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DIRECT PHOTON ASYMMETRIES IN THE LONGITUDINALLY POLARIZED PROTON-PROTON COLLISIONS AT AN ENERGY OF 27 GEV

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Abstract. In this paper, we explore the potential of the generative-adversarial network (GAN) in order to predict the production of direct photons in the collision of unpolarized or longitudinally polarized protons at an energy of $\sqrt{s}$ = 27 GeV. Our findings demonstrate that The GAN has been established to be capable of accurately reproducing the distributions of the physical characteristics of the produced direct photons. Moreover, the possibility to calculate the double longitudinal spin asymmetry of A_{LL} was shown taking as a basis the values predicted by the GAN.

Keywords: asymmetry, direct photons, neural network, generative-adversarial network

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АСИММЕТРИИ ПРЯМЫХ ФОТОНОВ В ПРОДОЛЬНО-ПОЛЯРИЗОВАННЫХ ПРОТОН-ПРОТОННЫХ СТОЛКНОВЕНИЯХ ПРИ ЭНЕРГИИ 27 ГЭВ

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Аннотация. В работе рассмотрено применение генеративно-состязательной сети (ГСС) для предсказания рождения прямых фотонов при столкновении неполяризованных либо продольно-поляризованных протонов при энергии $\sqrt{s}$ = 27 ГэВ. Установлено, что ГСС позволяет точно воспроизводить распределения физических характеристик рожденного прямого фотона. Показана возможность рассчитывать двойную продольную спиновую асимметрию A_{LL}, взяв за основу величины, предсказанные ГСС.

Ключевые слова: асимметрия, прямые фотоны, нейронная сеть, генеративно-состязательная сеть

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Introduction

Understanding the contributions to proton spin is a challenge that is far from resolved in modern physics [1]. There is no complete theoretical description of the contributions of quarks and gluons to the total proton spin. Therefore, further experiments are needed to explain the specific mechanisms and conditions responsible for nucleon spin [1].

A step in this direction may be provided by the Spin Physics Detector (SPD), measuring beam collisions at the NICA accelerator [1]. SPD is intended for studying the contribution of gluons to proton spin [1]. Gluon helicity functions $\Delta g(x)$ are used to describe this contribution [1].

Double longitudinal Spin Asymmetry (DLSA) occurs during production of particles in collisions of longitudinally polarized protons. DLSA studies were conducted for production of charged pions [2], (J/ψ) mesons [3] and jets [4]. However, their description is complicated as hadronization models should be introduced.

The reaction of direct photon production can be used to avoid using complex hadronization models in DLSA studies [5].

Unfortunately, other difficulties arise in studies of direct photons. Firstly, the number of such photons is small in each proton collision event [5]. Secondly, it is difficult to identify direct photons in the event due to the presence of other photon sources, for example, after the decay of the neutral pion π^0 [5].

A possible approach to eliminating these problems are generative machine learning methods [6], allowing to predict the production of direct photons in proton-proton collisions.

Making such predictions for the case of polarized proton collisions is of particular interest. As noted above, predictions for these collisions allow obtaining the gluon helicity function $\Delta g(x)$.

A generative adversarial network (GAN) is recommended for solving the problems outlined [7]. GAN was used in our previous study to construct an event generator for deep inelastic lepton-proton scattering, yielding good results [8].

Experimental procedure

Preliminary remarks. Let us consider the production of direct photons in proton collisions in more detail. Direct photons are those produced during parton scattering. Two phenomena make the greatest contribution to the total cross section of direct photon production: Compton scattering $gq(\bar{q}) \to \gamma q(\bar{q})$ (larger contribution) and quark-antiquark annihilation $q\bar{q} \to \gamma g$ [5]. As for production of two direct photons in the final state, for example, by the reaction $gg \to \gamma\gamma$, its contribution to the total cross section of the process is about 1% [5].

The cross section of the process for direct photons can be written as follows within the factorization theorem [5]:

$$d\sigma_{AB\to\gamma X} = \sum_{a,b=q\bar{q},g} \int dx_a dx_b f_a^A(x_a,Q^2) f_b^B(x_b,Q^2) d\sigma_{ab\to\gamma x}(x_a,x_b,Q^2), \tag{1}$$

where f_a^A, f_b^B are the parton distribution functions (PDFs) for hadrons A and B; x_a, x_b are the fractions of hadron momenta A or B carried by the parton a or b; Q^2 is the squared four-momentum transfer during scattering of partons a and b; $\sigma_{ab\to\gamma x}(x_a, x_b, Q^2)$ is the scattering cross section of partons a and b, which can be calculated within the framework of quantum chromodynamics [5].

In the case of a collision of longitudinally polarized protons $\vec{p}\vec{p}^{(\leftarrow)}$, DLSA is defined as

$$A_{LL} = \frac{d\Delta\sigma}{d\sigma}, \tag{2}$$

where $\Delta\sigma$ is the production cross section in the case of collision of longitudinally polarized protons; σ is the production cross section in the case of collision of unpolarized protons.

The cross section of direct photon production $d\Delta\sigma$ is described using PDFs in the case of collision of polarized protons, but for polarized partons [5]. Based on these functions, similarly to expression (1), the production cross section of direct photons is written as

$$d\Delta\sigma_{AB\to\gamma X} = \sum_{a,b=q\bar{q},g} \int dx_a dx_b \Delta f_a^A(x_a, Q^2)\Delta f_b^B(x_b, Q^2) d\Delta\sigma_{ab\to\gamma x}(x_a, x_b, Q^2), \tag{3}$$

where Δf_a^A, Δf_b^B are the distribution functions of polarized partons for hadrons A and B; $\Delta\sigma_{ab\to\gamma x}(x_a, x_b, Q^2)$ is the scattering cross section of polarized partons a and b [5].

Procedure The PYTHIA8 Monte Carlo generator was used to obtain the data [9]. Simulation was used due to lack of experimental data, since the SPD is still under construction.

The following PYTHIA8 parameters were used to study the reaction of direct photon production:

PromptPhoton: qg2qgamma = on,

PromptPhoton: qqbar2ggamma = on,

MultipartonInteractions: pT0Ref = 2.2.

PDF NNPDF31_nlo_as_0118 [10] was used to calculate collisions of unpolarized protons.

PDF NNPDFpol11_100 [11] was used to calculate collisions of polarized protons. This PDF was measured for longitudinally polarized proton–proton collisions $\vec{p}\vec{p}^{(\leftarrow)}$. Including it into the PYTHIA8 calculation allows to take into account the contribution from proton polarization, which was previously used, for example, in [3].

Samples of 500,000 proton collisions were generated using the PYTHIA8 generator configured with the above parameters with both unpolarized PDFs (NNPDF31_nlo_as_0118) and polarized PDFs (PDFpol11_100). Both calculations were performed at center-of-mass energy $\sqrt{s} = 27$ GeV.

The following quantities were obtained from the generated samples:

p_{zq1}, p_{zq2} are the z components of momentum of the first and second partons whose interaction produces a photon;

p_x, p_y and p_z are the momentum components of the direct photon produced.

Such a set of quantities was selected because it is sufficient for kinematic description of collisions and calculation of asymmetry A_{LL} by Eq. (3). Only the z components of parton momentum were used because the remaining components (x and y) in the center-of-mass frame of protons colliding along the z axis take zero values.

Another set of quantities was used to train the neural network, namely,

$$T(p_{z\,q1}) = \ln(p_{z\,q1}),\ T(p_{z\,q2}) = \ln(-p_{z\,q2}),\ p_x, p_y, p_z.$$

The converted quantities $T(p_{z\,q1})$ and $T(p_{z\,q2})$ are used because the distribution of quantities after the transformations becomes smoother and turns out to be closer to the normal distribution. This has a positive effect on training of the GAN [8].

The GAN architecture was constructed based on the results obtained in our earlier study [8]. A type of GAN with a loss function characteristic for the least squares method was used [12].

GAN training lasted 1,000 epochs. The batch value was chosen to be 500. RMSProp [13] was used as a gradient descent optimizer, the training steps for the generator and discriminator were $2\cdot10^{-4}$and 10^{-4}, respectively.

The architecture of the generator in GAN is based on processing a 128-dimensional vector whose elements are distributed normally with zero mean and unit standard deviations. This vector is supplemented with information about the type of polarization of the event, so that the generator can predict data with the required polarization. The generator has seven hidden layers, each containing 512 neurons. The Leaky ReLU function with a dropout of 0.2 is used as an activation function in each layer [14]. There are six neurons at the output of the generator, each corresponding to a certain physical quantity: $T(p_{z\,q1})$, $T(p_{z\,q2})$, p_x, p_y, p_z. The discriminator, in turn, takes input data predicted by the generator and information about the type of polarization. The discriminator architecture is similar to the generator architecture, but with added Spectral Normalization for each hidden layer [14]. The discriminator output is a single neuron with a linear activation function.

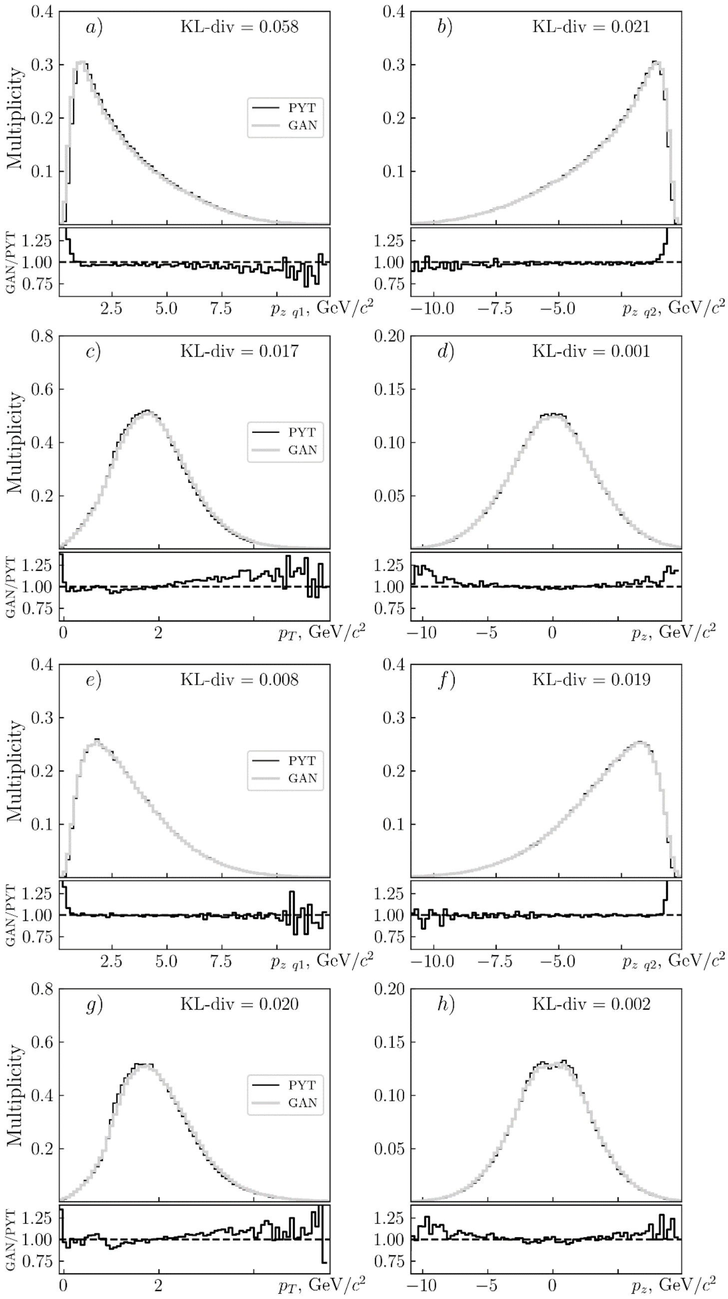

Fig. 1. Comparison of results obtained by GAN predictions and PYTHIA8 simulation (gray and black curves, respectively) for parton momenta $p_{z\,q1}$ and $p_{z\,q2}$ (*a*, *b*, *e*, *f*) and direct photon momenta p_T and p_z (*c*, *d*, *g*, *h*) for unpolarized (*a*–*d*) and longitudinally polarized (*e*–*h*) protons

Simulation results

Fig. 1 shows the results of PYTHIA8 simulations and GAN predictions for parton momentum distributions p_{zq1} and $p_{z\,q2}$ as well as direct photons $p_T = \sqrt{p_x^2 + p_y^2}$ and p_z in collisions between unpolarized and longitudinally polarized protons with center-of-mass energy $\sqrt{s}$ = 27 GeV. The momenta are expressed in units of GeV/c^2. Multiplicity is plotted along the vertical axes, defined as the number of samples in each histogram bin normalized by the total number of events. The ratios of GAN to PYTHIA8 predictions (GAN/PYT) are shown for each histogram. In addition, the values of the Kullback–Leibler divergence (KL-div) [16] for each distribution are given as numerical estimates of the similarity between the distributions of quantities.

Comparing the results obtained by simulation and GAN prediction, we can see that the distributions produced by GAN practically do not differ from the results of PYTHIA8 simulation, as evidenced by the graphs for the ratios of GAN to PYTHIA8 predictions. The predictions obtained from GAN also yield good agreement for the case of longitudinally polarized proton-proton collisions.

Fig. 2 shows the dependence of asymmetries A_{LL} (obtained by Eq. (2)) on the momentum fraction $x_T = 2p_T/\sqrt{s}$ of the direct photon, calculated based on GAN prediction and PYTHIA8 simulation. It follows from this figure that GAN predictions allow to obtain values of asymmetries A_{LL} coinciding with the PYTHIA8 values with the accuracy up to uncertainties. These uncertainties are associated with the chosen scale of the strong interaction in the range $(p_T/2)^2 < Q^2 < (2p_T)^2$.

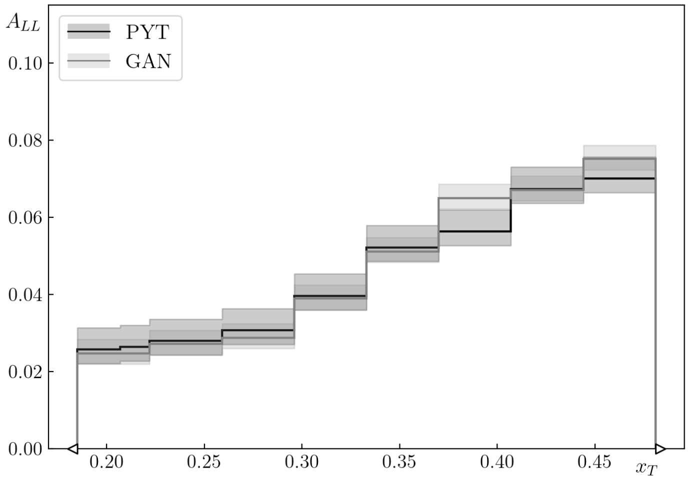

Fig. 2. Dependence of asymmetry A_{LL} on momentum fraction x_T of direct photon in collision of longitudinally polarized protons, at energy $\sqrt{s}$ = 27 GeV

The shaded area correspond to the uncertainty associated with the chosen scale of the strong interaction $(p_T/2)^2 < Q^2 < (2p_T)^2$. The data were obtained using GAN and PYTHIA8 (gray and black curves, respectively)

Conclusion

The paper considers a generative adversarial network (GAN) for predicting the characteristics of a direct photon generated in a proton collision at center-of-mass energy $\sqrt{s}$ = 27 GeV.

It is established that the developed GAN model shows high accuracy in predicting the components of direct photon momentum, as well as the p_z components of parton momentum producing the direct photon during their interactions in collisions of both unpolarized ($p + p$) and longitudinally polarized ($\vec{p}\vec{p}^{\,(\leftarrow)}$) protons.

Furthermore, it is confirmed that GAN can be used to accurately predict the values of double longitudinal spin asymmetry A_{LL}.

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