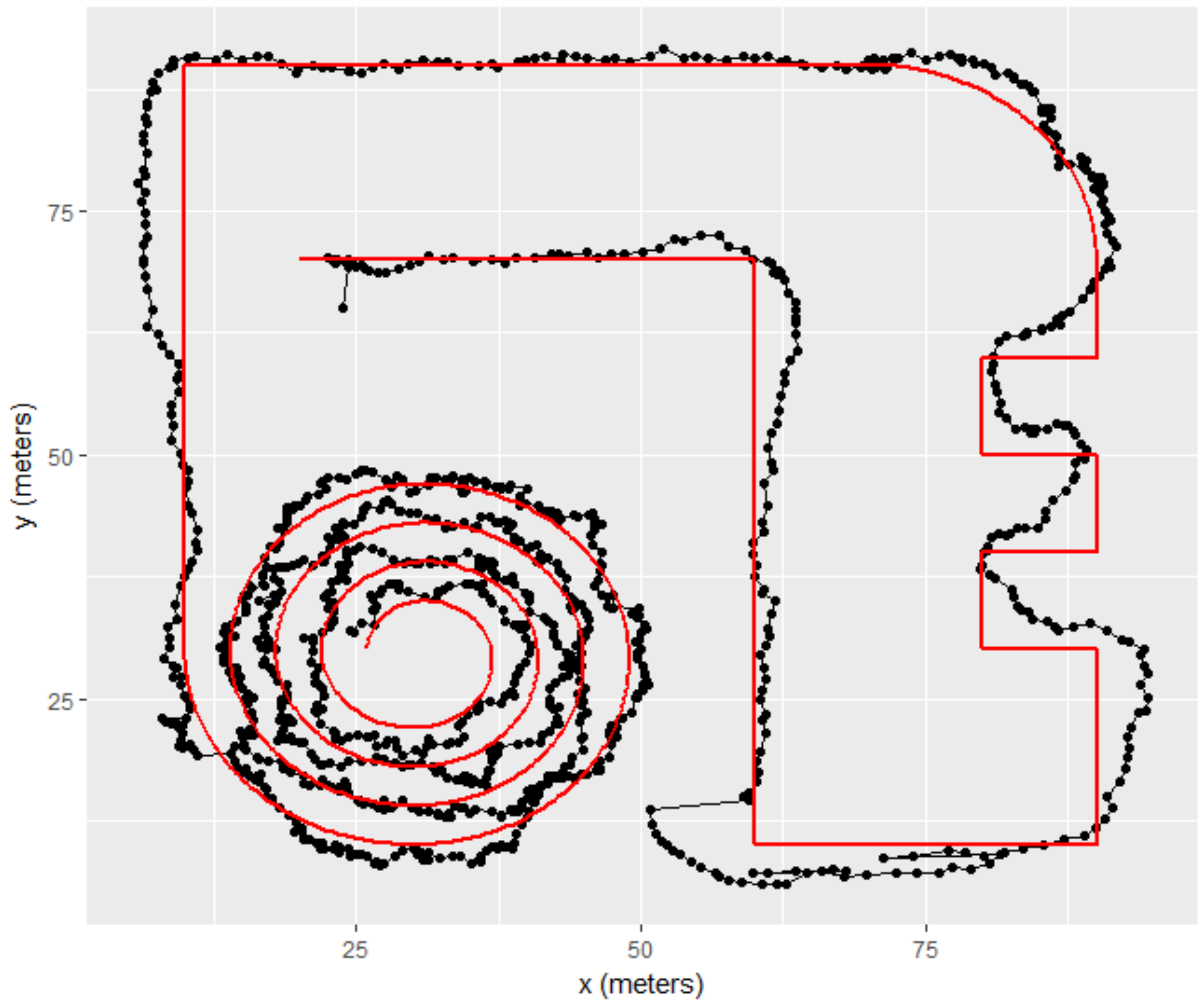
+ uncertainty estimate

+ cheap to run

- parameters not intuitive

- overshooting





Kalman Filter

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

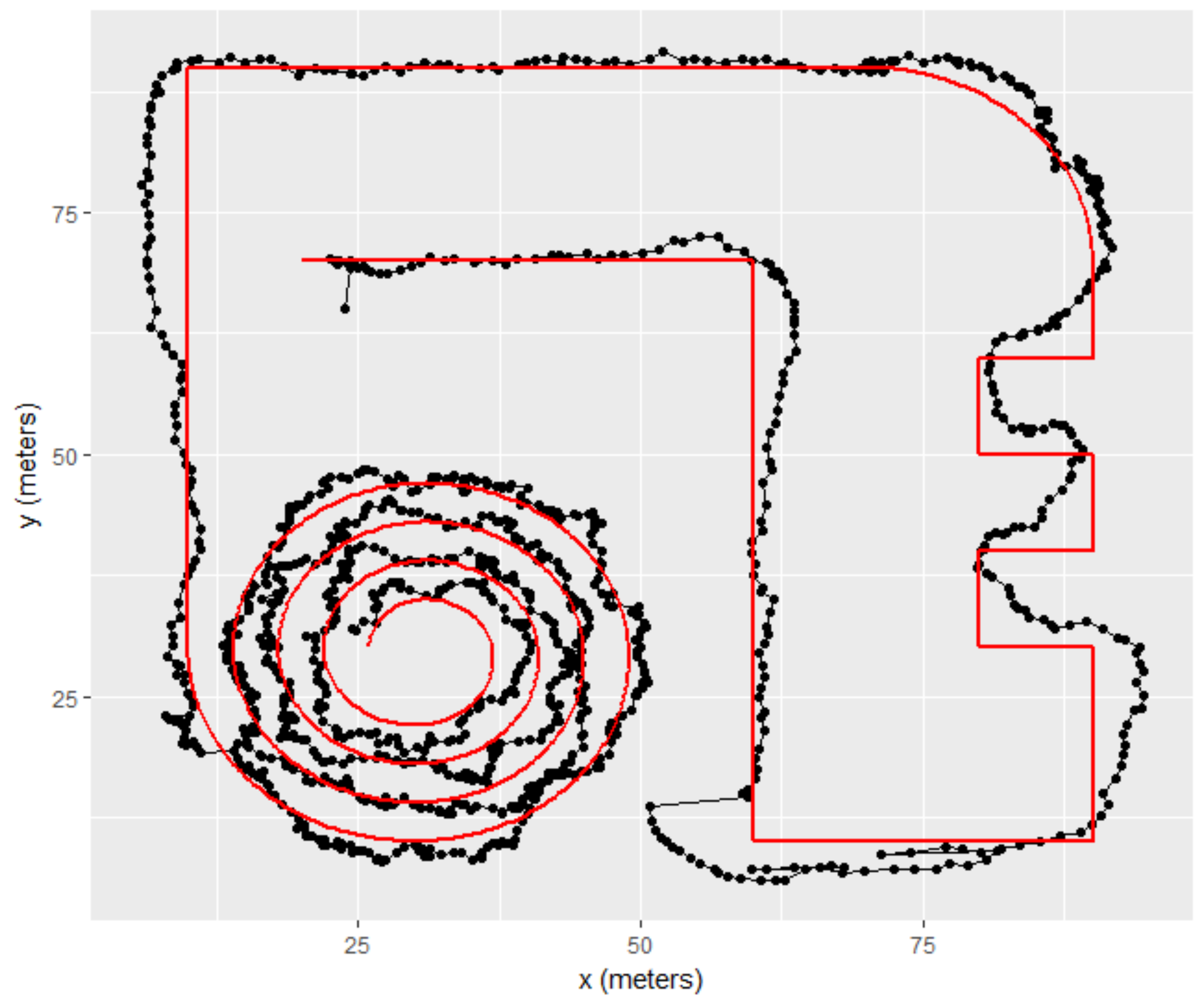
Bayesian

Gaussian

Linear

What if this is not the case?

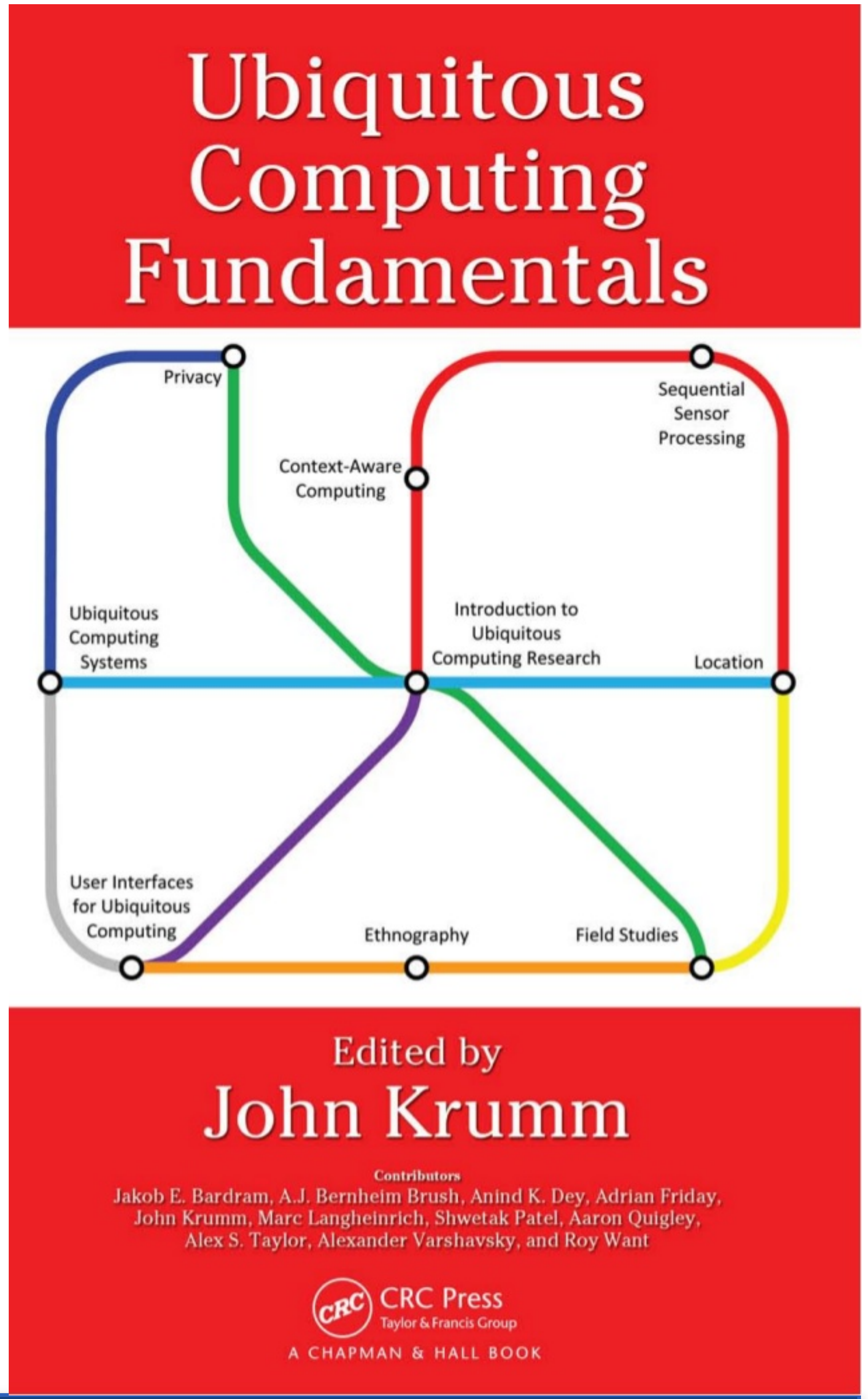
Online



- **Particle Filter**
  - Generate Hypotheses
  - Compute Weights
  - Resample

+ general
+ continuous or discrete variables
+ great results

- lots of memory
- very slow

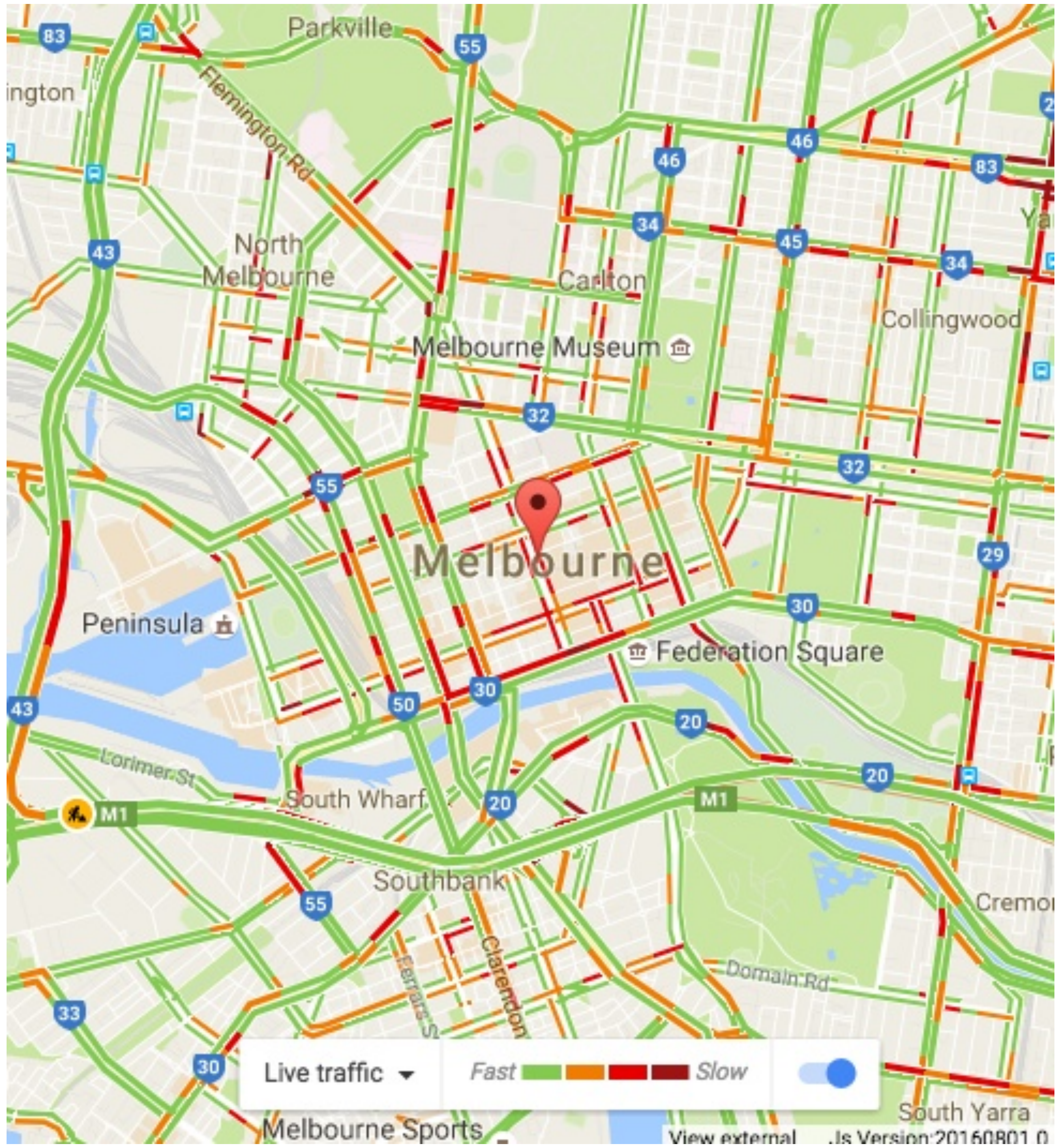


John Krumm's Chapter

Be good.

- Detailed movement profiles of citizens
- Communication data
  - Calls, duration, members, SMS, Email, calendar,…

- Optimising traffic flow
- Choice of public transport
- Personalised suggestions
  - Mode of transport
  - Travel start time
  - Destination



Movement Profiles

1. Sensors as a Driver for Ubiquitous Computing Technologies

2. What Constitutes a Sensor?

3. Challenges when Dealing with Sensor Data

4. Sensor Signal Processing: Dealing with these challenges

Summary