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SEPARATION OF QUARK AND GLUON JETS  
IN THE DIRECT PHOTON PRODUCTION PROCESSES  
AT THE LHC USING THE NEURAL NETWORK  
APPROACH

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## 1. Introduction.

There are two QCD processes mainly contributing to the production of a direct photon: the Compton-like process

$$qg \rightarrow q + \gamma \quad (1)$$

and the annihilation process

$$q\bar{q} \rightarrow g + \gamma. \quad (2)$$

It was proposed in our paper [1] to use the direct photon production processes to extract a gluon distribution function in a proton  $f^g(x, Q^2)$ . It can be done by selecting those “ $\gamma + jet$ ” events which satisfy the criteria pointed out in [2] and [3] to suppress the next-to-leading order diagrams with initial state radiation and the background to the direct photon production from the neutral decay channels of  $\pi^0, \eta, K_s^0, \omega$  mesons and the photons radiated from a quark in the QCD processes with big cross sections (like  $qg \rightarrow qg, qq \rightarrow qq$  and  $q\bar{q} \rightarrow q\bar{q}$  scatterings).

A percentage of Compton-like process (1) (amounting to 100% together with (2)) for different transverse energy  $E_t^{jet} (\approx E_t^\gamma)$  and pseudorapidity  $\eta^{jet}$  intervals are given in Table 1:

Table 1: A percentage of the Compton-like process  $qg \rightarrow \gamma + q$ .

Calorimeter part	$E_t^\gamma$ interval (GeV)		
	40–50	100–120	200–240
Barrel	89	84	78
Endcap+Forward	86	82	74

In the table above the string “Barrel” corresponds to the Barrel region of the CMS calorimeter ( $|\eta| < 1.4$ ) while the string “Endcap+Forward” corresponds to the Endcap+Forward region ( $1.4 < |\eta| < 5.0$ ).

Thus, an admixture of the processes with a gluon jet in the final state grows from the left upper corner to the right bottom one, i.e. with a jet energy. Therefore, to collect a clean sample of “ $\gamma + quark jet$ ” events sample it is necessary to reject “ $\gamma + gluon jet$ ” events. This is most important in the Endcap+Forward region for jets with  $E_t^{jet} > 100$  GeV where the part of the “ $\gamma + gluon jet$ ” events is more than 20% and where one can reach the smallest  $x$  values of the gluon distribution function  $f^g(x, Q^2)$  (see [1]).

The idea of using the Artificial Neural Network (ANN) to discriminate quarks from gluons was widely discussed in the literature ([4] – [8]). In [7], [8] the discrimination procedure is described for  $e^+e^-$  reactions at  $\sqrt{s} = 29, 92$  GeV with three different Monte Carlo (MC) generators: JETSET, ARIADNE and HERWIG. After

testing with a middle point criterion the network was able to classify correctly, on the average, 85% of quark and gluon jets for a testing set. The MC independence of the results was also demonstrated by training with the MC data simulated by one generator and by testing with the MC data from another. We also refer to [11], where MC independence (JETSET/HERWIG) of the quark/gluon separation procedure based on the moment analysis of jet particles is presented.

In [5] the ANN was applied to a set of  $p\bar{p}$  events at  $\sqrt{s} = 630 \text{ GeV}$  generated with PYTHIA [12]. The UA2 calorimeter geometry was used there to classify quark and gluon jets produced in the  $qq \rightarrow qq$ ,  $q\bar{q} \rightarrow q\bar{q}$  and  $gg \rightarrow gg$  QCD subprocesses alone. The 70 – 72% classification ability with respect to the middle point criterion was reached there. In this paper we use the ANN approach to get the most effective discrimination of quark and gluon jets in processes (1) and (2) selected by the cuts given in Section 3 (and earlier in [2], [3]). The close results were obtained in [9] by using two- and three-layered network for quark/gluon jets classification in the  $p\bar{p} \rightarrow 2 \text{ jets}$  events at  $\sqrt{s} = 630 \text{ GeV}$ .

The study was carried out using the JETNET 3.0 package <sup>1</sup> developed at CERN and the University of Lund [4].

## 2. Artificial Neural Network.

### 2.1 Generality and mathematical model of the neural network.

ANNs are often used to optimize a classification (or pattern recognition) procedure and was applied to many pattern recognition problems in high energy physics (see [5] – [8], [10], [17] – [19]) with a notable success. They usually have more input than output nodes and thus may be viewed as performing dimensionality reduction of input data set.

The ANN approach is a technique which assigns objects to various classes. These objects can be different data types, such as a signal and a background in our case. Each data type is assigned to a class which in the context of the given paper is 0 for the background (gluon jet) and 1 for the signal (quark jet). Discrimination is achieved by looking at the class to which the data belongs. The technique fully exploits the correlation among different variables and provides a discriminating boundary between the signal and the background.

ANNs have an ability to learn, remember and create relationships amongst the data. There are many different types of ANN but the feed forward types are most popular in the high energy physics. Feed forward implies that information can only flow in one direction and the output directly determines the probability that an event characterized by some input pattern vector  $X(x_1, x_2, \dots, x_n)$  is from the signal class.

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<sup>1</sup>It is available via *anonymous* ftp from thep.lu.se or from freehep.scri.fsu.edu.

The mathematical model of the Neural Network (NN) reflects three basic functions of a biological neuron:

- sum up all the information arriving at inputs of the node/neuron;
- if sum is greater than some threshold, fire neuron;
- after firing, return to the initial state and send a signal to each of the neighboring neurons in the network.

The neuron with these characteristics is known as an elementary perceptron. The perceptron is a simple feed forward system with several input connections and a single output connection.

Mathematically the output can be written as

$$O(x_1, x_2, \dots, x_n) = g\left(\frac{1}{T} \sum_i \omega_i x_i + \theta\right). \quad (3)$$

Here  $g$  is a non-linear transfer function and typically takes the following form (sigmoid function)

$$g = \frac{1}{1 + e^{-2x}}, \quad (4)$$

$(x_1, x_2, \dots, x_n)$  is the input pattern vector,  $O$  is the output,  $\omega_i$  and  $\theta$  are independent parameters called weights (which connect the input nodes to the output node) and a threshold of the output node.  $\beta = 1/T$  is called inverse temperature and defines the slope of  $g$ .

The pattern vector  $x_i$  is multiplied by the connection weights  $\omega_i$  so that each piece of information appears at the perceptron as  $\omega_i x_i$ . Then the perceptron sums all the incoming information to give  $\sum \omega_i x_i$  and applies the transfer function  $g$  to give the output (see (3)).

In a feed forward NN a set of neurons has a layered structure. Figure 2.1 shows the feed forward the NN with one hidden layer that is used here. In this case the output of NN is

$$O(x_1, x_2, \dots, x_n) = g\left(\frac{1}{T} \omega_j \sum_k \left(\frac{1}{T} \sum_k \omega_{jk} x_k + \theta_j\right) + \theta\right), \quad (5)$$

where  $\omega_{jk}$  is the weight connecting the input node  $k$  to the hidden node  $j$  and  $\omega_j$ 's connect the hidden nodes to the output node.  $\theta_j$  and  $\theta$  are the thresholds of the hidden and the output node respectively.

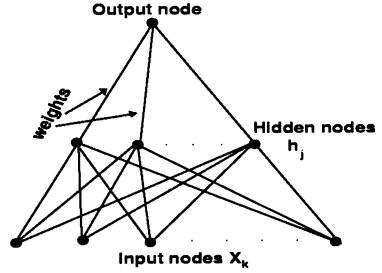


Fig. 1. Neural network with one layer of hidden units.

## 2.2 Learning of the perceptron.

The behavior of a perceptron is determined by independent parameters known as weights and thresholds. The total number of independent parameters in a neural network with a single layer is given by:

$$N_{ind} = (N_{in} + N_{on}) \cdot N_{hn} + N_{ht} + N_{ot} \quad (6)$$

where  $N_{in}$  is a number of input nodes,  $N_{on}$  is a number of output nodes,  $N_{hn}$  is a number of nodes in a hidden single layer,  $N_{ht}$  is a number of thresholds in a hidden single layer,  $N_{ot}$  is a number of output thresholds.

Learning is the process of adjusting these  $N_{ind}$  parameters. During learning every perceptron is shown examples of what it must learn to interpret. It is fulfilled on the training set consisting of two parts: training data (a collection of input patterns to the perceptron) and a training target, which is a desired output of each pattern.

Mathematically, the goal of training is to minimize a measure of the error. The mean squared error function  $E$  averaged over the training sample is defined by equation (7)

$$E = \frac{1}{2N_p} \sum_{p=1}^{N_p} \sum_{i=1}^N (O_i^{(p)} - t_i^{(p)})^2, \quad (7)$$

where  $O_i$  is the output of the  $i$ th node of the NN in equation (5);  $t_i$  is the training target (in our case, 0 for the background and 1 for the signal);  $N_p$  is the number of patterns (events) in the training sample;  $N$  is the number of network outputs ( $N = 1$  for our case).

There are several algorithms for error minimization and weight updating. Most popular are **Back propagation**, **Langevin** and **Manhattan** methods. In the last one the weight is updated during the learning by the following rule <sup>2</sup>:

$$\omega_{t+1} = \omega_t + \Delta\omega \quad (8)$$

$$\Delta\omega = -\eta \cdot \text{sgn}[\partial E / \partial \omega] \quad (9)$$

where  $\omega$  is the vector of weights and thresholds used in the network;  $t$  ( $t + 1$ ) refers to the previous (current) training cycle and  $\eta$  is the learning rate which is decreased in the learning process.

## 3. Event selection and Monte Carlo simulations for the ANN analysis.

Our selection conditions for “ $\gamma + jet$ ” events are based on the selection rules chosen in [2] and [3]. We suppose the electromagnetic calorimeter (ECAL) size to be limited by  $|\eta| \leq 2.61$  and the hadronic calorimeter (HCAL) is limited by  $|\eta| \leq 5.0$  (the CMS geometry; see [14] and [15]), where  $\eta = -\ln(\tan(\theta/2))$  is a pseudorapidity <sup>3</sup> defined

<sup>2</sup>see [6] for a more complete description

<sup>3</sup>not to be confused with the learning rate also designated by  $\eta$

through a polar angle  $\theta$  counted from the beam line. In the plane transverse to the beam line the azimuthal angle  $\phi$  defines the directions of  $\vec{E}_t^{jet}$  and  $\vec{E}_t^\gamma$ .

1. We select the events with one jet and one photon candidate with

$$E_t^\gamma \geq 40 \text{ GeV} \quad \text{and} \quad E_t^{jet} \geq 30 \text{ GeV}. \quad (10)$$

A jet is defined here according to the PYTHIA jetfinding algorithm LUCCELL<sup>4</sup>. The jet cone radius  $R$  in the  $\eta - \phi$  space is taken as  $R = ((\Delta\eta)^2 + (\Delta\phi)^2)^{1/2} = 0.7$ .

2. Only the events with “isolated” photons are taken to suppress the background processes. To do this, we

a) restrict the value of the scalar sum of  $E_t$  of hadrons and other particles surrounding a photon within a cone of  $R_{isol}^\gamma = ((\Delta\eta)^2 + (\Delta\phi)^2)^{1/2} = 0.7$  (“absolute isolation cut”)

$$\sum_{i \in R} E_t^i \equiv E_t^{isol} \leq E_t^{isol}_{CUT}; \quad (11)$$

b) restrict the value of a fraction (“relative isolation cut”)

$$\sum_{i \in R} E_t^i / E_t^\gamma \equiv \epsilon^\gamma \leq \epsilon^\gamma_{CUT}; \quad (12)$$

c) accept only the events having no charged tracks (particles) with  $E_t > 1 \text{ GeV}$  within the  $R_{isol}^\gamma$  cone around a photon candidate.

3. We consider the structure of every event with the photon candidate at a more precise level of the  $5 \times 5$  crystal cells window (size of one CMS HCAL tower) with a cell size of  $0.0175 \times 0.0175$ . To suppress the background events with the photons resulting from high-energy  $\pi^0$ ,  $\eta$ ,  $\omega$  and  $K_S^0$  mesons we require<sup>5</sup> that *either* (a1) there is no high  $E_t$  hadron in this  $5 \times 5$  crystal cells window (*at the PYTHIA level of simulation*):

$$E_t^{hadr} \leq 5 \text{ GeV}. \quad (13)$$

*or* (a2) the transverse energy deposited in HCAL in the radius  $R = 0.7$  counted from the center of gravity of the HCAL tower just behind the ECAL  $5 \times 5$  window, containing a direct photon signal, to be limited by (*at the level of the full event simulation*; see below) :

$$E_t^{HCAL} \leq 1 \text{ GeV}. \quad (14)$$

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<sup>4</sup>PYTHIA’s default jetfinding algorithm

<sup>5</sup>At the PYTHIA level of simulation this cut may effectively take into account the imposing of an upper cut on the HCAL signal in the tower behind the ECAL  $5 \times 5$  crystal cells window hit by the direct photon (see [20]).

4. The events with the vector  $\vec{E}_t^{jet}$  being “back-to-back” to the vector  $\vec{E}_t^\gamma$  within  $\Delta\phi$  in the plane transverse to the beam line with  $\Delta\phi$  defined by equation:

$$\phi_{(\gamma,jet)} = 180^\circ \pm \Delta\phi \quad (\Delta\phi = 15^\circ, 10^\circ, 5^\circ) \quad (15)$$

(5° is the size of one CMS HCAL tower in  $\phi$ ) for the following definition of the angle  $\phi_{(\gamma,jet)}$ :  $\vec{E}_t^\gamma \vec{E}_t^{jet} = E_t^\gamma E_t^{jet} \cdot \cos(\phi_{(\gamma,jet)})$  with  $E_t^\gamma = |\vec{E}_t^\gamma|$ ,  $E_t^{jet} = |\vec{E}_t^{jet}|$ .

5. To discard more the background events, we choose only the events that do not have any other (except one jet) minijet-like or cluster high  $E_t$  activity with the  $E_t^{clust}$  higher than some threshold  $E_{tCUT}^{clust}$ . Thus we select events with

$$E_t^{clust} \leq E_{tCUT}^{clust}, \quad (16)$$

where clusters are found by the same jetfinder LUCCELL used to find a jet in the same event.

The following values of cut parameters were used here:

$$E_{tCUT}^{isol} = 5 \text{ GeV}; \quad \epsilon_{CUT}^\gamma = 7\%; \quad \Delta\phi < 15^\circ; \quad E_{tCUT}^{clust} = 10 \text{ GeV}. \quad (17)$$

To obtain the results of this paper we used two types of the generations:

(a) by PYTHIA alone, based on the averaged calorimeter cell sizes  $\Delta\eta \times \Delta\phi$ :  $0.087 \times 0.087$  in the Barrel,  $0.134 \times 0.174$  in the Endcap and  $0.167 \times 0.174$  in the Forward parts;

(b) by CMSJET – the full-event fast Monte Carlo simulation package for a response in the CMS detector [13] with the switched on calorimeter and magnetic field effects.

The following  $E_t^\gamma$  intervals were considered for both types of generations:  $40 < E_t^\gamma < 50$ ,  $100 < E_t^\gamma < 120$  and  $200 < E_t^\gamma < 240 \text{ GeV}$ . Besides, for every  $E_t^\gamma$  interval we separate the regions to which the jet belongs: Barrel ( $|\eta^{jet}| < 1.4$ ) and Endcap+Forward ( $1.4 < |\eta^{jet}| < 4.5$ ). Since the jet is a spatially spread object, some energy leakage from one calorimeter part to another is possible. To distinguish cases when a jet is in the Barrel or in the Endcap+Forward regions the following restriction was added to cuts 1 – 5:

$$\Delta E_t^{jet} / E_t^{jet} = 0 \text{ – for the PYTHIA level study}; \quad (18)$$

$$\Delta E_t^{jet} / E_t^{jet} \leq 0.05 \text{ – for the CMSJET level study}. \quad (19)$$

Here  $\Delta E_t^{jet}$  is the jet  $E_t$  leakage from that part of the calorimeter in which the jet gravity center was found.

#### 4. Training and testing of ANN.

There are two stages in the neural network analysis. The first is training of the network and the second is testing. NN is trained with samples of signal and background

events and tested by using independent data sets. Training of the network corresponds to step-by-step changing of the weights  $\omega_{jk}$  such that a given input vector  $X^{(p)}(x_1, x_2, \dots, x_n)$  produces an output value  $O^{(p)}$  that equals the desired output or target value  $t^{(p)}$  (see (5) and (7)).

The input parameters used in the 0th (input) layer of the network (Fig. 1) were chosen as follows. In “Set 01” and “Set 02” we analyzed the jet information obtained in PYTHIA simulation. In Set 01 we assigned  $E_t$ ,  $\eta$  and  $\phi$  of the first  $E_t$  leading cell to the nodes  $x_1$ ,  $x_2$  and  $x_3$  respectively. Then we took the second leading cell and assign its  $E_t$ ,  $\eta$  and  $\phi$  to the nodes  $x_4$ ,  $x_5$  and  $x_6$ . The same was done for the remaining 13 cells. So, we had 45 input nodes in total <sup>6</sup>. In Set 02 we added 46th input node with a number of charged tracks  $N_{track}$  inside a jet with  $E_t^{ch} > 1 \text{ GeV}$ . For “Set 1” and “Set 2” we repeated the previous procedure but with respect to the cells of jets found after the fast Monte Carlo simulation of the whole event by using CMSJET. Analogously, we had 45 and 46 (+ $N_{track}$  information) input nodes for Sets 1 and 2.

To ensure convergence and stability, the total number of training patterns (events) must be significantly (20 – 30 times) larger than the number of independent parameters (see (6)). About 7000 signal (with a quark jet) and background (with a gluon jet) events were chosen for the training stage, i.e. about 30 patterns per a weight.

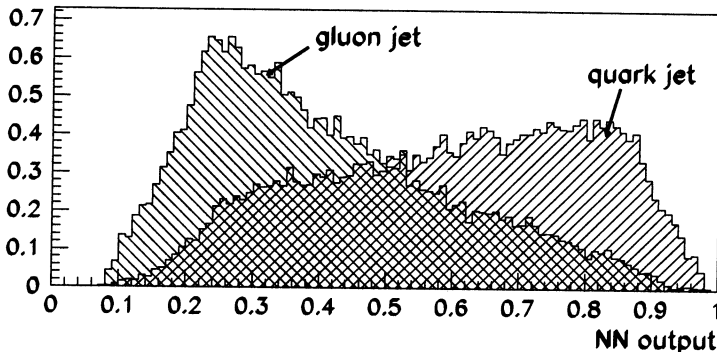


Fig. 2: Neural network output for quark and gluon jets that were found in the Endcap+Forward region,  $40 < E_t^\gamma < 50 \text{ GeV}$ .

After the NN was trained, a test procedure was implemented in which the events not used in the training were passed through the network. The same proportion of the signal and background events (about 7000 of each sort) was used at the

<sup>6</sup>This input set is the same as in [5]. It was checked out that variation down to 10 or up to 20 cells data at the input do not much affect the result.



generalization stage. An output was provided for each event and could be considered as a probability that an event is either from signal or background sample. If the training is done correctly, the probability for an event being signal is high if the output  $O$  is close to 1. And conversely, if the output  $O$  is close to 0, it is more likely to be a background event (see Fig. 2 for the case of jets found in the Endcap+Forward region and  $40 < E_t^\gamma < 50 \text{ GeV}$  as an example of a typical NN output).

## 5. The choice of neural network architecture and learning parameters.

To investigate dependence of the separation possibility on the learning parameters, we trained a neural network with 7000 signal events and 7000 background events found after the CMSJET simulation. In those events the direct photon  $E_t$  was chosen to be  $100 < E_t^\gamma < 120 \text{ GeV}$  and jets were found in the Barrel region.

The network was tested with an independent set of 7000 signal and background events. Sensitivity to different NN parameters was tested from the point of view of the NN quark/gluon separation probability with respect to the “0.5-criterion” (point 0.5 of the NN output). These parameters are listed below and the corresponding plots are given in Figs. 3 and 4.

- *Number of training cycles*

We varied the number of training cycles from 100 to 1000 to investigate the effect of training on the network performance. The result shown in Fig. 3 indicates the network stability if more than 200 training cycles are used.

- *Inverse temperature*

The inverse temperature determines the steepness of the transfer function  $g(x)$  (4). On the left-hand upper plot of Fig. 4 the quark/gluon separation probability drops by 1% as one goes from  $\beta = 0.5 - 1$  to  $\beta = 1.5 - 1.8$ .

- *Number of hidden nodes*

One hidden layer is used here because it is sufficient for most classification problems [4]. Sensitivity of the quark/gluon separation probability to a number of hidden nodes  $N_h$  was tested with  $N_h = 3 - 15$ . All resulting points fall within 1% (71 – 72%) window (see Fig. 4)<sup>7</sup>.

- *Learning rate  $\eta$*

The learning rate  $\eta$  is a factor in updating the weights. We varied its value between 0.0001 and 0.05 (see left-hand bottom plot in Fig. 4). The value  $\eta = 0.005$  was chosen for our analysis.

- *Scale parameter  $\gamma_{scale}$*

The optimal learning rate  $\eta$  varies during learning while the network converges towards the solution. The scale factor for its changing is determined by the

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<sup>7</sup>To be exact, a bit better result is achieved with  $N_h = 11$ .

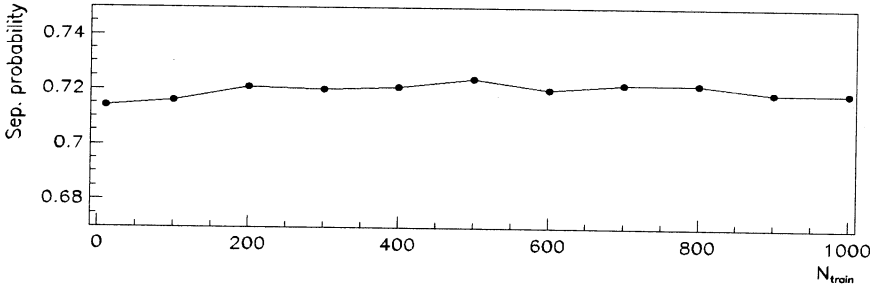


Fig. 3: The quark/gluon separation probability using “0.5-criterion” as a function of the number of training cycles  $N_{train}$ .

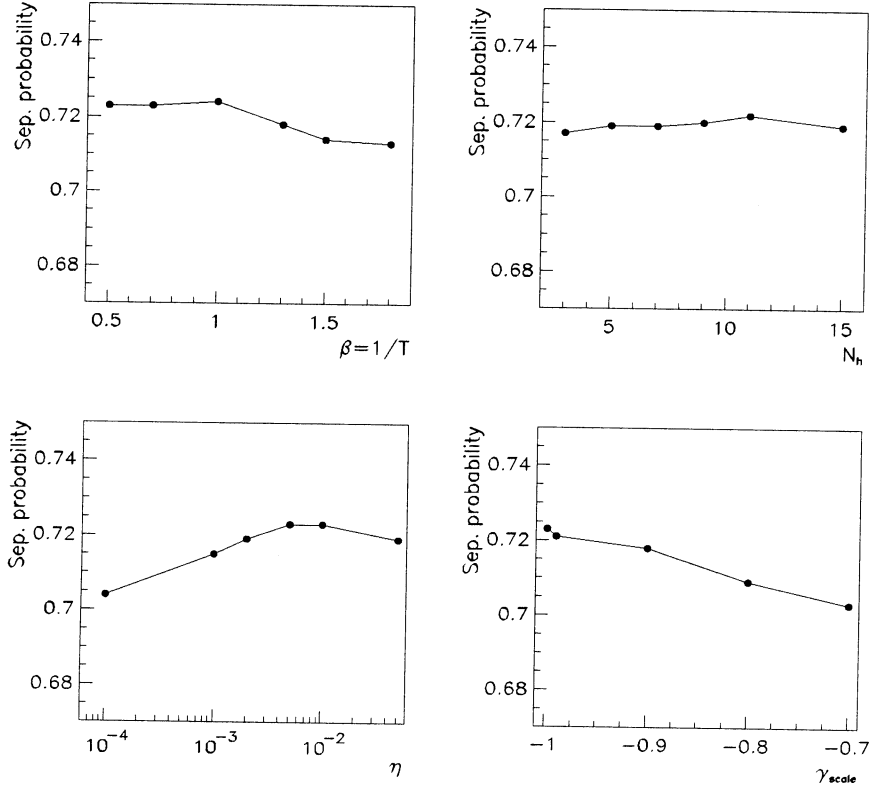


Fig. 4: The quark/gluon separation probability using the “0.5-criterion” criterion for various network parameters: inverse temperature  $\beta = 1/T$ , the number of hidden nodes  $N_h$ , learning rate  $\eta$ ,  $\eta$  updating scale parameter  $\gamma_{scale}$ .

parameter  $\gamma_{scale}$ . The right-hand bottom plot in Fig. 4 shows that the optimal performance is achieved at the default value  $\gamma_{scale} = -1$ .

As was mentioned above, the Manhattan updating method was used here during the training procedure. In Table 2 for the case of jets in the Barrel region and  $100 < E_t^\gamma < 120 \text{ GeV}$  (Set 2) this method is compared with other updating algorithms with various values of learning parameters: learning rate  $\eta$  (Backpropagation, Langevin) and noise term  $\sigma$  (Langevin). It is seen that by varying  $\eta$  and  $\sigma$  from their

Table 2: A dependence of the separation probability (%) using “0.5-criterion” on the method. CMSJET, Set 2, Barrel region,  $100 < E_t^\gamma < 120 \text{ GeV}$ .

Method	Backpropagation			Langevin		
Parameters	$\eta=1.$	$\eta=0.5$	$\eta=0.1-$ $\eta=0.001$	$\eta=1.0$ $\sigma=0.01$	$\eta=0.1-0.01$ $\sigma=0.01$	$\eta=0.01$ $\sigma=0.001$
Probab.(%)	51	68	71	69	70	71

default values in the JETNET package (the first column for each algorithm) one can approximately reach the value of the separation probability obtained by using the Manhattan algorithm (72%).

## 6. Description of the results.

As an example of the “0.5-criterion” application, Table 3 presents the discrimination powers obtained after the simulation at the PYTHIA level and events selection according to the cuts (10) – (18) of Section 3 for three various intervals of the direct photon  $E_t$ .

Table 3: The quark/gluon separation probability (%) using “0.5-criterion”. Barrel and Endcap+Forward regions. PYTHIA level simulation.

Simulation type	Set No.	$E_t^\gamma$ interval (GeV)		
		40 – 50	100 – 120	200 – 240
Barrel	01	74	76	79
	02	75	77	82
Endcap+ Forward	01	70	69	69
	02	73	74	75

The error is of order of 1.5 – 2% for all numbers in the table above.

We see that by using the “0.5-criterion” for the ANN output, when the output node value  $O > 0.5$  is interpreted as a quark jet and  $O < 0.5$  as a gluon jet, the

network correctly classifies 75 – 82% (73 – 75%) of jets at the PYTHIA level in the Barrel (Endcap+Forward) region with the input data that correspond to Set 01 and Set 02 (see Section 4). The separation probability is seen to grow by 1 – 3% after introducing the information on the number of tracks  $N_{track}$  in the Barrel region. The analogous increase for the Endcap+Forward region is 3 – 6%.

To give an understanding of such an improvement we plot, as an example, a distribution of the number of events over the number of tracks with  $E_t > 1 \text{ GeV}$  in quark and gluon jets, i.e.  $N_{track}^q$  and  $N_{track}^g$ , for  $40 < E_t^\gamma < 50 \text{ GeV}$  and  $200 < E_t^\gamma < 240 \text{ GeV}$  in the Endcap+Forward region (Fig. 5)<sup>8</sup>. Due to the larger probability of bremsstrahlung from a gluon than from a quark we obtain the  $\langle N_{track}^g \rangle / \langle N_{track}^q \rangle$  ratio equal to 1.27 for  $40 < E_t^\gamma < 50 \text{ GeV}$  and 1.46 for  $200 < E_t^\gamma < 240 \text{ GeV}$ .

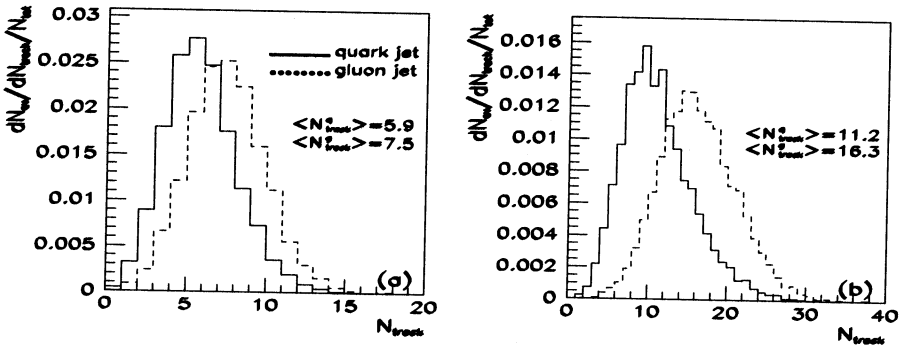


Fig. 5: Distribution over the number of charged tracks with  $E_t^{ch} > 1 \text{ GeV}$  for jets found in the Endcap+Forward region:  $40 < E_t^\gamma < 50 \text{ GeV}$  (a) and  $200 < E_t^\gamma < 240 \text{ GeV}$  (b).

Figures 6 – 8 obtained after the full event simulation with the help of CMSJET also explain the choice of the variables at the input to NN in Section 4. As is seen from Figs. 6 and 7,  $E_t$  of the leading cell (“ $Et1$ ” in the plots) in a quark jet is, on the average, 25 – 30% greater than in a gluon jet. The difference in  $E_t$  for the next-to-leading cells (“ $Et2$ ” on the plots) in quark and gluon jets is about 10 – 20% (it is smaller for jets with a higher  $E_t$ ).  $E_t$  of a complete quark jet is also greater than  $E_t$  of a complete gluon jet (by 4 – 10%). Again, the difference becomes smaller with growing jet  $E_t$ .

Figure 8 shows a distribution of the averaged  $E_t$  in quark and gluon jets over the distance from the jet  $E_t$  leading cell  $R_{ic}$  for all  $E_t^\gamma$  intervals and calorimeter regions considered in this paper. One can note that in all cases the averaged  $E_t$  in a

<sup>8</sup>For a comparison, see also quark and gluon jet multiplicities found in experiments at DELPHI [21], OPAL [22] and D0 [23] collaborations.

quark jet up to  $R_{ic} \approx 0.12 - 0.14$  is greater than in a gluon jet and, vice versa, the averaged  $E_t$  in a quark jet for  $R_{ic} \geq 0.14$  is lower than in a gluon jet.

It is more useful for practical applications to investigate the Signal/Background ratios for different the NN output thresholds <sup>9</sup>. This analysis was done after the full simulation with CMSJET and event selection according to cuts (10) – (19).

The Signal/Background ratios corresponding to the “Set 2” input NN information are given in Table 4 for three  $E_t^\gamma$  intervals and two calorimeter regions. As a complement to Table 4, in Fig. 10 shows the quark selection and gluon rejection efficiencies in the case of the full simulation for the same  $E_t^\gamma$  intervals and calorimeter regions.

Table 4: Signal/Background. The full event simulation using CMSJET. Set 2.

$E_t^\gamma$ (GeV)	Region	NN output cut					
		0.3	0.4	0.5	0.6	0.7	0.8
40 – 50	Barrel	1.45	1.91	2.40	3.11	4.19	6.16
	Endcap+Forward	1.41	1.81	2.38	3.10	4.04	5.85
100 – 120	Barrel	1.72	2.63	3.26	4.04	4.59	6.37
	Endcap+Forward	1.75	2.19	2.95	3.61	4.21	5.41
200 – 240	Barrel	1.76	2.37	3.35	4.26	5.56	7.36
	Endcap+Forward	1.64	2.40	3.17	4.16	5.39	7.45

The Signal/Background ratio grows both with growing NN output threshold value and with increasing  $E_t^\gamma$  value (see Table 4). So, it grows from 2.4 to 3.2 at the NN output cut  $O > 0.5$  and from 4.0 to 5.4 at  $O > 0.7$  for the Endcap+Forward region. The curves in Fig. 10 show that for the last cut ( $O > 0.7$ ) about 38% and 44% of the events with the quark jet are selected for  $40 < E_t^\gamma < 50$  GeV and  $200 < E_t^\gamma < 240$  GeV, respectively, while about 66 – 67% of the events with quark jet are selected at  $O > 0.5$  for the both  $E_t^\gamma$  intervals and the same calorimeter region.

The Signal/Background ratio dependence on the NN output cut at the PYTHIA level is presented in Figs. 12 and 13.

It is also important for practical realizations to know a dependence of the Signal/Background ratios on the quark jet selection efficiencies. This dependence is plotted in Fig. 11 for two extreme considered in this paper intervals  $E_t^\gamma$  and two calorimeter regions. We present two curves obtained with Set 1 and Set 2 of input information after the full CMSJET event simulation (thin and thick solid lines) and one curve (dotted line) obtained with Set 02 after event simulation at the PYTHIA level.

<sup>9</sup>not only for the point 0.5 as in Table 3 above

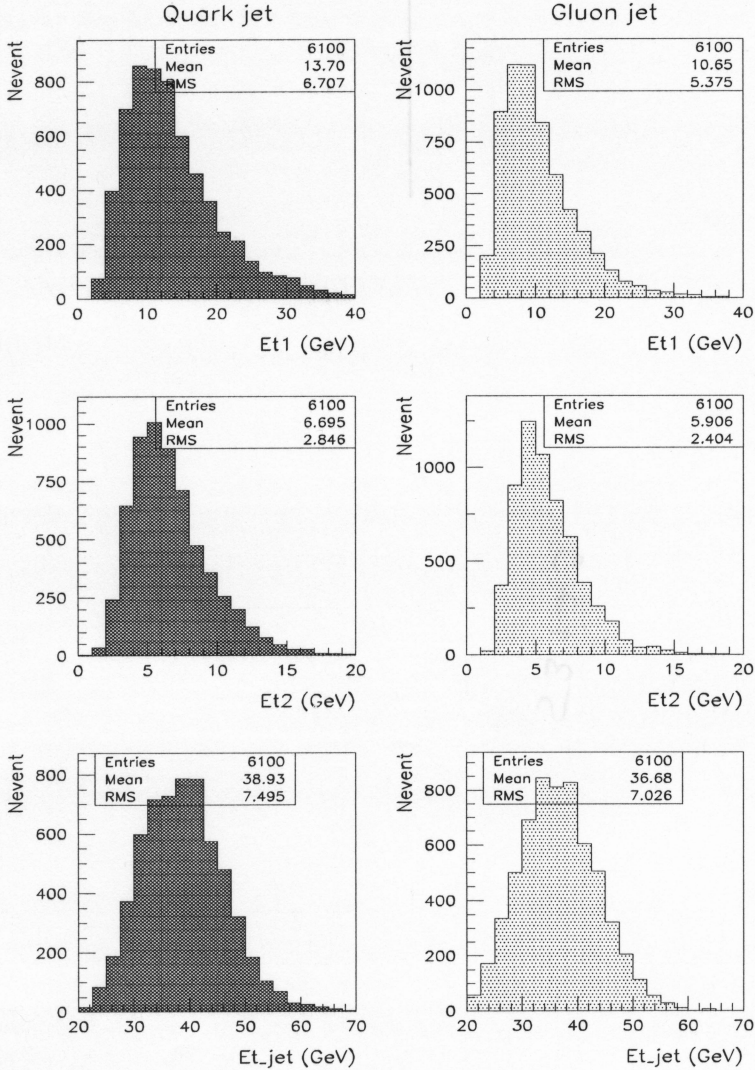


Fig. 6: Distribution over  $E_t$  of leading cell ( $E_{t1}$ ),  $E_t$  of next-to-leading cell ( $E_{t2}$ ) and  $E_t$  of the full quark and gluon jets. CMSJET, Endcap+Forward,  $40 < E_t^\gamma < 50$  GeV.

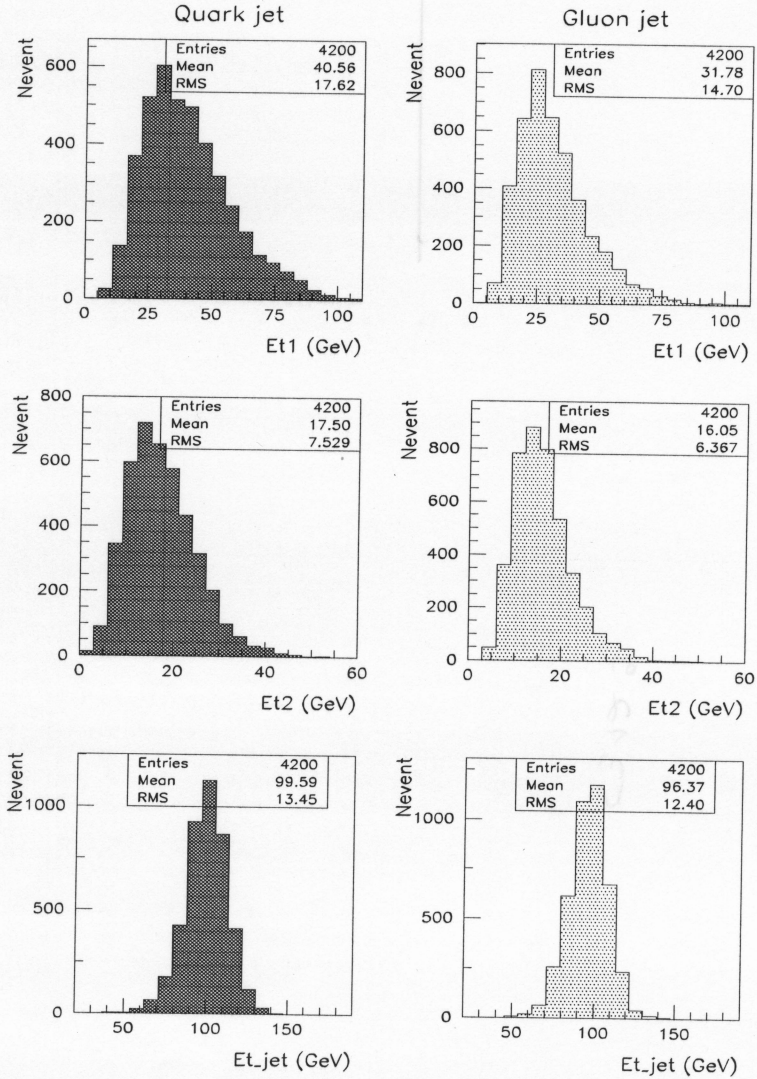


Fig. 7: Distribution over  $E_t$  of leading cell ( $E_{t1}$ ),  $E_t$  of next-to-leading cell ( $E_{t2}$ ) and  $E_t$  of the full quark and gluon jets. CMSJET, Endcap+Forward,  $100 < E_t < 120$  GeV.

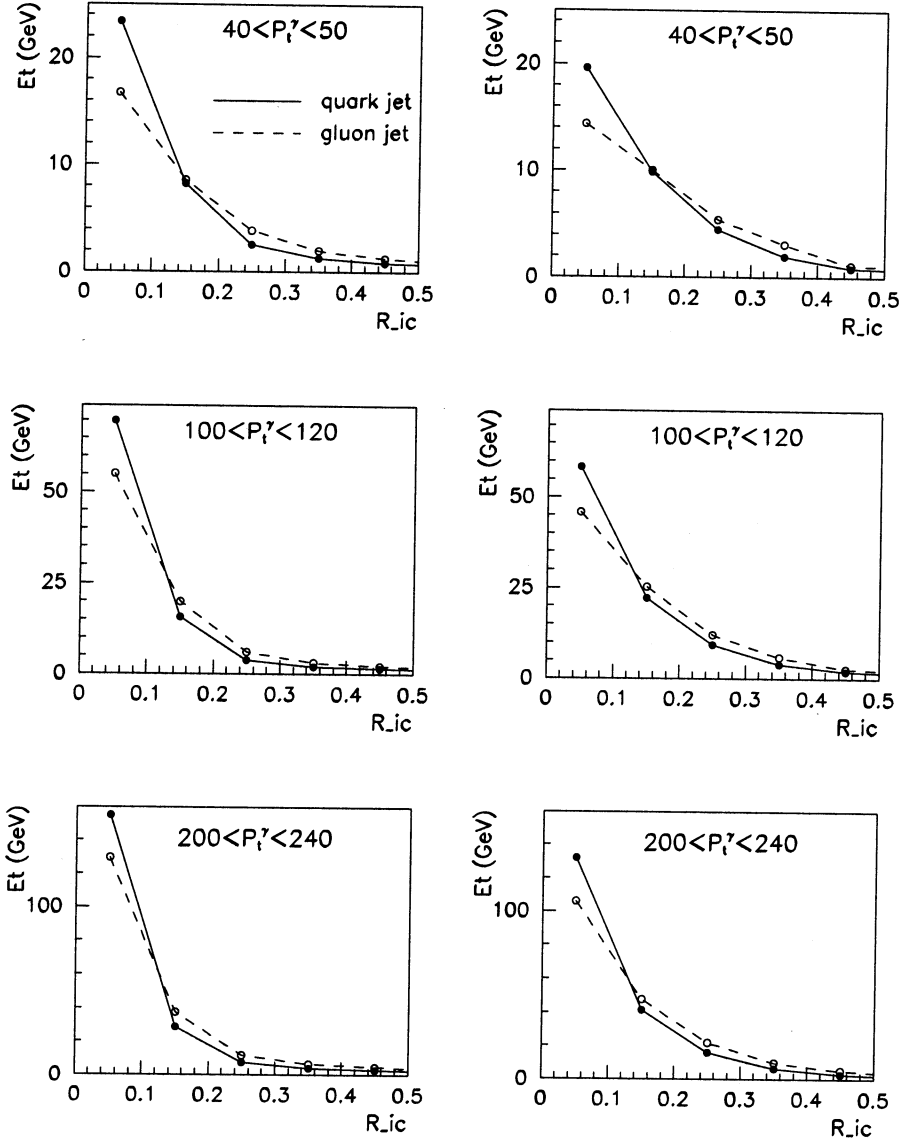


Fig. 8: Distribution of  $E_t$  over the distance  $R_{ic}$  (in the  $\eta - \phi$  space) from the initiator cell inside quark (solid line) and gluon (dashed line) jets. The left-hand column corresponds to the Barrel region and the right-hand to the Endcap+Forward region. The CMSJET simulation.



## 7. Some additional remarks.

The results obtained with the quark and gluon jets found in the CMSJET simulation were compared with the results obtained after passing the quark and gluon jet particles through the electromagnetic (ECAL) and hadronic (HCAL) calorimeters in the CMSIM package [16]. The discrimination probabilities obtained after the cell analysis in CMSIM are found to be in good agreement (up to 1 – 2%) with those obtained in CMSJET. It was also found that almost the same discrimination powers can be achieved both in CMSET and in CMSIM by using the network input information about  $E_t$  of the first,  $E_t$ -ordered 15 ECAL and 15 HCAL cells (i.e. 30 input nodes) instead of 45 input nodes as considered above (see Section 4).

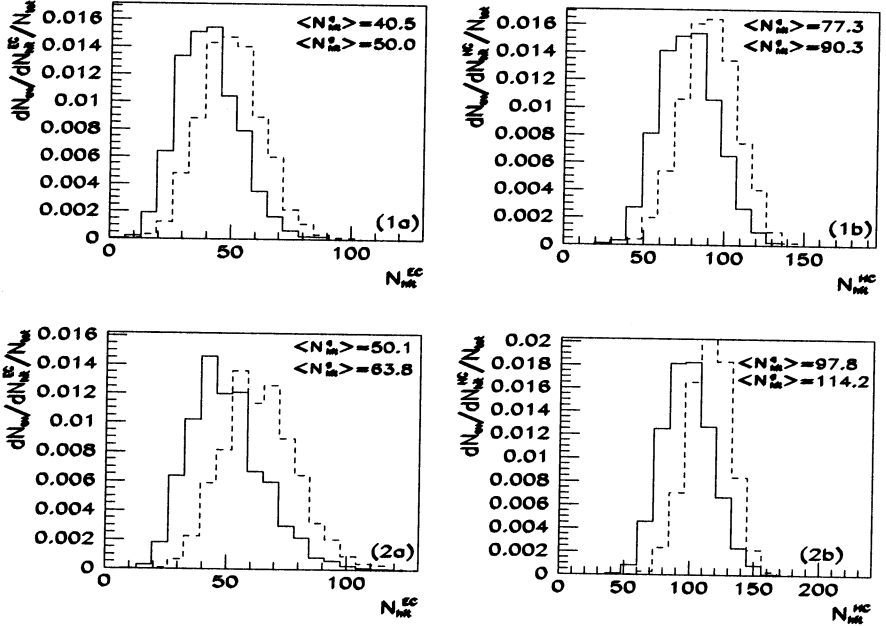


Fig. 9: Distribution over the number of ECAL (plots 1a and 2a) and HCAL jet cells (plots 1b and 2b),  $N_{hit}^{EC}$  and  $N_{hit}^{HC}$ , for jets found in the Barrel region:  $40 < E_t^\gamma < 50 \text{ GeV}$  (1a, 1b) and  $200 < E_t^\gamma < 240 \text{ GeV}$  (1b, 2b).

The sensitivity of the network to some parameters is also noteworthy. So, the network is able to classify correctly quark and gluon jets with respect to the “0.5-criterion” in 65% (67%) of events with  $40 < E_t^\gamma < 50 \text{ GeV}$  ( $200 < E_t^\gamma < 240 \text{ GeV}$ ) by using the  $N_{track}$  variable alone. These results can be improved by 2 – 3% if we also add to  $N_{track}$  two more input variables: the numbers of activated cells (towers) in the ECAL and the HCAL belonging to quark and gluon jets. The distributions over

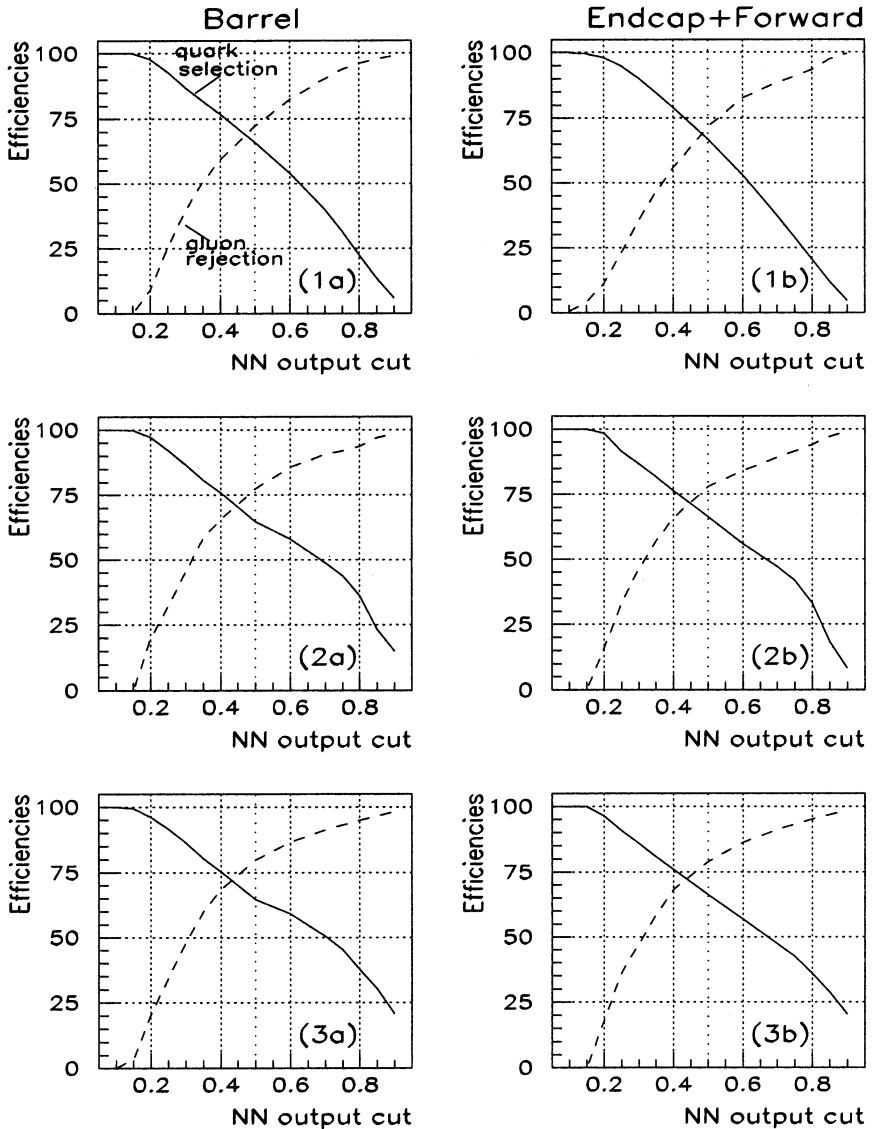


Fig. 10: Quark jet selection and gluon jet rejection efficiencies as a function of neural network output cut. Left-hand (1a, 2a, 3a) and right-hand (1b, 2b, 3b) columns correspond to the Barrel and the Endcap+Forward regions respectively. The first row plots (1a, 1b) are distributions for events selected with  $40 < E_t^\gamma < 50 \text{ GeV}$ , in the second (2a, 2b) with  $100 < E_t^\gamma < 120 \text{ GeV}$  and in the third (3a, 3b) with  $200 < E_t^\gamma < 240 \text{ GeV}$ . Set 2.

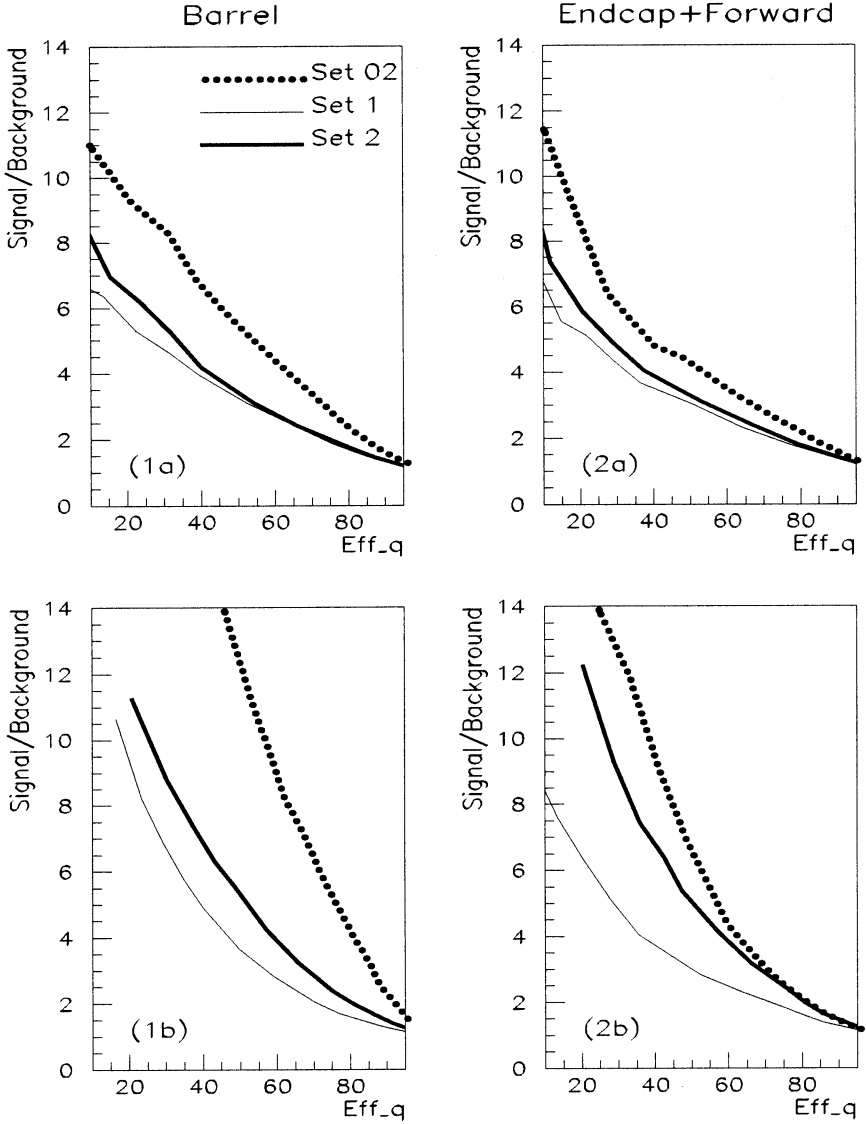


Fig. 11: Signal to background ratio via quark jet selection efficiency. The left-hand column (1a, 1b) correspond to the events with jets found in the Barrel and the right-hand (2a, 2b) correspond to the events with jets found in the Endcap+Forward region. In the first row (1a, 2a) are distributions for events selected with  $40 < E_t^\gamma < 50 \text{ GeV}$  and in the second with  $200 < E_t^\gamma < 240 \text{ GeV}$ .

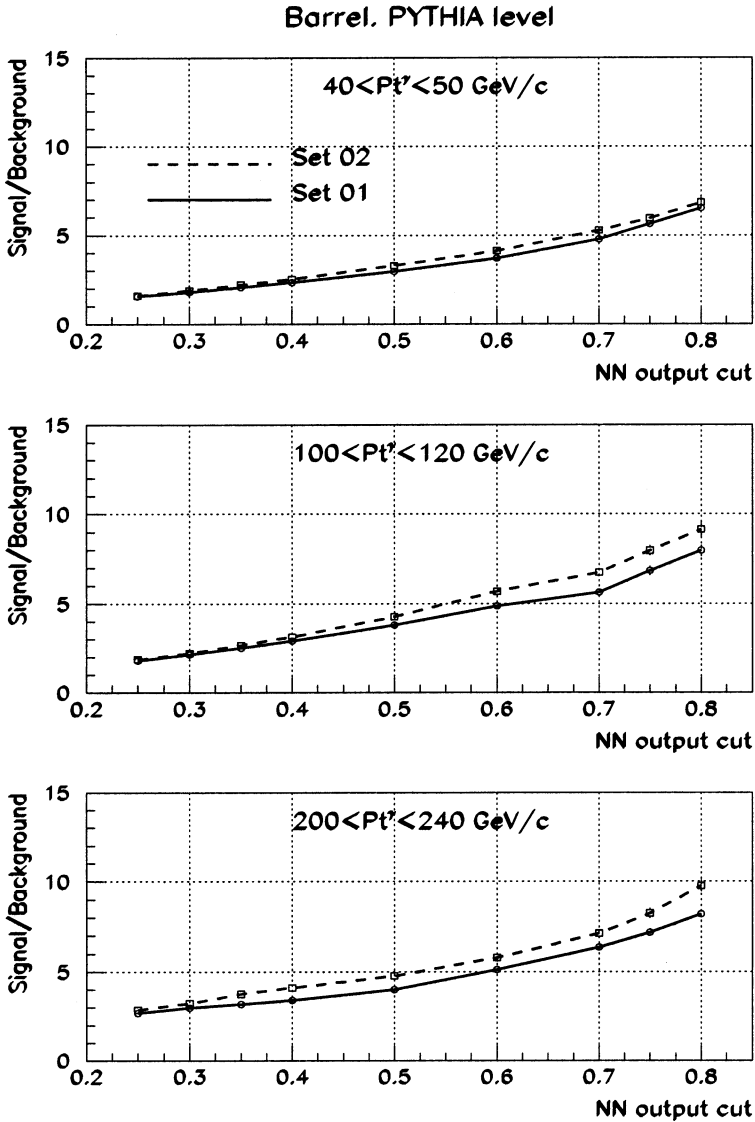


Fig. 12: Signal/Background ratio as a function of the NN output threshold value at the PYTHIA level. Barrel region.

### Endcap+Forward. PYTHIA level

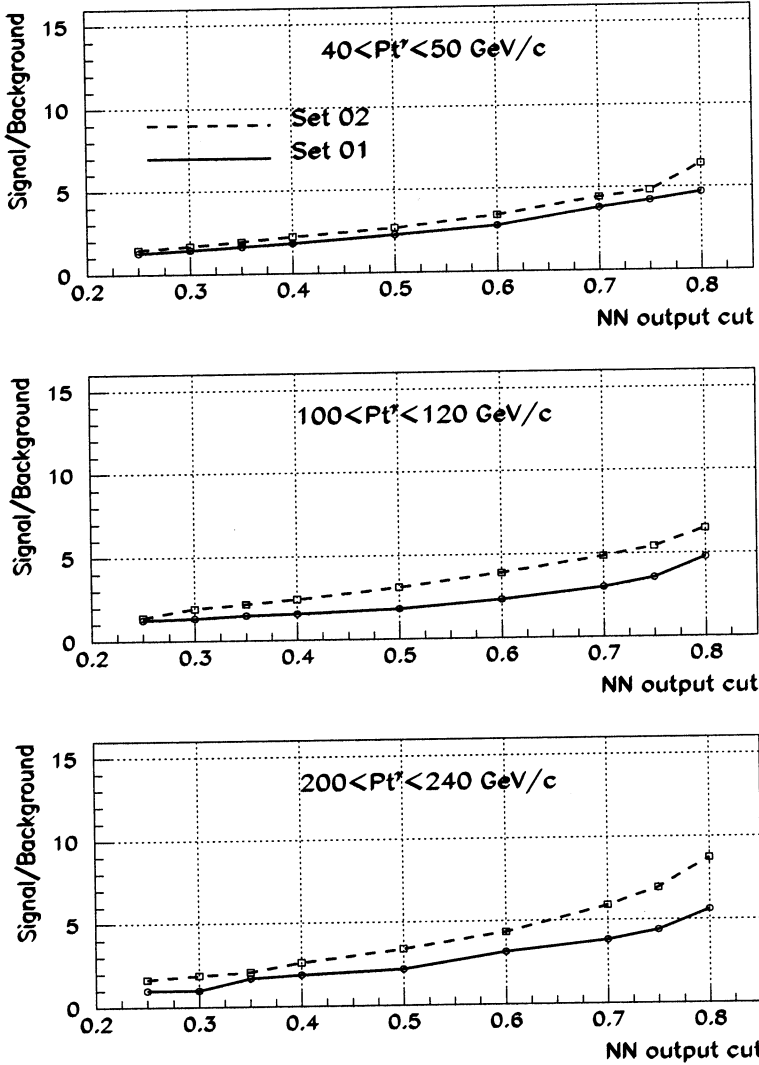


Fig. 13: Signal/Background ratio as a function of the NN output threshold value at the PYTHIA level. Endcap+Forward region.

those numbers are shown in Fig. 9 for two  $E_t^\gamma$  intervals:  $40 < E_t^\gamma < 50 \text{ GeV}$  and  $200 < E_t^\gamma < 240 \text{ GeV}$ . We see that mean number of the activated cells in the ECAL for the case of gluon jets  $\langle N_{hit}^g \rangle$  exceeds that for the case of quark jets  $\langle N_{hit}^q \rangle$  by a factor of 1.23 for  $40 < E_t^\gamma < 50 \text{ GeV}$ . This difference grows up to the factor of 1.28 for  $200 < E_t^\gamma < 240 \text{ GeV}$ . And in both intervals the ratio of the mean numbers of the activated cells  $\langle N_{hit}^g \rangle / \langle N_{hit}^q \rangle$  in the HCAL is about 1.16 – 1.17.

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Разделение кварковых и глюонных струй  
в процессах рождения прямых фотонов на LHC  
с использованием метода нейронных сетей

В работе использована техника нейронных сетей для разделения кварковых и глюонных струй в процессах  $qg \rightarrow q + \gamma$  и  $q\bar{q} \rightarrow g + \gamma$  на LHC. Рассматривая нейронную сеть как триггер, используя монте-карловский генератор событий PYTHIA и пакет CMSJET для быстрого моделирования отклика на событие в CMS-детекторе, авторы получили отношения сигнал/фон.

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Separation of Quark and Gluon Jets  
in the Direct Photon Production Processes  
at the LHC Using the Neural Network Approach

A neural network technique is used to discriminate between quark and gluon jets produced in the  $qg \rightarrow q + \gamma$  and  $q\bar{q} \rightarrow g + \gamma$  processes at the LHC. Considering the network as a trigger and using the PYTHIA event generator and the full event fast simulation CMSJET package for the CMS detector we obtain signal-to-background ratios.

The investigation has been performed at the Dzhelepov Laboratory of Nuclear Problems, JINR.

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