Skymions are topologically protected non-trivial field configurations that are observed in chiral magnetic materials. Their stability, nanometer size, and coherent dynamics make them attractive candidates for applications such as race-track-like memories. Current numerical methods are far from exhaustive and computationally expensive.

We seek to generate viable equilibrium configurations using several custom Generative Adversarial Networks that incorporate some of the micromagnetic physical laws into their architectures via physics-aware loss functions.

### Magnetic Skyrmions

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### Computational Micromagnetics

The magnetization field \( M(r) = M_0 \chi(r) \) is expressed as a vector field where \( r \) denotes a unit length vector. The energy of the system is computed as:

\[
E(\chi) = \int \left( \varepsilon_0 \chi + \varepsilon_1 \chi \cdot \nabla \chi + \varepsilon_2 \chi \right) d^3 r
\]

where \( \varepsilon_0, \varepsilon_1, \) and \( \varepsilon_2 \) are the symmetric exchange, the Dzyaloshinskii-Moriya, and the Zeeman energy densities, respectively. The first variational derivative of the energy functional \( E(\chi) \) with respect to \( \chi \) is called the effective field \( H_{eff}(\chi) \). The magnetization field dynamics is governed by the Landauf-Lifshitz-Gilbert (LLG) equation:

\[
\frac{d\chi}{dt} = \gamma H_{eff} \chi - \alpha \chi \times (\chi \times H_e)
\]

where \( \gamma \) is the modified gyromagnetic ratio and \( \alpha \) is the Gilbert damping, which for this study was chosen to be FeGe, with \( \alpha = 0.1 \). Let \( L_x \) := \( \hat{m} \times r \times H_e \). A dynamically steady state (equilibrium state) is reached when \( L_x \) is close to \( 0 \).

### Evaluation

For every combination of strategy and \( L_{phys} \), samples were generated from a newly-instanciated PhysGAN trained for 1000 epochs. Results were checked how physically plausible they were according to the following criteria:

- Are the samples diverse and visually similar to the training data?
- Is the \( L_{phys} \) being reduced over the epochs?
- Is the average energy density \( E(\chi) \) and the average cross product \( L_x \) (ACP) of a batch of generated samples close to reference values computed from the training data which are \( E \approx 8.19 \times 10^{-6} \), ACP: [1.76, 6.78, 1.83] \times 10^{-5}.

### Results

### Conclusion

The proposed PhysGAN shows promising although not yet perfect results regarding physics data generation. Future work improvements:

- Conditional PhysGAN.
- Vary the parameters dependent on the material. Check what magnetizations arise. This might assist the discovery of new helimagnetic materials.
- Apply the core ideas of the PhysGAN to other scientific domains.