Nuclei Identification by Multiple Energy Losses in Detectors of the PAMELA Spectrometer.

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Problem Statement

Goal: to identify kind of a particle by a vector of energy loss values.

- Magnetic spectrometer (tracker): 6 × 2 = 12 values;
- Calorimeter: 4 first values (Y projection).



Training and test samples were generated with Geant4 software.

Selection criteria:

- No signals in anticoincidence systems.
- No more than one paddle triggered in each plane of the time-of-flight system.
- Particle track reconstructed by at least 3 points in the deflecting projection X, and by 2 points in projection Y.

Classification algorithm

First step

For each particle, for small rigidity ranges, find 4% and 95% quantiles (q_0 and q_1) of the energy loss distribution (from empirical distribution).



Classification algorithm

The second step

For each particle, fit q_i /Rigidity dependences by smooth curve of special form:

$$q_i(x) = \left(\exp(ax^b + c) + d\right)^2 \text{ (for tracker)};$$
$$q_i(x) = \left(\exp(ax^b + c) + dx^e + f\right)^2 \text{ (for calorimeter)}$$



Classification Algorithm

The third step

We assume that dE/dx distribution for fixed particle and rigidity takes a form:

$$\mathcal{L}(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma} + e^{-\frac{x-\mu}{\sigma}}\right)\right)$$

For given rigidity x we can compute quantiles $q_0(x)$ and $q_1(x)$, than reconstruct μ and σ parameters by two quantiles.



Classification Algorithm

Likelihood function for a nuclei type i is a function:

$$MLE_i(x; R) = \sum_{j=1}^N \ln L(x_j, \mu_{ij}(R), \sigma_{ij}(R)),$$

where j = 1, ..., N are detector numbers, $x = (x_1, ..., x_N)$ are energy losses in correspondent detectors, R is a magnetic rigidity of the particle.

Result of classification algorithm is a nucleus \hat{n} , which minimizes $MLE_i(x)$.

$$\hat{n} = \arg\min_{i} MLE_{i}(x; R).$$

Error measurement

Confusion matrix M consists of a priori classification errors.

$$M_{ij} = P(answer = j | real = i).$$

Error measurement Confusion matrices

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Now assume we know a nuclei distribution in cosmic rays. Confusion matrix Q consists of a posteriori classification errors.

$$Q_{ij} = P(\text{real} = j | \text{answer} = i) = \frac{P(\text{real} = j)M_{ij}}{\sum_{k} P(\text{real} = k)M_{ik}}$$





Predicted

Real

Results R = 1.5...2.0 GV



REAL

Results

Comparison with machine learning

Left: our algorithm. Right: gradient boosting method, R>1 (power spectrum), with calorimeter data.

