CDF note 8402

Measurement of the $t\bar{t}$ production cross section in the all-hadronic channel (1.02 fb^{-1})

The CDF Collaboration
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We present here the measurement of the $t\bar{t}$ production cross section in the all-hadronic channel, where both $W's$ decay hadronically. The analysis is performed using 1.02 fb^{-1} of $p\bar{p}$ collisions collected with a multijet trigger at $\sqrt{s} = 1.96$ GeV with the Collider Detector at Fermilab. After the application of an optimized neural net kinematical selection we observe an excess of events with 6 or more jets, including one or more b jets, relative to background expectations. Based on the number of tagged jets we measure the production cross section $\sigma_{t\bar{t}} = 8.3^{+2.3}_{-1.9}$ pb for a top mass of 175 GeV/c^2.

Preliminary Results for Summer 2006 Conferences

I. INTRODUCTION

This note describes the measurement of the $t\bar{t}$ production cross section in $p\bar{p}$ collisions at $\sqrt{s} = 1.96$ TeV with the CDF[1] detector at Fermilab Tevatron. In this analysis we search for events in which both W bosons decay into a $q\bar{q}'$ pair, leading to an all-hadronic final state characterized by a nominal 6-jet topology. This final state has the advantage of a large branching ratio ($BR \approx 4/9$) and of being fully reconstructed. The major drawback is that it competes against a very large QCD multijet background which dominates by three order of magnitude even after the application of a specific multijet trigger.

To improve the signal-to-background ratio, S/B, we consider a set of kinematical variables and build a neural network discriminator which favors $t\bar{t}$ candidates leading to $S/B \approx 1/16$ with a good efficiency ($\epsilon_k = 4.8\%$ for a top mass of 175 GeV/c^2). This is clearly not enough and we need to require the presence of displaced secondary vertices (*tags*) in the event to increase the S/B and to extract a $t\bar{t}$ signal. The analysis presented here represents an improvement of the strategies used by CDF in Run I [2, 3] (109 pb^{-1}) and Run II [4] (311 pb^{-1}) for the observation of $t\bar{t}$ production in this final state.

II. MONTE CARLO SAMPLES

In this analysis, Monte Carlo simulations are used only for the generation of $t\bar{t}$ samples intended for the training of the neural network, the optimization of the kinematical selection and the evaluation of its efficiency and the corresponding systematic uncertainties.

A large sample of events generated with PYTHIA [6] (6.216) with a top mass of 175 GeV/c^2 has been used for the neural network training, while additional samples generated with PYTHIA and HERWIG [7] (6.508) under different conditions of ISR/FSR modeling and using different p.d.f. sets have been produced for the evaluation of the systematic uncertainty on the efficiency.

All samples have been processed with a realistic simulation of the CDF detector response in order to reproduce the performances of the Silicon detector.

III. DATA SAMPLE AND EVENT SELECTION

We summarize here the procedure used to isolate all-hadronic $t\bar{t}$ candidates in the $p\bar{p}$ collisions collected by CDF in the period 2002/2006 and corresponding to 1.02 fb^{-1}.

A. Multijet trigger

A special multijet trigger has been devised specifically for this analysis. This trigger requires at least four calorimeter clusters with $E_T \geq 15$ GeV (with respect to $z = 0$) and a total transverse energy exceeding 125 GeV. Such a threshold has been increased at a certain time to 175 GeV to accomodate for higher rates due to higher instantaneous luminosities delivered by the Tevatron. For simplicity we apply at analysis level always the higher threshold. This trigger has a cross section of about 5 nb and an efficiency of about 85% on all-hadronic $t\bar{t}$ events (about 61% on all $t\bar{t}$ events). The signal-to-background ratio at this level amounts to about 1/1300 (assuming $\sigma_{t\bar{t}} = 6.7$ pb as expected in theory for a top mass of 175 GeV/c^2 considering all possible $t\bar{t}$ events).

B. Prerequisites

We define some pre-requisites in order to have a sample of events as well defined and as clean as possible:

1. at least one *good quality* vertex with $|z_{vert}| < 60$ cm;
2. $\not{E}_T/\sqrt{\sum E_T} < 3$ to avoid overlap with the $\not{E}_T$ + jets analysis;
3. removal of events with a *good, high-P_T central electron or muon* to avoid overlap with other leptonic analyses.

After such pre-requisites we remain with about $3,004,000$ data events.

C. Topological cut

The all-hadronic $t\bar{t}$ events we are interested in have, nominally, 6 jets in the final state. The number of jets actually seen can be smaller or larger due to initial state or final state radiation and acceptance/threshold effects on the jets. We found quite appropriate though, in terms of S/B to begin our event selection with the request for $6 \leq N_{jet} \leq 8$ jets where each jet has at least 15 GeV of transverse energy (corrected for detector and reconstruction effects) and is produced with pseudo-rapidity $|\eta| < 2.0$. To avoid partial overlapping between jets we request also that the minimum distance between jets in the $\eta - \phi$ plane be $\Delta R \geq 0.5$ units. Such two requests select about $507,000$ events. The number of expected ($\sigma_{t\bar{t}} = 6.7$ pb) $t\bar{t}$ events at this level is about 1370.

D. Neural network based kinematical selection

The neural network chosen here is the Multilayer perceptron (MLP[8]) as implemented inside ROOT through the class *TMultiLayerPerceptron*. This is a simple feed-forward network with an input layer, hidden layers and an output layer.

The aim of the training/learning process is to minimize the total error on a set of weighted examples. The *TMultiLayerPerceptron* class implements a variety of learning methods, and we used the Broyden, Fletcher, Goldfarb, Shanno (BFGS) method, which implies the computation of a $N_{weights} \times N_{weights}$ matrix and is considered to be powerful and fast at the same time.

We do the training on background/signal samples of equal amount: about 380 thousand events with $6 \leq N_{jet} \leq 8$ and $\Delta R \geq 0.5$. Half of the samples are used for the training and half of them are used as test samples. The training is repeated for 100 epochs (defined as reading and testing over the whole training sample). For the signal we use Monte Carlo $t\bar{t}$ events, while for the background we prefer (given the wery low S/B) to use the data themselves.

We have studied several configurations in terms of input variables and number of hidden layers and nodes, and among these, the one which behaves the best in terms of S/B ratio and efficiency has 11 inputs and two hidden layers with 20 and 10 nodes respectively. The single output node provides the variable NN_{out} on which we will base the selection.

The 11 inputs considered are:

1. total transverse energy, $\sum E_T$
2. sub-leading transverse energy, $\sum_3 E_T = \sum E_T - E_T^1 - E_T^2$
3. centrality, $C = \sum E_T/\sqrt{\hat{s}}$
4. aplanarity, A
5. the minimum dijet mass, M_{2j}^{min}
6. the maximum dijet mass, M_{2j}^{max}
7. the minimum trijet mass, M_{3j}^{min}
8. the maximum trijet mass, M_{3j}^{max}
9. $E_T^{1\star} \equiv E_T^1 \cdot \sin^2\theta_1^\star$
10. $E_T^{2\star} \equiv E_T^2 \cdot \sin^2\theta_2^\star$
11. $\langle E_T^\star \rangle_{3N}$

where $\theta^\star$ is the cosine of the polar angle of the jet as measured in the all-jets rest frame. The last variable represent the geometric average of the $E_T^\star = E_T \cdot \sin^2\theta^\star$ quantities over all jets but the first two (i.e. the 2 highest-E_T jets).

The output of the network, as evaluated on the test samples, is shown in Figure 1. When we apply the neural network to the whole background and signal ($m_t = 175$ GeV/c^2 and $\sigma_{t\bar{t}} = 6.7$ pb) samples we obtain the distribution of Figure 2. The region $NN_{out} \geq 0.8$ is where we gain quite much in S/B, because of the fast rise in the signal distribution. The cut on NN_{out} which performs the best will be chosen later, after the b-tagging request and the evaluation of the background.

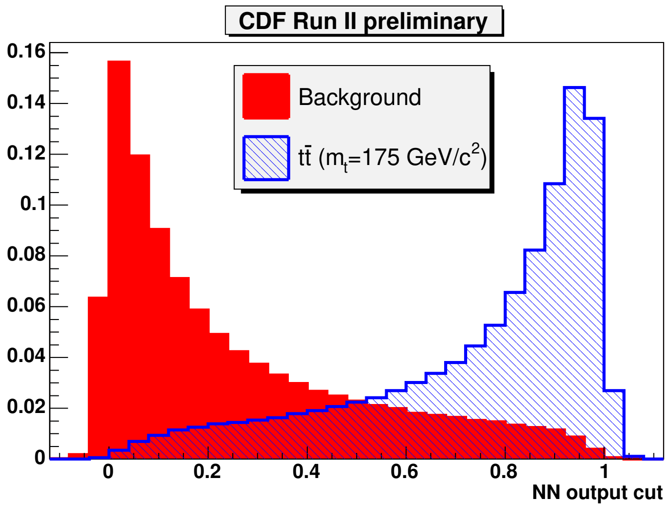

FIG. 1: NN_{out} distribution for the "test sample".

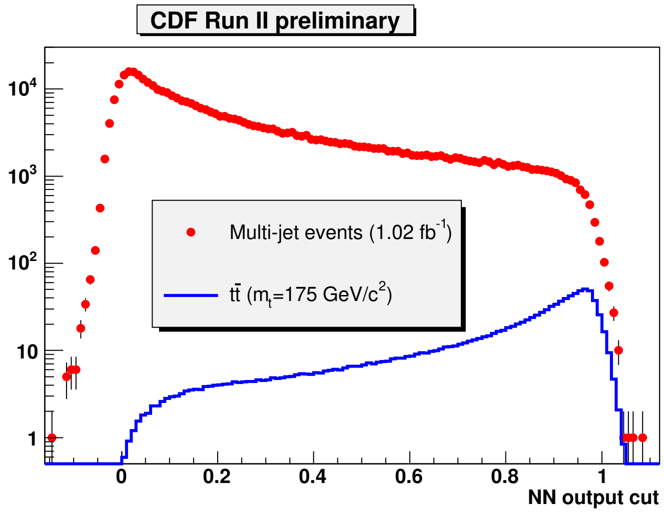

FIG. 2: NN_{out} distribution for the whole sample (the $t\bar{t}$ distribution is normalized to the expectation of 1370 events with $6 \leq N_{jet} \leq 8$ and $\Delta R_{min} \geq 0.5$).

IV. DISPLACED VERTEX TAGGING

In order to further improve the S/B we require the presence of secondary vertices reconstructed with at least two good quality tracks with hits in our Silicon vertex detector. To be called *tags* the jets with secondary vertices need to have a signed displacement from the primary vertex with a significance larger than 5.0. The cross section measurement is performed using the total number of tagged jets (not events) in order to avoid the explicit calculation of the background for double tagged events (which cannot be easily obtained in a data-driven background estimate).

The average number of tags in a $t\bar{t}$ event passing the kinematical selection is $n_{tag}^{ave} = 0.95 \pm 0.005(\text{stat.}) \pm 0.07(\text{syst.})$, as derived from simulations and comparison to b-enriched events.

A. Background estimate

The data-driven method we use to estimate the background is based on the verified assumption that even if the relative contribution from all QCD processes might change as a function of jet multiplicity, the probability for a *taggable* jet (that is a jet inside the vertex detector acceptance) to be tagged remains flat increasing the jet multiplicity. This allows to use the probability extracted from a signal-depleted control sample (events with $N_{jet} = 4$) on jets in events with higher jet multiplicity in order to estimate the number of tags expected in the signal sample. Such a probability (*tag rate*) is defined as:

$$\mathcal{P} = \frac{\#\ of\ tagged\ jets}{\#\ of\ taggable\ jets}$$

To account for the different conditions of the control and the signal samples, the tag rate is parametrized in terms of jet-E_T, number of tracks reconstructed in the vertex detector (N_{trk}) and number of primary vertices (N_{vert}).

Before the neural network kinematical selection the multijet sample is composed, essentially, by background events only. The goodness of the parametrization and of the resulting estimates across different jet multiplicities can be seen in Figs. 3, 4 and 5.

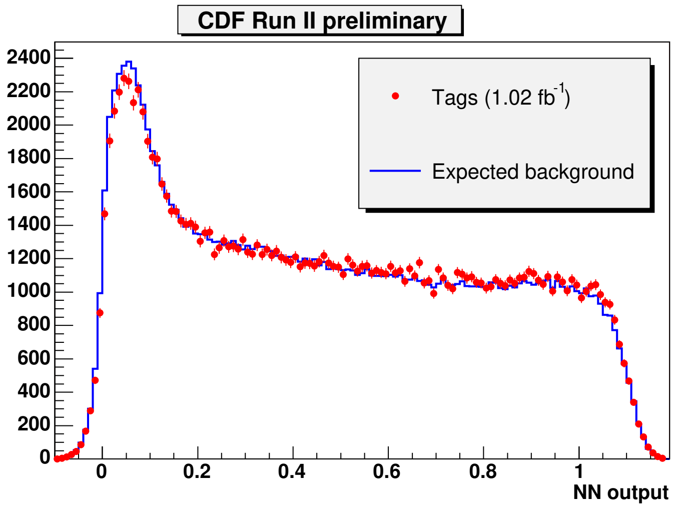

FIG. 3: NN_{out} distribution for observed and expected tags. Events with 4 jets.

B. Systematics uncertainties on the background estimate

The topological request for $6 \leq N_{jet} \leq 8$ and the neural network based kinematical selection change the event characteristics with respect to those found in the control sample (events with $N_{jet} = 4$) where the parametrization has been derived. Possible biases due to both requirements are evaluated and are treated as systematic uncertainties on the background prediction. By considering the agreement between the estimated background and the observed tags, and allowing for the expected presence of $t\bar{t}$ events (with the theoretical cross section of 6.7 pb) we evaluate a relative systematic uncertainty of 2.5% on the background prediction after the topological and neural network kinematical selection.

V. NEURAL NETWORK BASED SELECTION

We use the neural network output as a discriminator between signal and background and cut on the value of the neural network output, NN_{out} to select candidate events with a good S/B.

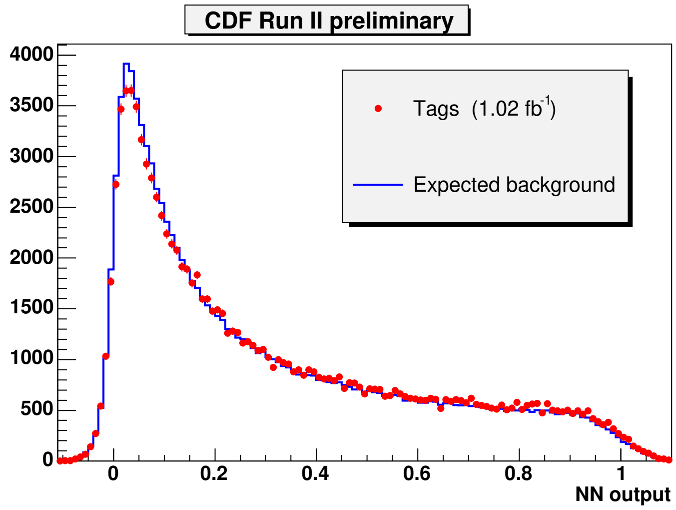

FIG. 4: NN_{out} distribution for observed and expected tags. Events with 5 jets.

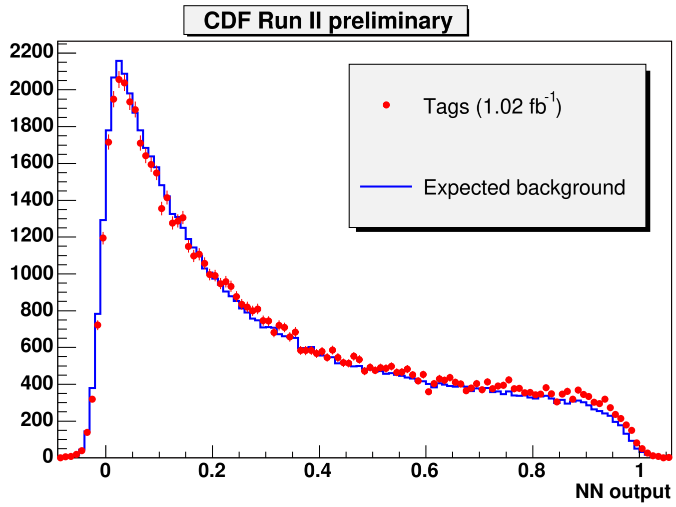

FIG. 5: NN_{out} distribution for observed and expected tags. Events with 6 to 8 jets.

A. Optimized selection

After the initial preselection and the topology cuts, we seek an optimal kinematical selection which provides the smallest relative total uncertainty expected on the cross section measurement, $\Delta\sigma/\sigma$. This quantity is approximately equal to $\Delta(B+S)/S$ where S is expected signal ($\sigma_{t\bar{t}} = 6.7$ pb), B is the background and $\Delta(B+S)$ the total uncertainty expected on the candidates. As signal we consider $t\bar{t}$ Monte Carlo events, while as background we consider the estimate derived from the application of the data-driven parametrization. The cut on NN_{out} which is expected to have the best performance on the cross section measurement is the one which provides the largest value for $\Delta(B+S)/S$, and is $NN_{out} \geq 0.94$, as shown in Figure 6.

Such a selection isolates (before b-tagging) 4205 candidate events with an efficiency of $4.8 \pm 0.8\%$ (on all $t\bar{t}$ events) and $S/B \approx 1/16$. The relative systematic uncertainty on the efficiency is quite large (17%) and dominated by the uncertainties on the jet energy scale (see Table I).

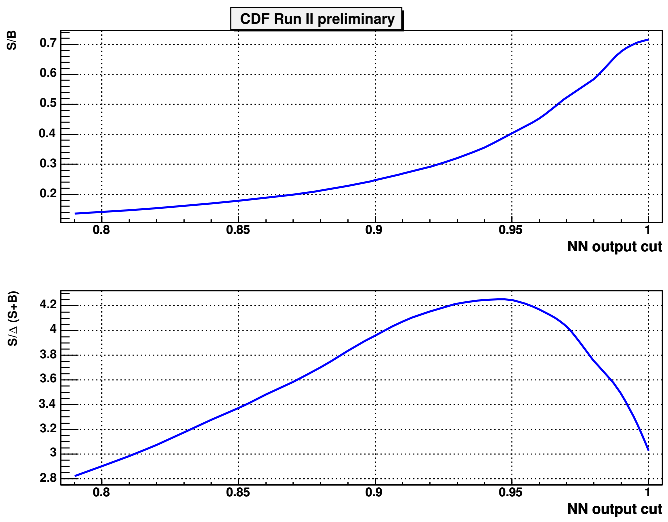

FIG. 6: S/B and $\Delta(B+S)/S$ as a function of the cut on NN_{out}. Events with 6 to 8 jets and $\Delta R \geq 0.5$.

Source	$\delta\epsilon/\epsilon$ (%)
Jet energy scale	16.3
ISR/FSR modeling	2.9
Multiple interactions	2.5
p.d.f.	1.4
Generator	1.1
NN training	0.1
Total	17.0

TABLE I: Relative systematic uncertainties on the kinematical efficiency.

B. Background estimate after the kinematical selection

The background estimates for each jet multiplicity bin after the neural network kinematical selection are summarized in Table II. The backgrounds estimated as described above have been iteratively corrected for the observed presence of $t\bar{t}$ events in the pre-tag sample.

N_{jet}	4	5	6	7	8	6-8
Events	118657	16157	2575	1069	561	4205
Background	15961 ± 677	2653 ± 112	481 ± 20	223 ± 10	142 ± 7	846 ± 37
$t\bar{t}$ ($\sigma = 8.3$ pb)	120 ± 20	266 ± 45	242 ± 41	101 ± 17	38 ± 7	381 ± 65
Background + $t\bar{t}$	16081 ± 677	2919 ± 121	723 ± 46	324 ± 20	180 ± 10	1227 ± 76
Observed Tags	16555	3139	725	349	159	1233

TABLE II: Observed tags and background estimate after the neural network kinematical selection. The uncertainties correspond to the quadrature sum of statistical and systematic uncertainties. The statistical uncertainties on the background for different jet multiplicities are correlated and are summed linearly.

VI. CROSS SECTION MEASUREMENT

After the application of the kinematical selection to a multijet sample of 1.02 fb^{-1}, we are left with 4205 events, out of which 1020 events have at least one tag, for a total of $n = 1233$ candidate tags. The total background expectation in the signal region, provided by the tag rate parametrization, and corrected for the presence of $t\bar{t}$ events in the pretag

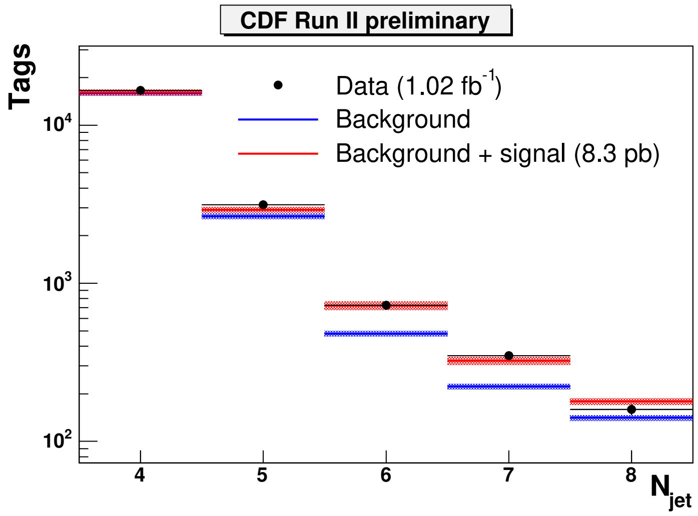

FIG. 7: Number of tagged jets *vs* jet multiplicity. Data (points), background with uncertainty band and $t\bar{t}$ expectation ($\sigma_{t\bar{t}} = 8.3$ pb). ($4 \leq N_{jet} \leq 8$ in log scale).

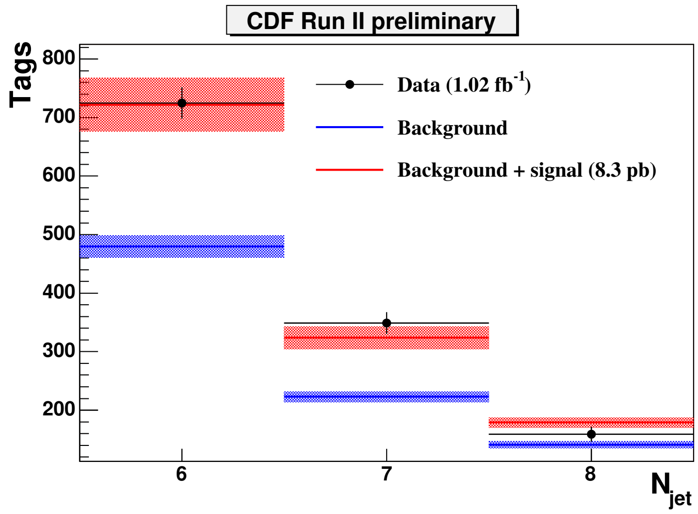

FIG. 8: Number of tagged jets *vs* jet multiplicity. Data (points), background with uncertainty band and $t\bar{t}$ expectation (assuming $\sigma_{t\bar{t}} = 8.3$ pb). ($6 \leq N_{jet} \leq 8$ in linear scale).

sample, amounts to $b = 846 \pm 37$ tags. The excess of tags with respect to the background is ascribed to $t\bar{t}$ production and from this excess we measure the production cross section.

The inputs we use for the cross section measurement are shown in Table III and the central value of the cross section is given by

$$\sigma_{t\bar{t}} = \frac{n - b}{\epsilon_{NN} n_{tag}^{ave} L}$$

The value of the $t\bar{t}$ production cross section, measured in the all-hadronic channel is then:

$$\sigma_{t\bar{t}} = 8.3 \pm 1.0(stat) \pm 0.5(lum)\ ^{+2.0}_{-1.5}(syst) = 8.3^{+2.3}_{-1.9}\ pb$$

Figures 7 and 8 show the number of tagged jets as a function of the jet multiplicity and the comparison to the sum of background and signal (assuming our measured value $\sigma_{t\bar{t}} = 8.3$ pb) expectations.

Variable	Symbol	Input value
Integrated luminosity (fb^{-1})	L	1.02 ± 0.06
Candidate tags	n	1233
Expected background	b	846 ± 37
Neural network selection efficiency (%)	ϵ_{NN}	4.8 ± 0.8
Average number of tags per $t\bar{t}$	n_{tag}^{ave}	0.95 ± 0.07

TABLE III: Input values for the cross section calculation

VII. CONCLUSIONS

We have discussed here the measurement of the $t\bar{t}$ production cross section in the all-hadronic channel using a sample of 1.02 fb^{-1} events collected by CDF with a multijet trigger in the period 2002/2006. Starting from a very small signal-to-background ratio at trigger level ($S/B \approx 1/1300$), we improve it to $S/B \approx 1/2$ by applying a specific neural network based kinematical selection ($\epsilon_{NN} = 4.8 \pm 0.8\%$) and the request of presence of displaced secondary vertices ($n_{tag}^{ave} = 0.95 \pm 0.07$). The background estimate is completely data driven and based on a parametrization of the tag rate on a multijet sample that is signal depleted but kinematically similar to our signal region. The counting of tags shows an excess of 387 tags with respect to a background of 846 ± 37 tags. Abscribing such an excess to $t\bar{t}$ production, we measure the cross section to be

$$\sigma_{t\bar{t}} = 8.3 \pm 1.0(stat) \pm 0.5(lum)\ ^{+2.0}_{-1.5}(syst) = 8.3^{+2.3}_{-1.9}\ pb$$

Acknowledgments

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[1] F. Abe, et al., Nucl. Instrum. Methods Phys. Res. A **271**, 387 (1988); D. Amidei, et al., Nucl. Instum. Methods Phys. Res. A **350**, 73 (1994); F. Abe, et al., Phys. Rev. D **52**, 4784 (1995); P. Azzi, et al., Nucl. Instrum. Methods Phys. Res. A **360**, 137 (1995); The CDFII Detector Technical Design Report, Fermilab-Pub-96/390-E

[2] F. Abe *et al.*, *First Observation of the All-Hadronic Decays of $t\bar{t}$ Pairs*, Phys. Rev. Lett. 79, 1992 (1997).

[3] A. Sidoti *et al*, *Investigation of $t\bar{t}$ in the full hadronic final state at CDF with a Neural Network approach*, Nucl. Instrum. Meth. A 466:538-550 (2001)

[4] See The CDF Collaboration, http://www-cdf.fnal.gov/physics/new/top/confNotes/cdf7793_allhadxsec.ps

[5] M. Cacciari, et al., The $t\bar{t}$ Cross-section at 1.8 TeV and 1.96 TeV: A Study of the Systematics due to Parton Densities and Scale Dependence, JHEP **404**, 68 (2004).

[6] T. Sjostrand et al., High-Energy-Physics Event Generation with PYTHIA 6.1, Comput. Phys. Commun. **135**, 238 (2001).

[7] G. Corcella et al., HERWIG 6: An Event Generator for Hadron Emission Reactions with Interfering Gluons (including supersymmetric processes), JHEP **01**, 10 (2001).

[8] See http://schwind.home.cern.ch/schwind/talks/ITseminar/index.htm and http://www.fynu.ucl.ac.be/users/c.delaere/level2/MLP/ for a description of MLP.