A Genetic Algorithm for Astroparticle Physics - Review

Advanced Methods in Applied Statistics

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Article & Abstract

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A genetic algorithm for astroparticle physics studies☆

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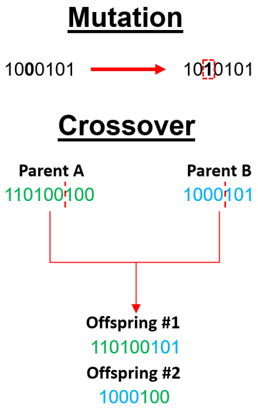
ABSTRACT

Precision measurements of charged cosmic rays have recently been carried out by space-born (e.g. AMS-02), or ground experiments (e.g. HESS). These measured data are important for the studies of astro-physical phenomena, including supernova remnants, cosmic ray propagation, solar physics and dark matter. Those scenarios usually contain a number of free parameters that need to be adjusted by observed data. Some techniques, such as Markov Chain Monte Carlo and MultiNest, are developed in order to solve the above problem. However, it is usually required a computing farm to apply those tools. In this paper, a genetic algorithm for finding the optimum parameters for cosmic ray injection and propagation is presented. We find that this algorithm gives us the same best fit results as the Markov Chain Monte Carlo but consuming less computing power by nearly 2 orders of magnitudes.

Program summary
Operating system: Linux
Programming Language: C
Software Package: ROOT
Libraries: cmath, cstdio, cstdlib, ctime

Genetic algorithms

- Global optimization strategy for complicated search spaces.
- Solve optimization problems using evolutionary concepts.
  - "Fitness function" to be maximized.
  - "Populations" and "generations" of solutions.
  - Evolutionary operations; mutations and crossover.
  - Optimization by "natural selection".
- Advantages/disadvantages
  - Searches different parts of the solution space.
  - Search spaces do not need to be well-behaved.
  - Natural selection ensures fitness increases.
  - No obvious way to estimate errors.
  - Less efficient for problems with simpler search spaces.



The problem - a complex CR Model

- Data is CR energy spectra (from several experiments)
- Model is the transport equation: $\frac{\partial \psi}{\partial t} = Q + \vec{\nabla} \cdot (D \vec{\nabla} \psi) - \psi \Lambda + \frac{\partial}{\partial E}(\dot{E} \psi)$
  - Param. dependencies: $\psi(E, r, z)$, $Q(\Lambda_j, \psi_j)$, $\Lambda(\beta, n, \sigma)$, $D(D_0, \rho_0, \rho, r, z, \delta(z))$
  - In total: 8 parameters to be optimized! **Not easy!**
- For MCMC:
  - Viable, but slow/inefficient computation time
  - Some MCMC methods more prone to local maxima convergence
- For GA:
  - Less prone to convergence on local maxima (Crossover & mutations)
    - However, crossover not implemented in article!
  - Much faster/more efficient computations
  - Great for seeding the initial param. for MCMC!

Genetic Algorithm - implementation

- Fitness function is: $F(\vec{P}) = e^{-\frac{1}{2}\chi^2(\vec{P})}$

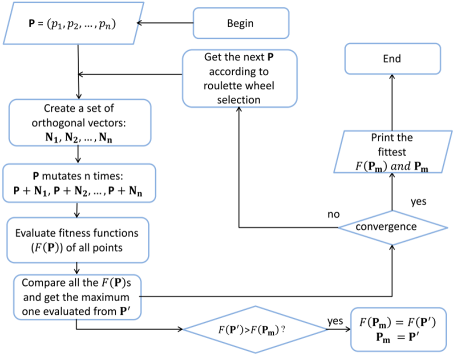


Fig. 1. The flowchart of the genetic algorithm.

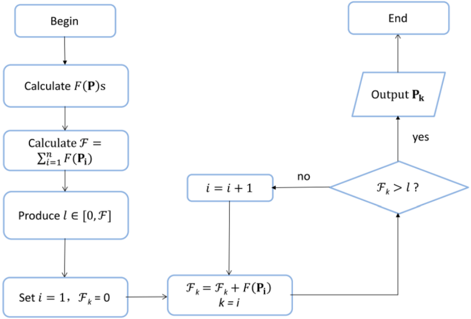


Fig. 2. The flowchart of the roulette wheel selection.

GA vs. MCMC - Data fitting

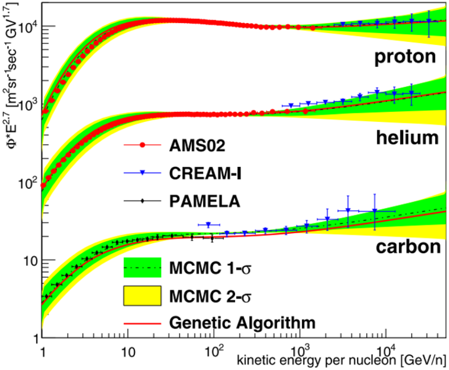


Fig. 3. Model prediction for proton, He and C fluxes compared with the experimental data [4,5,7,54,55]. The black dash line is the best fit of MCMC, while the red solid line is that of Genetic Algorithm.

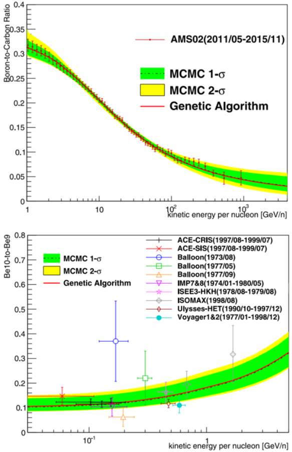
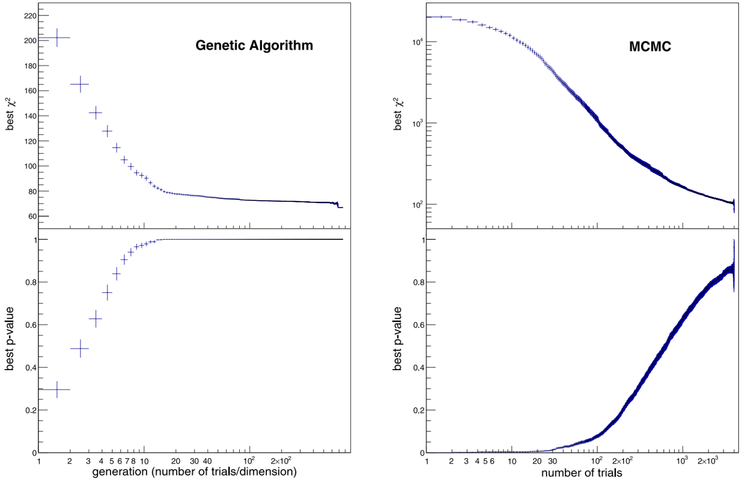


Fig. 4. Top: Prediction of B/C compared with data [54,56–58]. Bottom: Prediction of $^{10}Be/^{9}Be$ compared with data [59–68]. The black dash line is the best fit of MCMC, while the red solid line is that of Genetic Algorithm.

GA vs. MCMC - Speed difference



Conclusion

- High speed-up is promising.
- Further improvement possible by using crossover.
- Major downside: Error estimation.