Differentiable nuclear deexcitation simulation for low energy neutrino physics

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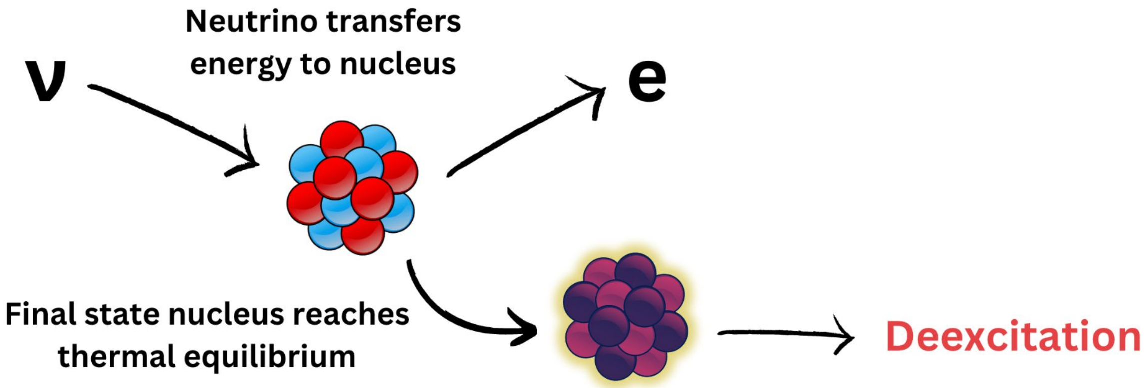
LOW ENERGY NEUTRINO-NUCLEUS INTERACTIONS

- Correct modelling of neutrino-nucleus interactions at **low energy (<100 MeV)** is key for detecting and studying **supernova, solar and atmospheric neutrinos**.



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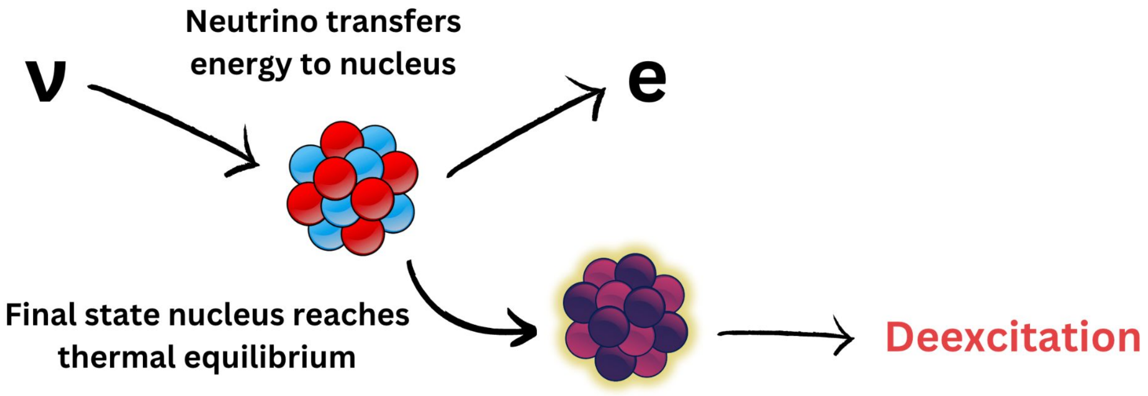

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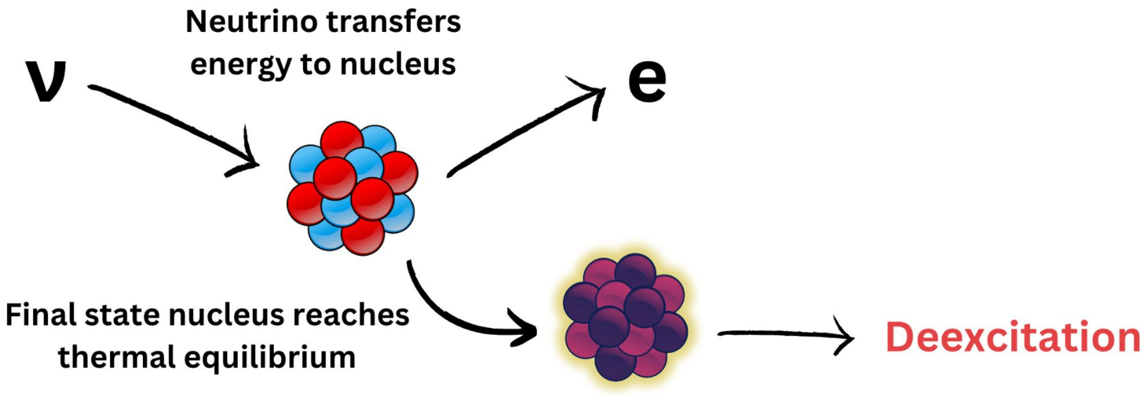
- The deexcitation process is modelled using statistical methods under the assumption of the formation of a **compound nucleus** state → Hauser-Feshbach model.



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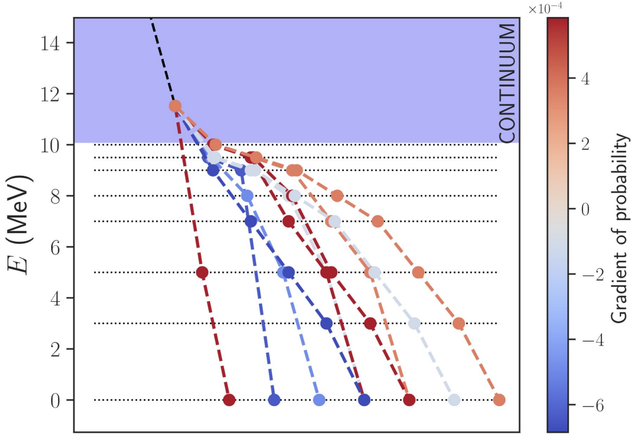
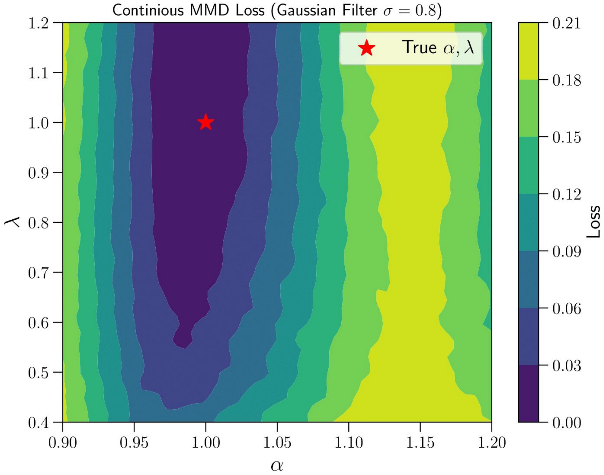
    - Compute **probabilities** and their gradients for **discrete energy levels**.

RESULTS

- Sampling and gradient estimation **vectorised** and **running on GPU.**
- Using a pathwise estimator allows us to take derivatives of and **“move” individual events**.
- **Gradient descent for parameter tuning** working using MMD loss:
  - Some **instabilities** due to variance in gradient estimation.
  - Convergence achieved even with a **fraction of the discrete paths** computed!



Discrete paths and their probability gradients



MMD loss contour plot

PROSPECTS AND CONCLUSIONS

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Conclusions:

- Demonstrated the **feasibility of a differentiable implementation** of the key components of a nuclear deexcitation model.
- Sampling and gradient estimation is fast and robust, but model fitting needs stability work.
- There is **much work to do** but we are confident in the scaling of our method!

Thank you for listening!

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