Identification of high-energy antiprotons on electrons background based on calorimeter data in PAMELA experiment

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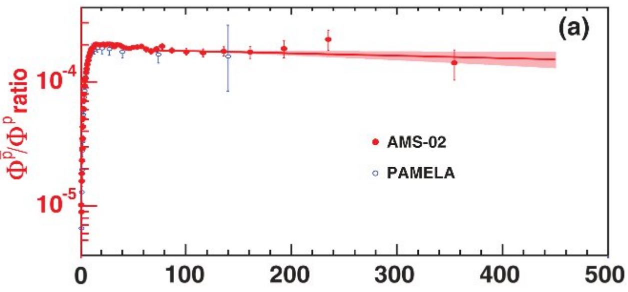
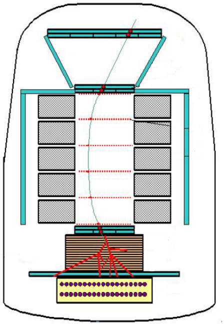
Antiproton to proton ration in primary cosmic rays



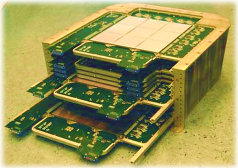
What PAMELA can do now?

- Increase statistics if
  - improve the efficiency and quality of identification algorithms
  - process data after 2009 year up to now
- Obtain results at
  - low energies (less than few GeV, solar modulation)
  - higher energies ($E > 100$ GeV, dark matter, propagation of CR in Galaxy etc.)

PAMELA magnetic spectrometer



– Time-of-Flight (ToF) system
– Anticoincidence (AC) system
– Magnetic spectrometer
– The sampling imaging electromagnetic calorimeter
– Bottom Scintillator S4 and Neutron Detector

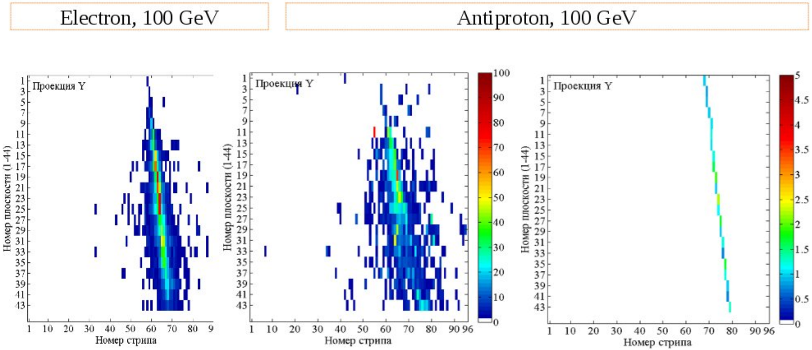


Electromagniting calorimeter W/Si sampling (22 W plates with 22 double-sides Si sensors) 16.3 X_0, 0.6 λ_I

Basic principles of particle's identification

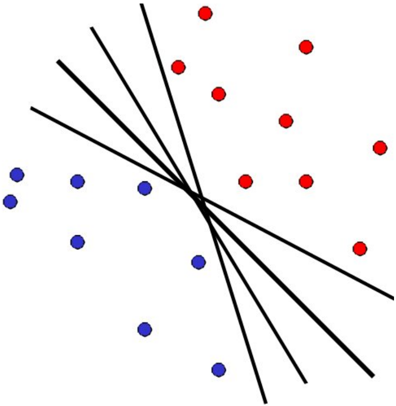
- **ToF**: identification of albedo particles measurements of velocity
- **AC**: background rejection
- **Magnetic spectrometer**: measurement of the rigidity and sign of charge by deflection in the magnetic field
- **Calorimeter**: identification of electromagnetic showers and hadron interactions of electrons/positrons and antiprotons/protons
- **Neutron Detector S4**: increase of calorimeter efficiency

Geant4 based simulation



Significant differences in longitudinal and transverse profiles of interactions, energy releases in and out of track of leader particle etc.

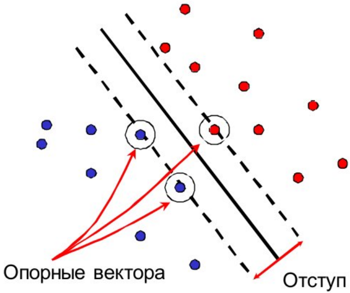
Classification methods



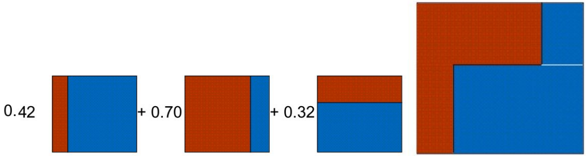
- Neural network
- Regression model
- Random forest
- Support vector machin
- Adaboost

Base idea

SVM

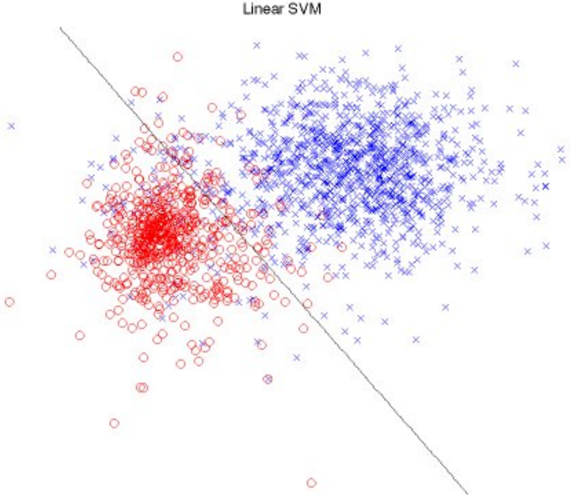


AdaBoost



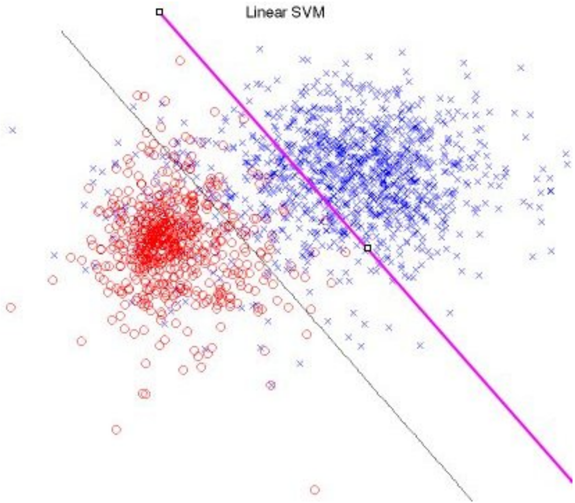
Standard SVM

Optimal hyperplane



Weighted SVM

Use weights for classes



Calorimeter characteristics

Qtot – the total energy release in the calorimeter;

Qmax – maximum energy release in the calorimeter;

Qtrack – the energy release along the shower axis;

Qcyl(*Ncyl*) – the energy (number of triggered strips) in the cylinder radius of 4 strips around the shower axis;

Qpre(*Npre*) – the energy (number of triggered strips) in the cylinder radius of 8 strips around the axis of the shower in the first three planes;

etc.

Totaly 20 calorimeter features and particle rigidity (from track system)

Data set

Antiprotons and electrons are modeled by **Geant4**
with **Rigidity** $\in [10GV, 1TV]$

Sets statistic:

particles	**train**	**test**	**total**
Antiprotons	$\sim$ 24 000	$\sim$ 10 000	$\sim$ 34 000
Electrons	$\sim$ 19 000	$\sim$ 8 000	$\sim$ 27 000

Train test ration is 1/3

Results SVM

The best results ($C = 0.2$ and $w = 39$)

Statistic for particles with **R** > -1000 GV

true / predicted	**Antiprotons**	**Electrons**
Antiprotons	85.903%	14.097%
Electrons	0.072%	99.928%

Statistic for particles with **R** $\in [-500GV, -10GV]$

true / predicted	**Antiprotons**	**Electrons**
Antiprotons	9173 (90.064%)	1012(9.936%)
Electrons	**2** (0.029%)	6869 (99.971%)

Results AdaBoost

The best results ($w_{antiprotons} = 39$)

Statistic for particles with $\mathbf{R} > -1000$ GV

true / predicted	**Antiprotons**	**Electrons**
Antiprotons	92.185%	7.815%
Electrons	0.072%	99.928%

Statistic for particles with $\mathbf{R} \in [-500GV, -10GV]$

true / predicted	**Antiprotons**	**Electrons**
Antiprotons	9128 (96.005%)	386(3.995%)
Electrons	**0** (0%)	6808 (100%)

Conclusion

- Machine Learning algorithms can be used for identification of antiprotons on electrons background based on calorimeter features
- Classifier AdaBoost and SVM showed good rejection of electrons using classes weight
- Need more statictic for stable classification of antiprotons
- SVM results are more stable although it identify antiprotons worther than Adaboost classifier