Machine learning and differential programming for detector simulation

Deadlines

First major milestone would be January 31, 2022 for the arXiv submission

- Too ambitious considering the late start: Mid January deadline for contributions and 1 week review before the upload deadline

Aiming for March 15th is more realistic

- Contribution deadline: January 31st
- First draft ready by mid-February
- 2-3 weeks for general feedback loop before submission deadline

Time Schedule

- January 31, 2022: White Paper submission to arXiv (preferred) or at least title and abstract to topical group conveners
- March 15, 2022: Official deadline for white paper submission to arXiv
- May 31, 2022: Preliminary reports by the Topical Groups
- June 30, 2022: Preliminary reports by the Frontiers
- July, 2022: Snowmass Community Summer Study (CSS) at UW-Seattle
- September 30, 2022: All final reports by TGs and Frontiers
- October 31, 2022: Snowmass Book and the on-line archive documents

General structure of the document and submissions

Provide a review of ongoing efforts to improve detector simulation and a look for future directions

- Structure the document more as a summary, so you don't need to perform additional studies (but welcome if you have the time!)
- Around 2 pages for each contribution and overall document O(10) pages long
- For each contribution the proposed structure would be (feedback welcome!):
  - **Introduction**: what is the particular part of simulation that needs to be addressed and how does your idea addresses it
  - **Method concept**: More details of your approach and what kind of improvements you achieved or expect to achieve with it
  - **Future directions**: If you had infinite amount of money and computational resources, how would you make it better? Even bold ideas are welcome as a look into 10 years into the future

List of planned contributions

- SNOWMASS21-CompF2_CompF3-AF1_AF6_Lehe-075: **Machine learning and surrogate models for simulation-based optimization of accelerator design**
- SNOWMASS21-CompF2_CompF3_Evangelos_Kourlitis-009: **Pre-Learning a Geometry Using Machine Learning to Accelerate High Energy Physics Detector Simulations**
- SNOWMASS21-CompF3_CompF0-AF1_AF0_Winklehner-108: **Application of Machine Learning to Particle Accelerator Simulation**
- SNOWMASS21-CompF3_CompF2-EF0_EF0-NF1_NF6_Kagan-129: **Differentiable Simulators for HEP**
- SNOWMASS21-CompF3_CompF2-NF1_NF5-CF1_CF2-IF8_IF3_Monzani-084: **The Future of Machine Learning in Rare Event Searches**
- **CaloFlow: Fast and Accurate Generation of Calorimeter Showers with Normalizing Flows**
- **CMS ML4Sim efforts**

A peek into the future

- **Generality:**
  - multiple detectors can profit from a common algorithm
  - Pretrained models can be fine tuned for specific needs: transfer learning
  - Pre-learning basic geometries and fine tuning to specific detector application
- **Multi-purpose generator simulation:**
  - Getting more than simulated events such as calibrations from conditional models
  - Simulation-based optimization for accelerator design and physics inspired models
  - Differentiable simulators for parameter optimization: particle reconstruction, conditional simulation on physics parameters of interest
- **Interplay between different approaches:**
  - Can we gain more by combining ideas?
- **Centralized and up to date repository containing current detector simulation settings used for different experiments:**
  - Support for common physics simulators
  - Folding instead of unfolding
  - Up to date calibrations (ongoing works in this direction: https://indico.cern.ch/event/1087522/)
  - Similar to containers
- **Flexibility**
  - Facilitate the development and testing of new detector geometries
  - Physics fidelity with interpretable models: How to ensure non-standard signatures are properly modeled
  - How much effort is needed to incorporate detector changes

Want to collaborate?

Send me an email or ping me on Slack

Send suggestions to our google doc