Studying the Cosmic Ray Antiproton with the Support Vector Machine

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Abstract

We performed a series of discussions about the antiproton excess in the AMS-02 data. For the efficiency of calculation, we adopted the Support Vector Machine (SVM) to quickly reproduce the theoretical prediction of cosmic ray fluxes. We ensured the uncertainties introduced by such Machines are acceptable, and carried out the scans throughout the favoured parameter space to exhibit in what sense the dark matter is needed in the explanation of current data. Different proton-proton collision hadronic models are considered,

Combining a series of trained $\Phi_i(E)$ models, we then estimate the background cosmic ray fluxes. **Uncertainty:** Comparing thousands of SVM estimations with the true values, the uncertainties are obtained.



and the effect of solar modulation is shown. More interested cases are to be investigated.

Support Vector Machine (SVM)

We introduced the **SVM** to quickly reproduce the simulation result, in order to **speed up the scan**:

 $n \min \longrightarrow \mathcal{O}(0.1) \mathrm{s}$

SVM is a machine learning model used to perform **classification** or **regression** analysis.

Classification: Given a set of *n*-dimension data points each belong to one of two classes, the SVM would try to search for the **maximum-margin hyperplane** to split them:

 $\mathbf{w} \cdot \mathbf{x} + b = 0.$



E_{kin}[GeV] E_{kin}[GeV] E_{kin}[GeV]

Figure 2: The SVM calculation uncertainty, in comparison with the error of AMS-02 data.

Given the necessary properties of DM, one could then estimate the DM contribution to \bar{p} flux with the integration

 $\int \mathrm{d}E_j \Phi_{DM}^{\delta}(E_j \to E_i) \frac{\mathrm{d}N}{\mathrm{d}E}(E_j).$

In the case that DM with a mass of 30GeV annihilate in bb channel, we take a random test parameter point as an example, comparing the SVM estimation with the real simulation result. It could be seen that the differences between the estimation and real simulation is always smaller than $1\%_0$.



Figure 3: The DM contribution to antiproton from the SVM estimation and the real simulation.

Fitting the antiproton data

Varying the propagation parameters, p injection parameters and p solar modulation parameters ϕ_p within the 2σ region in the previous study, we fitted the AMS-02 \bar{p}/p data.

Figure 1: The maximum-margin hyperplane found in a classification problem.

Nonlinear case: When the data are nonlinear, we could apply the so-called "kernel trick", in which the dot product $\mathbf{x}_i \cdot \mathbf{x}_j$ is replaced by a nonlinear kernel function $k(\mathbf{x}_i, \mathbf{x}_j)$. We choose the Gaussian radial basis function in this work:

 $k(\mathbf{x}_i, \mathbf{x}_j) \equiv \exp(-\gamma ||\mathbf{x}_i - \mathbf{x}_j||^2).$

Regression: If each of the given data points \mathbf{x}_i is assigned with a value y_i , the SVM could perform a regression analysis which result in a target function

 $f(\mathbf{x}) = k(\mathbf{w}, \mathbf{x}) + b,$



Background CR: We investigated two factors that may affect the prediction of CR \bar{p} , the choice of generator and the assumption on solar modulation ϕ .

generator	$\phi_n/\phi_{\bar{n}}$ region	$\phi_n/\phi_{\bar{n}}$	χ^2
Tan & Ng	$\frac{p_{p}}{1.1}$	$\frac{pppp}{1}$	$\frac{1}{49.8}$
Tan & Ng	[0.67.1.5]	1.27	47.7
Winkler	[0.67, 1.5]	1.5	37.5

Figure 4: The best-fit spectrum without the DM component.

DM contribution: In the three considered cases, we then added the DM component to investigate in what sense such a extra component is needed.



which satisfy $f(\mathbf{x}_i) \approx y_i$, and is used to estimate the value of any new point.

Training

We train the SVM with input parameters obtained in our previous work **1701.06149**, in which we performed a scaning to search for the **propagation parameters**, p injection parameters, and solar modulation pa**rameter** ϕ favoured by the B/C and p flux measurements. 10⁴ sets of parameters was choosen, and trainings for **different input values was** performed:

• χ^2 in fitting of the B/C and p flux; the flux of background CR at energy E; • $\Phi_i(E)$ • $\Phi_{DM}^{\delta}(E_i \to E_i)$ the DM contribution to \bar{p} flux at energy E_i resulted from a delta injection $\delta(E-E_i)$.

Figure 5: The $1, 2, 3 - \sigma$ favoured parameter region of the DM component.

Conclusions

• We introduced the SVM method to quickly reproduce the simulation result of CR propagation.

- With the well trained models, we fit the AMS-02 data with different background CR fluxes, and investigated in what sense the DM component is needed in each case.
- With the DR propagation model, the uncertainty on $\phi_{\bar{p}}$ would affect the property of required DM.
- The hadronic model from Winkler would predict more high energy antiproton than that from Tan & Ng, and thus tends to require a low-mass DM, but both of them would corresponding to a significance less then 2σ in the current study.

• More interesting generators, more propagation models, and different choice of data are to be studied.