Particle Swarm Optimisation in GW signal Detection

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Outline

- GW Detection Problem
- Optimisation Detection Statistics
- Particle Swarm Optimisation(PSO)
- Usefulness of PSO in GW detection problem
- Applying PSO based application on real data
- Results and Conclusions

GW Detection Problem

The output from a GW detector, a time series $s(t)$ can be written as:

$$s(t) = \begin{cases} n(t) & \text{in absence of GW signal} \\ n(t) + h(t) & \text{in presence of GW signal} \end{cases}$$

Here, n(t) is detector noise and h(t) is GW signal from astrophysical sources.

Signal is astrophysical modelled based on Einstein or alternative theory which we call a signal template, $q(t;\theta)$

We expect that the model signal/template match with astrophysical GW signal for specific model parameter say θ_0.

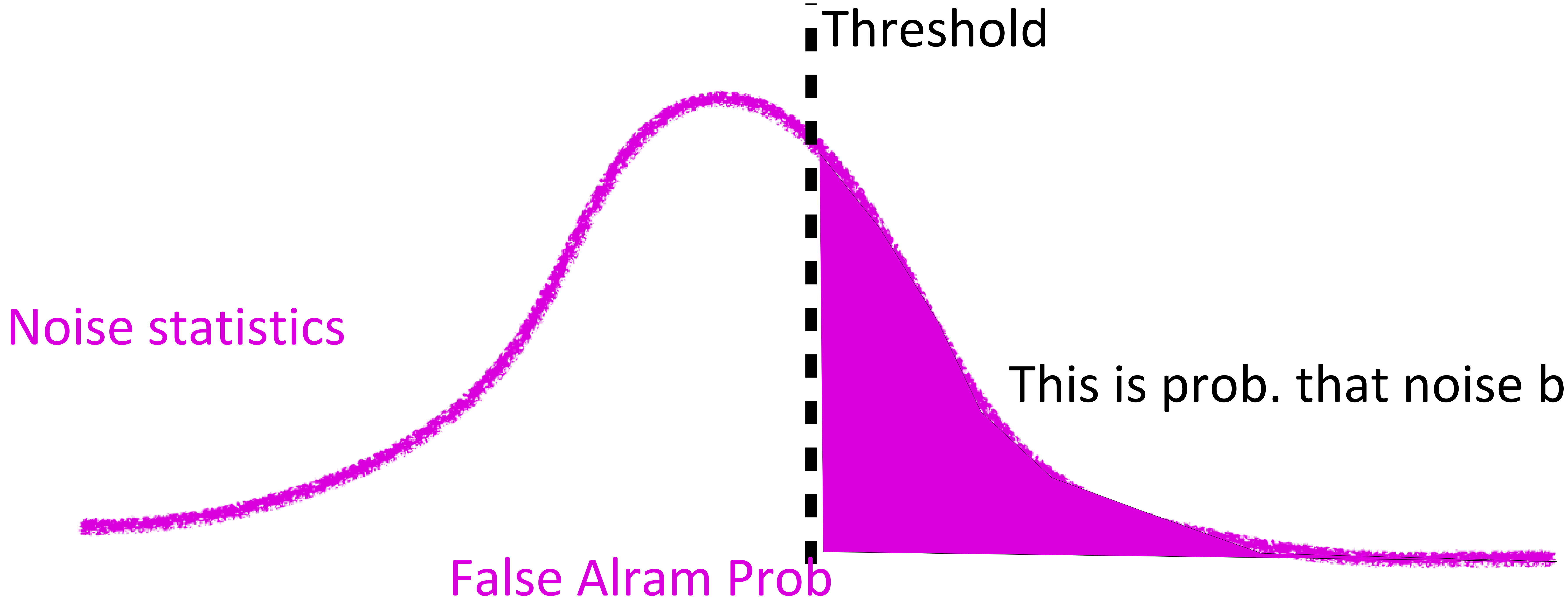
Our goal is to pick the part of detector output with astrophysical signal

Neyman–Pearson criterion

The detection probability is given by the match or weighted correlation with noise PSD, $S(f)$, is given by,

$$R(\theta) = 4\int_{f_{min}}^{f_{max}} \frac{\tilde{s}(f)\ \cdot \tilde{q}(f;\theta)}{S(f)} df$$

It can be shown that $R(\theta)$ is optimal statistic for Guassian noise.



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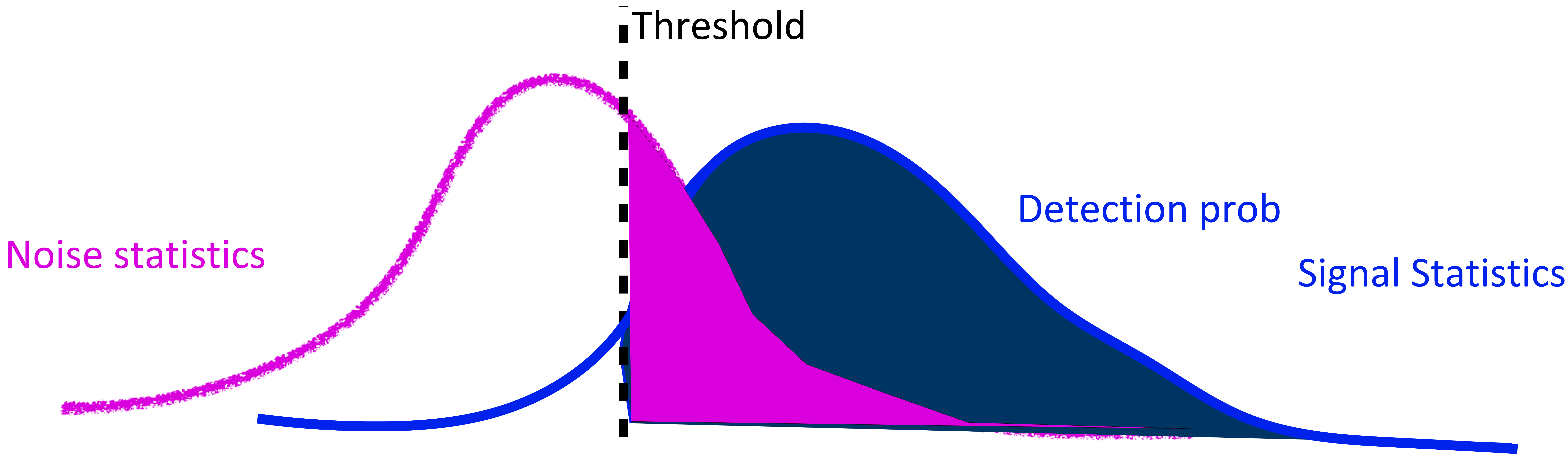

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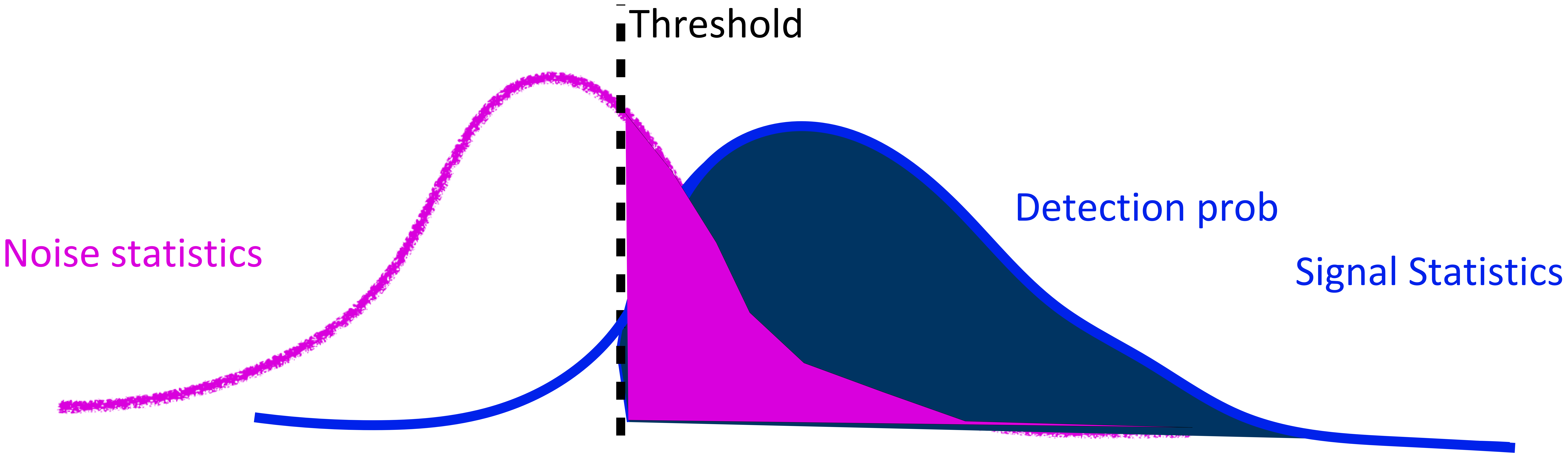


Neyman−Pearson criterion: Maximise the detection statistic over model parameters θ using a threshold provided by a given false-alarm probability.

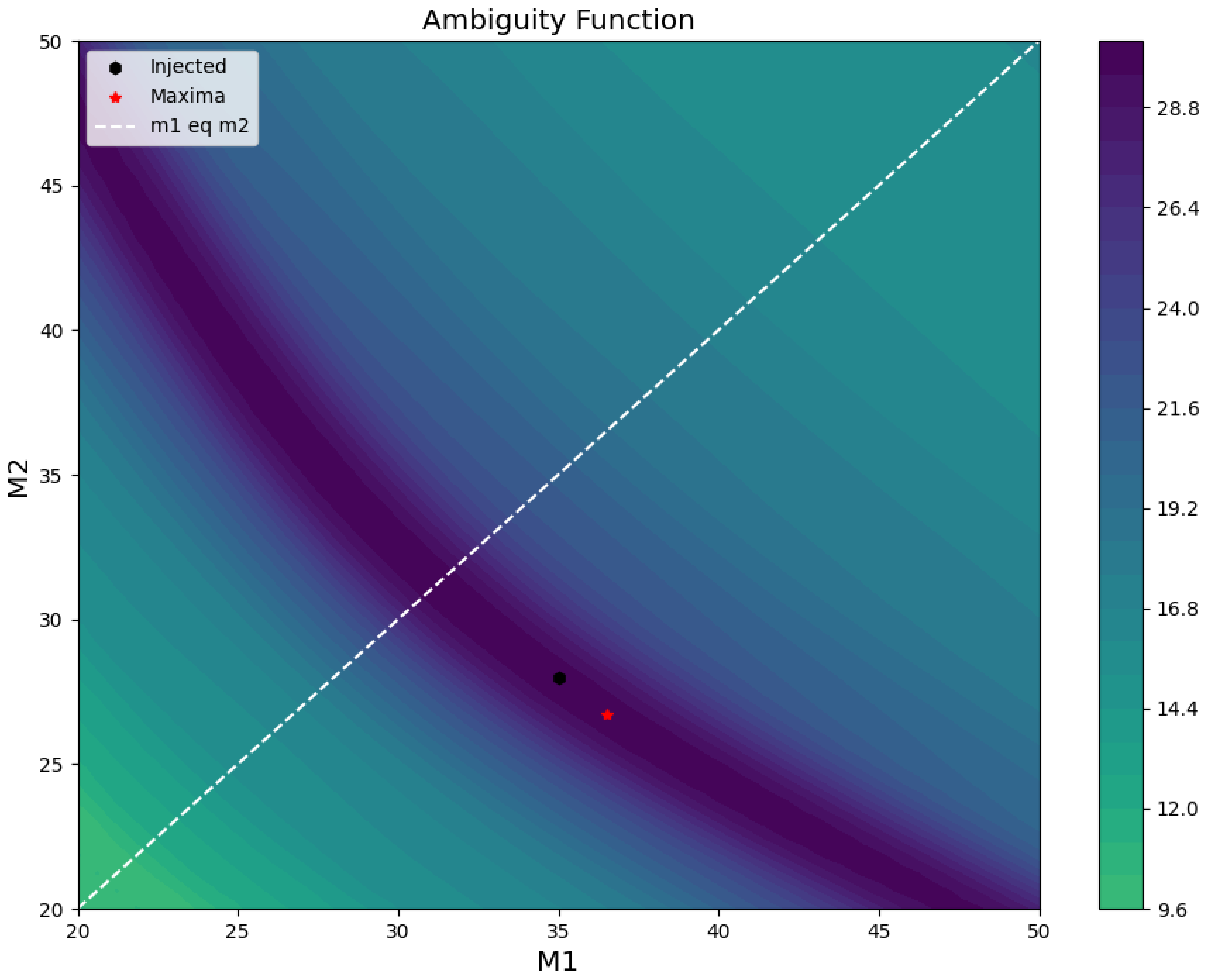
Some interesting points!

Match-making is expensive!

$$R(\theta) = 4\int_{f_{min}}^{f_{max}} \frac{\tilde{s}(f)\ \cdot \tilde{q}(f;\theta)}{S(f)} df$$

- Even for the simple waveforms.
- Complex waveforms contribute additional difficulty

Noise brings in local peaks and maximisation scheme can get trapped



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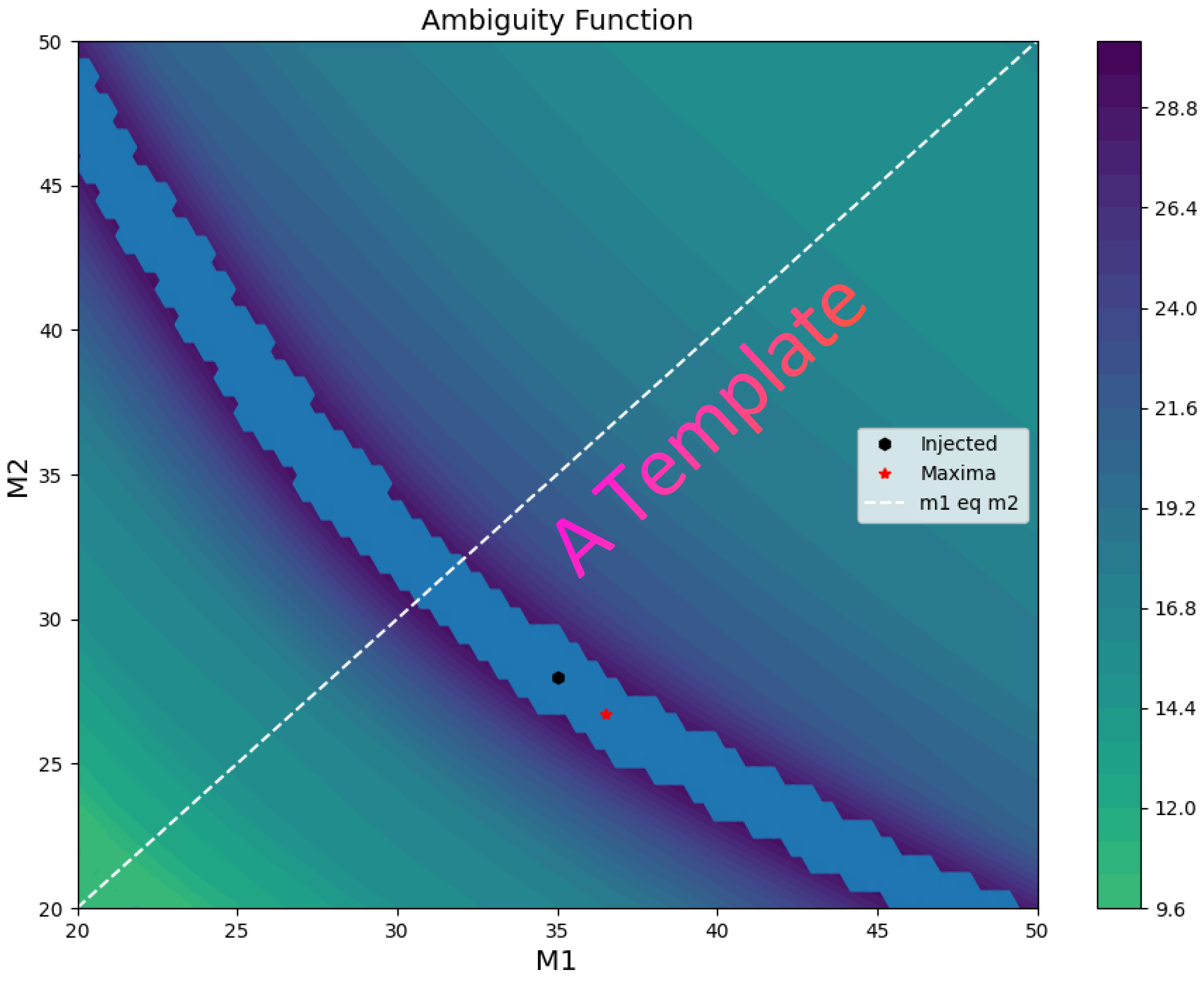

Particle Swarm optimisation!

In this method, a set of particles makes a “controlled” random walk in given parameter space to optimise a given function. Members share helpful information with the entire swarm and converge to an optimal point in the parameter space.

We start with an uniform distribution of particles in a N $-$dimensional parameters with position of a particle at $n-th$ step is given by $\vec{X}_n$

The velocity of $\vec{V}_n$ at $n-th$ step evolves as per rule

$$\vec{V}_{n+1} = \alpha\, r_0\, \vec{V}_n + \beta\, r_1 \left(\vec{X}_{pbest} - \vec{X}_n\right) + \gamma\, r_2 \left(\vec{X}_{gbest} - \vec{X}_n\right)$$

$\alpha, \beta \text{and} \gamma$ are parameters of the algorithm, (r_0, r_1, r_2) are set of random number between $(0,1)$.

$\vec{X}_{pbest}$ is the best location sampled by a given particle converge to an optimal point in the parameter space.

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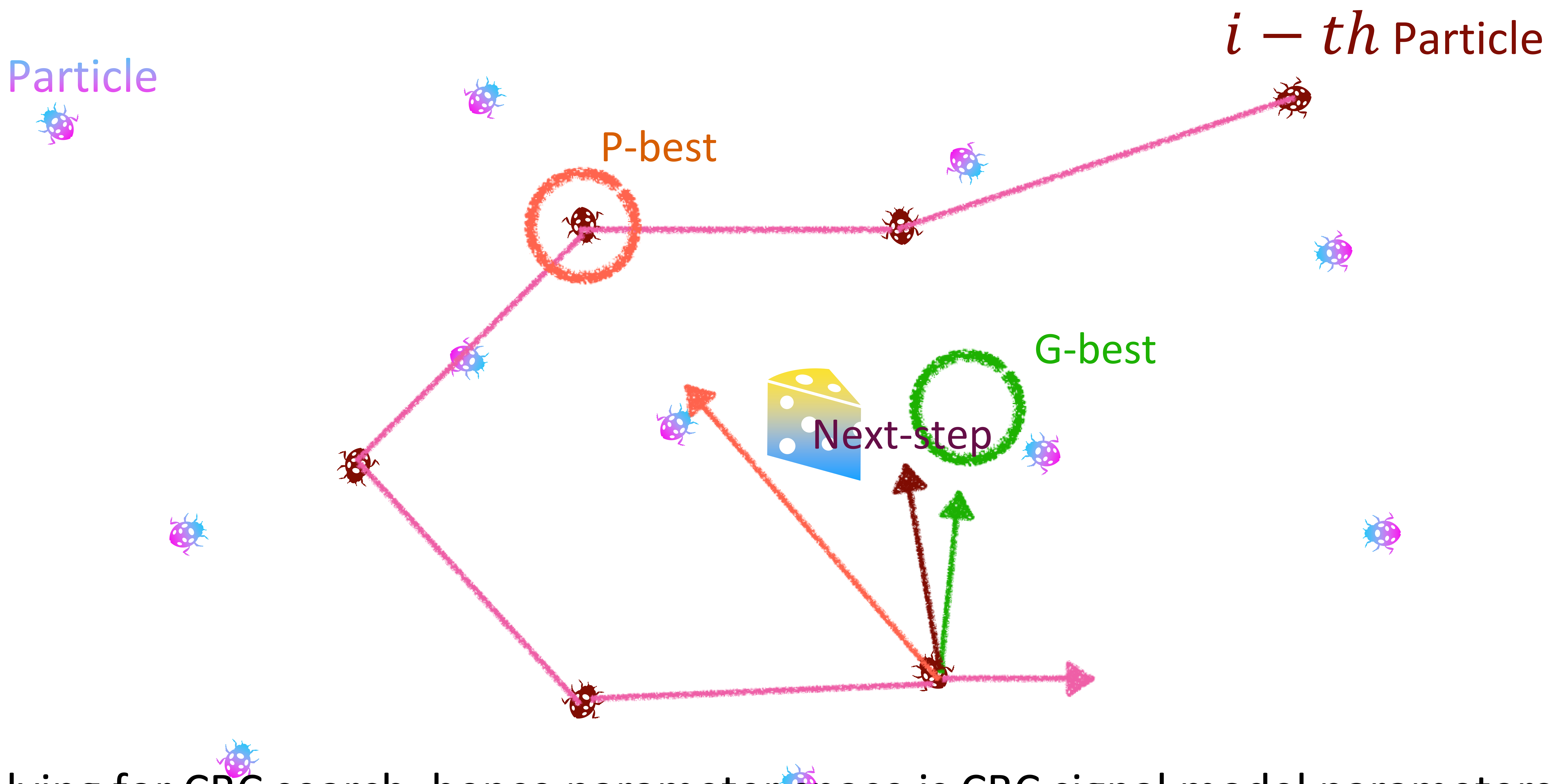
$\vec{X}_{pbest}$ is the best location sampled by a given particle till current step

$\vec{X}_{gbest}$ is the best location sampled by entire swarm

The position evolution at $n-th$ step is given by

$$\vec{X}_{n+1} = \vec{X}_n + \vec{V}_{n+1}$$

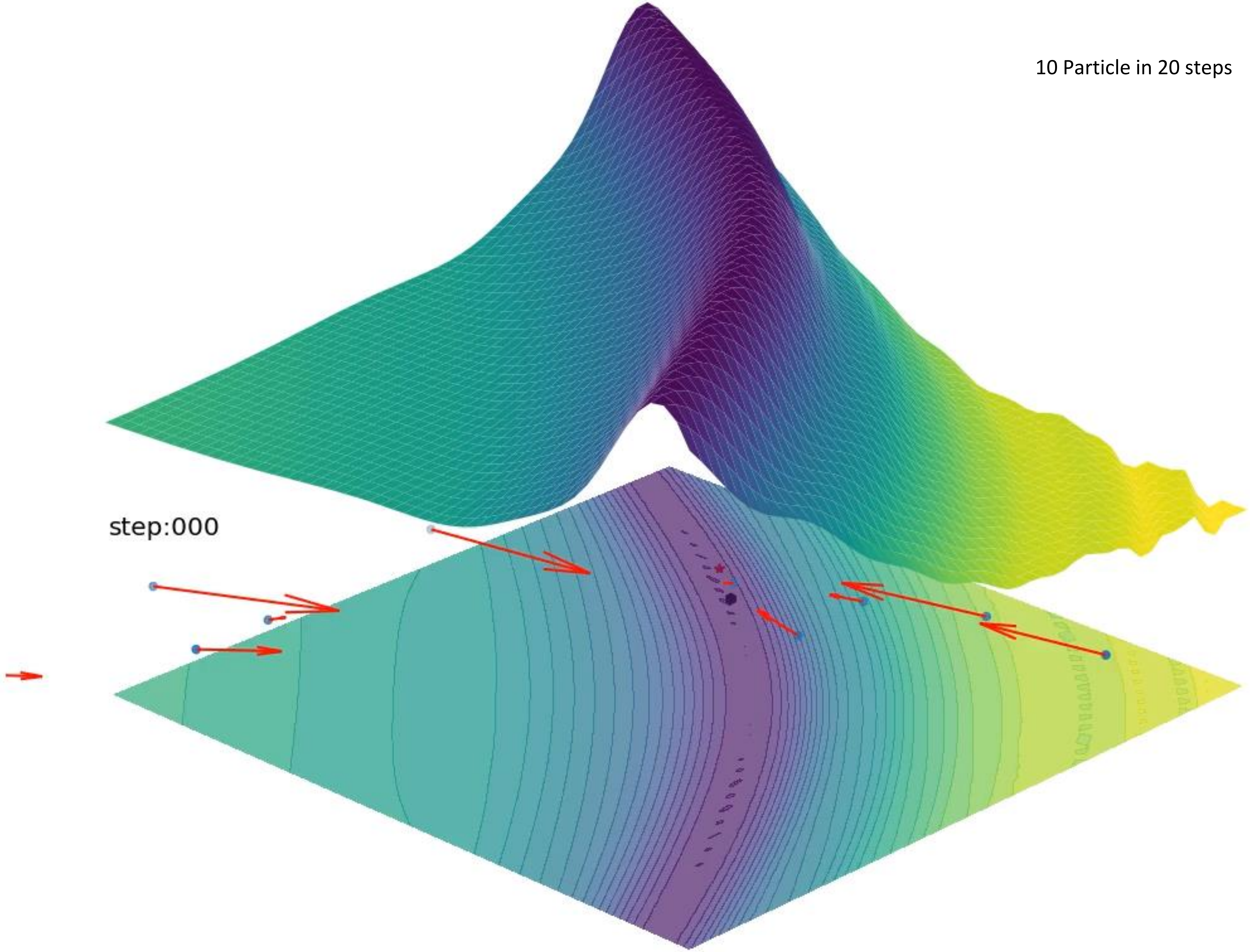
Particle Swarm optimisation!



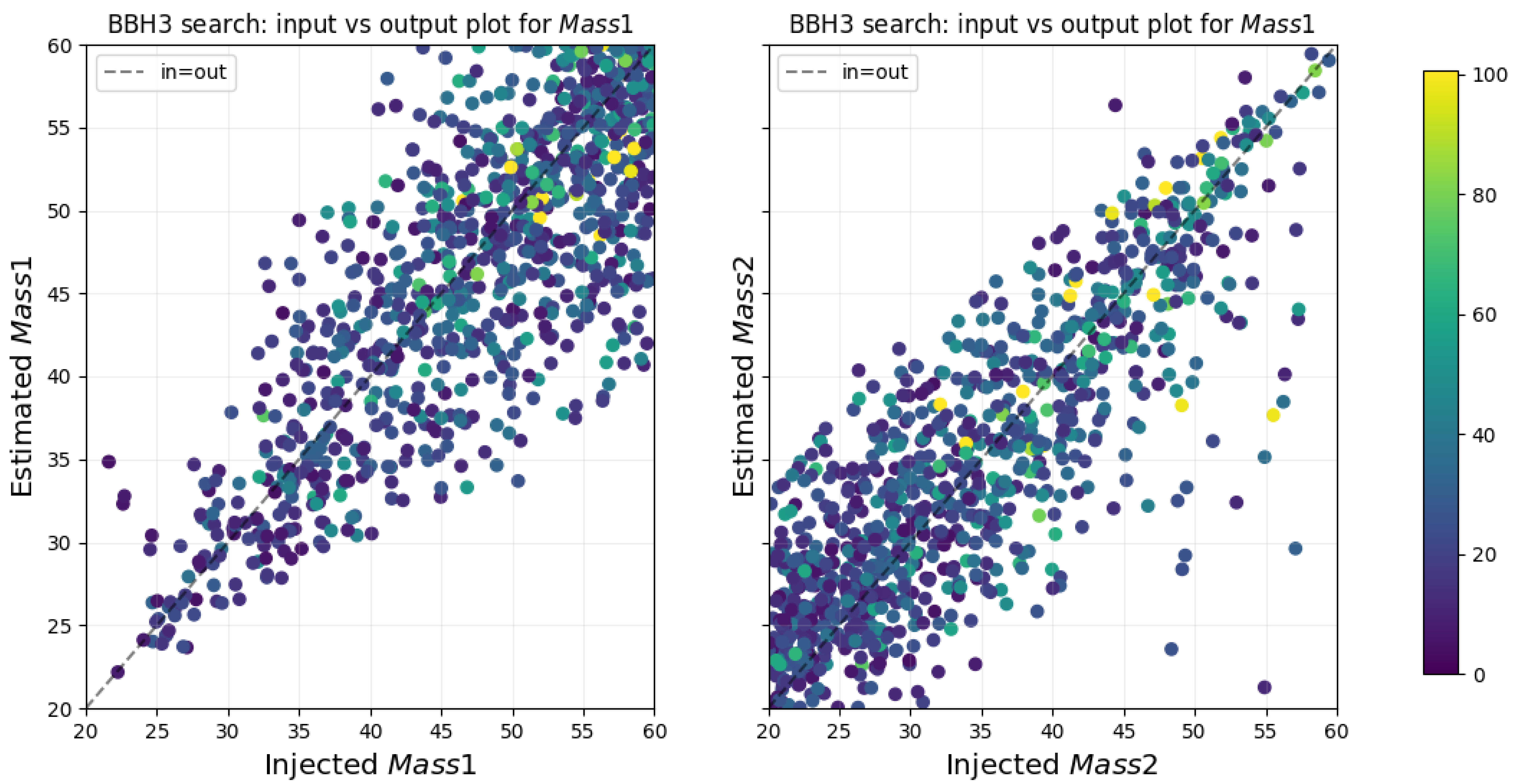
We are applying for CBC search, hence parameter space is CBC signal model parameters,

while optimising the statistics $\mathcal{L}(\Theta) = \int_{f_{min}}^{f_{max}} \tilde{s}(f) \frac{\tilde{h}(f;\Theta)}{S_h(f)} df$

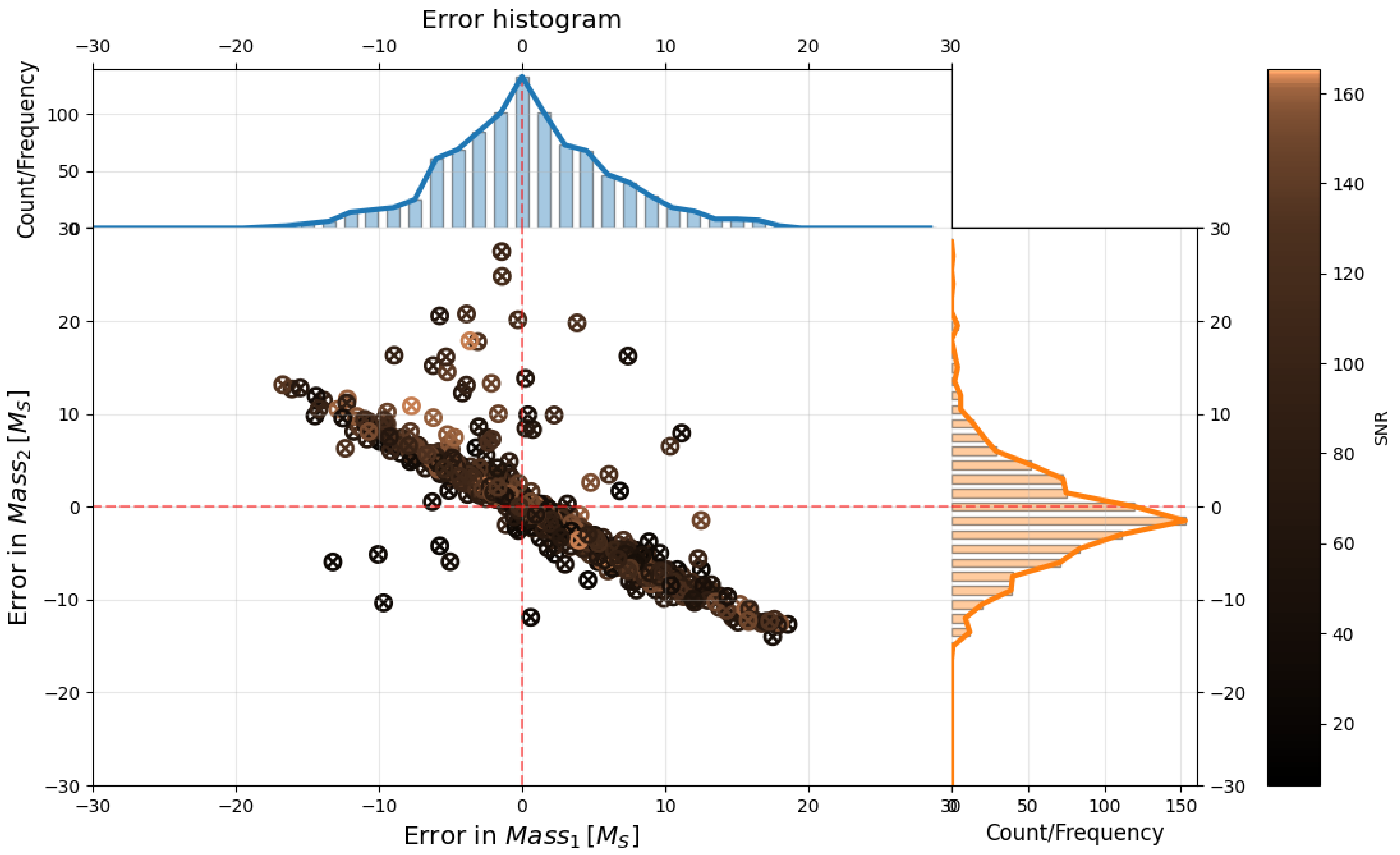
10 Particle in 20 steps



Injected Vs Estimated M_1 and M_2 Non-spinning



Error Estimated M_1 and M_2 aligned-spin



Real Detector data

Real detector data is far more complex.

Noise glitch

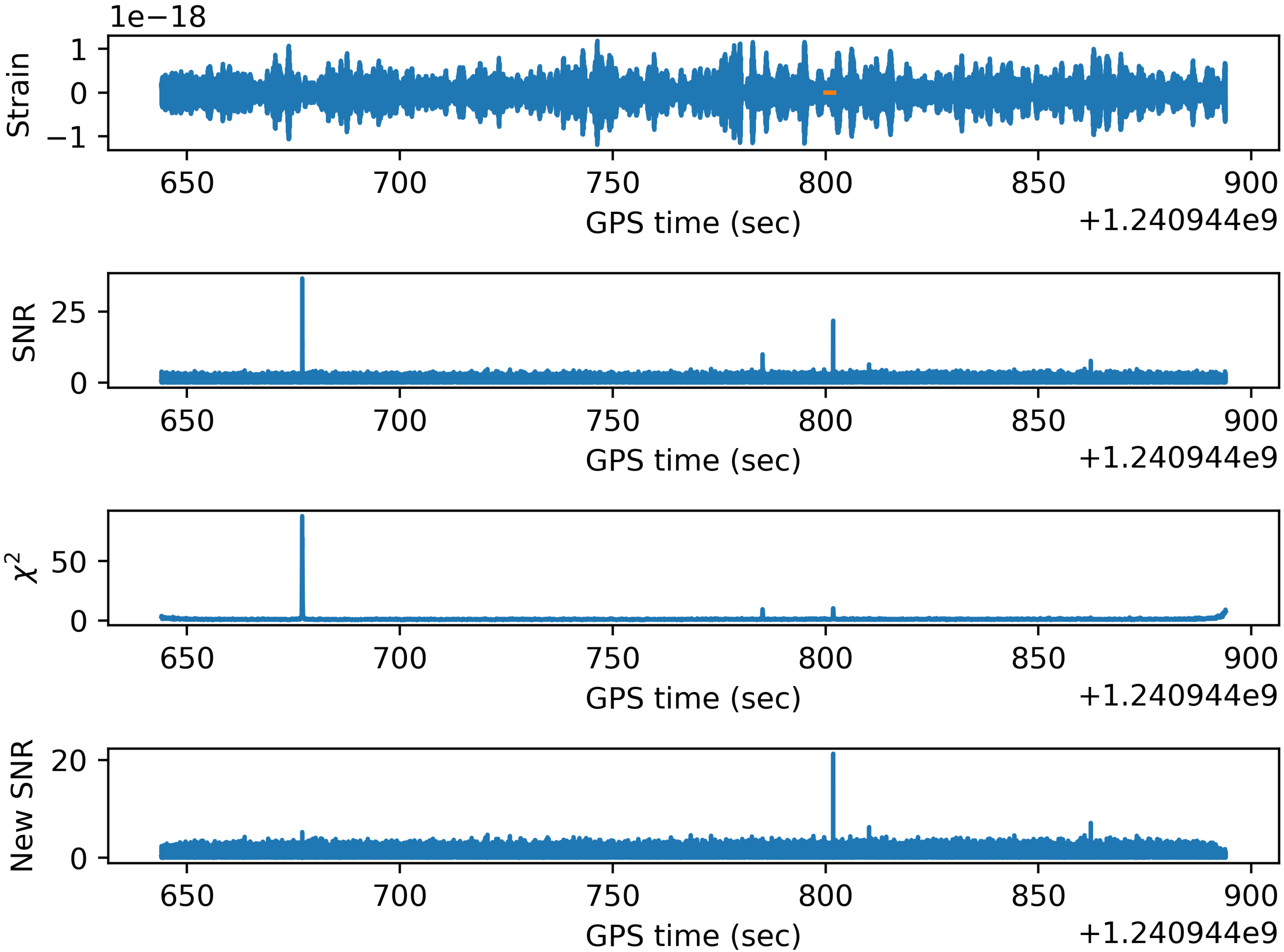
Unlike simulated noise, real noise generated lots of high SNR triggers

Here we need χ^2 for discriminating noise from signal and we use new-SNR.

However, for reducing the computational cost, we compute new-SNR only if SNR cross a thresho

As PSO evolves in the parameters space while optmising SNR, whenever the SNR cross a certain

Remaining trigger's are stored



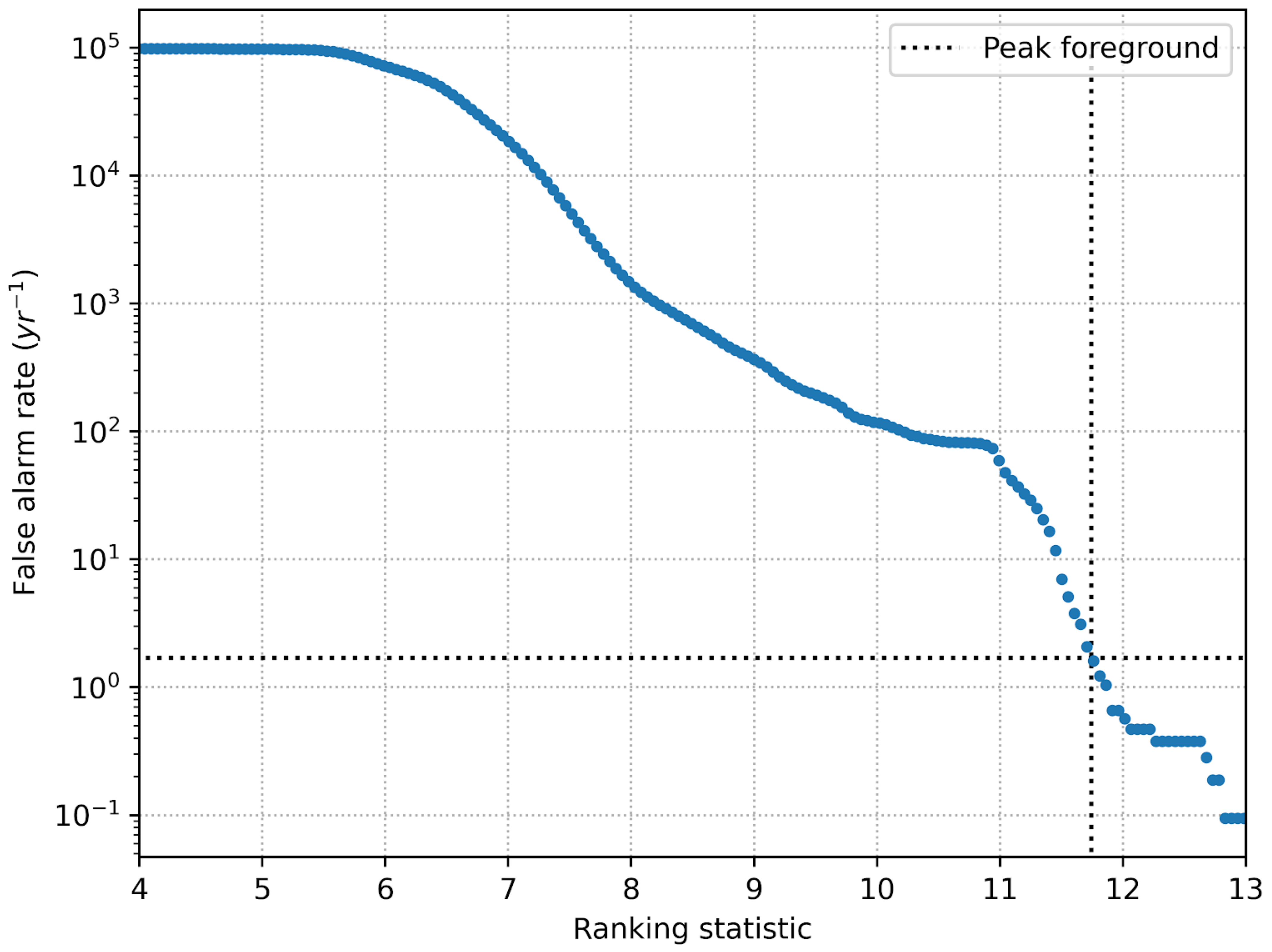
1e−18
Strain
1
0
−1
SNR
25
0
χ²
50
0
New SNR
20
0
650
700
750
800
850
900
GPS time (sec)
+1.240944e9

Significance estimation - Coincidence mode!

- We use standard time-sliding mechanism to compute the false alarm.
- All the trigger (with new-SNR) are collected from each IFO
- Trigger are grouped (with arrival time) to generate a event. Simple time-clustering and averaging is currently employed. This may be developed further in future.
- Triggers forming a coincidence give foreground candidates that may be further constrained by network SNR (somewhere 8-9).
- Triggers shifted in time by more than time-of-flight (~ 10 ms for HL) plus a timing error (some 5ms) between two detectors give rise to background events.

Example: GW190503_185404

- We use only H1, L1 data (no trigger in V1).
- Analysis duration ~ 4096 sec around each event.
- Time-shift interval ~ 50 ms.
- Background time generated ~ 10 yr [= 4096 sec x 4096 sec) / (50 ms)]
- FAR (of a foreground event) = (No. of background events louder than the given foreground event) / (Total background time generated).
- If the (no. of background events louder than the given foreground event) < 1, then assign a FAR: < 1 / (Total background time generated).



Concluding remarks

- PSO based search pipe-line is implemented and successfully applied on real data. Not need for a prior template bank.
- Useful when when it becomes hard or impossible to compute template bank.
- Better source parameter are by-product of search pipe-line, no need for additional rapid PE
- Extremely useful if search parameter have to extended.
- Fully precessing search [Varun Srivastava, K Rajesh Nayak, Sukanta Bose: arXiv:1811.02401]
- Eccentric search [LIGO-G2200981]

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