# Description for general public

On the Franco-Swiss border near Geneva, 175 meters underground there is a circular 27-kilometres long tunnel. This is the Large Hadron Collider (LHC) - the largest experiment ever made, run by the European Organization for Nuclear Research - CERN. Inside, two-particle beams are accelerated almost to the speed of light, and then collided with each other. During these collisions, thanks to the enormous energy density, exotic particles and states of matter that only existed for a fraction of a second after the Big Bang can be observed.

Currently, experiments at the LHC are on hold and the LHC is undergoing a major upgrade. When it is completed, much more data will be recorded during the operation of the collider. In some experiments, this number will increase up to a thousand times.

This will create new exciting opportunities for high energy physics but also pose new challenges. All four major CERN experiments use statistical Monte Carlo-based simulation methods to reconstruct the collisions at the LHC. Those methods are very precise, but at the same time extremely slow and requires a lot of computing power. The expected increase in the number of recorded collisions means that even the largest computer gird in the world owned by CERN, that consists of half a million processors, will not meet this demand.

For this reason, it is essential to improve the current simulation methods. As part of the project, we propose an alternative solution, the core of which is an artificial neural network capable of automatically learning the laws of physics and complex interactions in particle collisions. This type of artificial intelligence will be able to directly simulate the result of a collision in a fraction of the time needed before.

The starting points for this task are Generative Adversarial Networks (GAN) and Variational Autoencoders (VAE). They have already amazed the world with their capabilities by creating faces of non-existent people that are indistinguishable from real ones. However, simulating physical processes is much more challenging. The subjective opinion of the observer and his belief that something looks "real" is not enough. The output of neural networks must meet the strict, measurable requirements set by high energy physics. Previous attempts to create such a solution have faced problems witch capturing the influence of particle characteristics on the outcome of the simulation and obtaining good quality results for all, even rare scenarios.

For this reason, we intend to develop new generative models, created especially for the task of fast simulation and free from the disadvantages described above.

The results of our research will find practical application also outside the field of high energy physics. The developed solutions can be used in other fields with demand for cost-efficient fast simulations of complex processes. Examples include renewable energy generation in the energy industry, novel models of the universe in cosmology or simulations of chaotic economic processes in finance.