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Introduction to STAR Level-2 Trigger Algorithms[1]

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1 Introduction

We address the problem of finding a correlation analysis method for 2-D electromagnetic calorimeter (EMCAL) energy distributions [1] applicable to collision systems from p-p to Au-Au and p-Au which can be used in the formation of one or more trigger criteria for the STAR detector at RHIC [2], and which may also be incorporated into the EMCAL data analysis task at other levels. The standard analysis methods for EM calorimeter energy distributions are based on the assumption that a significant fraction of the produced transverse energy for some events is strongly correlated in (η, ϕ) into one or a few localized 'jets,' corresponding to the hadronization of struck partons, and that by determining the lowest moments of and kinematic relationships among these localized jet distributions one may derive information about hadronic structure functions, parton-parton interactions at the early stages of the collision, and subsequent jet-medium interactions such as jet quenching.

This approach is more difficult to apply at higher A values because the number of jets and the magnitude of the 'minijet' background are increasing with A, the fraction of events containing 'findable' jets falls rapidly. However, the failure of a classical jet-finding approach for a given event does not mean that the transverse energy distribution is without significant correlation related to partonic interactions or other effects of physical interest. Our approach has been to develop a completely *model-independent* correlation analysis of 2-D density distributions which can be used to extract all available information from each event. We find that the resulting correlation measures can be used both to form efficient trigger criteria for EMCAL and may be used to carry out a more general analysis of EMCAL data.

2 Standard analysis of transverse energy distributions

In a standard jet analysis of an EMCAL energy distribution [3, 4] it is assumed that in some collision events an energetic struck parton and its trailing color field hadronize into a number of detectable particles which are thereby localized or correlated in (η, ϕ). This correlated system is called a jet, and this jet 'represents' the initial struck parton kinematically. The lowest moments of the resulting localized energy distribution deposited in an EMCAL yield an estimate of the jet centroid, the jet width and total jet energy which depend on the kinematics of the initial parton-parton interaction, and also on subsequent hadronization processes and interactions in the nuclear medium at the parton and hadron level.

The acceptance of the EMCAL is divided by construction into a number of bins or towers. Each tower receives some amount of energy E_T during a collision event. A typical jet analysis (e.g., UA1) involves a correlation analysis of the E_T distribution assuming that a jet is a localized energy distribution bounded by a circle about 0.7 units in radius located in the acceptance (η, ϕ). The distribution elements E_T are sorted in magnitude, and the largest is selected as a seed tower. This tower is adopted as a provisional jet center and a new centroid is calculated from the energy distribution contained inside the circle centered on this tower. This process is iterated a few times until the circle position stabilizes. Then the energy integral inside the circle is compared with a designated jet threshold energy. If the integral passes the test this tower subset is set aside as a jet and the analysis proceeds to the next highest prospective seed tower outside any found jet until no more towers exceed a predetermined seed tower energy threshold, which concludes the jet finding. We have ignored here important details such as background subtractions, thresholds, etc.

The effectiveness of this analysis depends strongly on the magnitude of the background energy distribution (from soft processes) and the number of jet-like energy concentrations that occur in an event. In heavier collision systems the overlap of concentrations due to increasing jet number and the larger background due to soft processes make impractical the identification of features that might with any confidence be called jets. This requires careful study of the jet-finding efficiency for different collision systems with increasing A [6, 5].

This breakdown in the *jetfinding* approach for some events does not mean that significant correlations are not present. We find that even for Au-Au collisions there is still a significant correlation content to transverse energy distributions which can be used for trigger purposes. It is possible that the residual correlations are also useful for significant tests of physical models.

The approach could be adopted that jetfinding be used up to some value of A, and a different approach or no approach be used for heavier systems. We feel that a unified approach over all A values, if achievable, is more desirable, and further that it would be highly desirable to relate as closely as possible the jetfinding approach with the general correlation analysis approach in light systems where they are both applicable.

3 A generalized correlation analysis based on Renyi entropies

We often need to determine quantitatively the degree of correlation contained in a multidimensional density distribution. An elementary example of a correlation measure is the linear correlation coefficient. Such elementary measures can be insensitive to much of the correlation present in a distribution. They are sensitive only to specific *model* correlations such as a straight line or curve. As we noted above a jet-finding algorithm looks for the presence of a specific model correlation - a peaked concentration of energy contained within a bounded region. This model becomes ineffective when the energy distribution is too complex, which is the case for heavy collision systems.

After due consideration of the general problem of correlation analysis we have concluded that the basis of correlation measurement is the determination of the degree of *dimension lowering* in magnitude and scale of a given distribution compared to a reference distribution. To understand what this statement means requires an introduction to the concepts of scaled entropy and dimension, which will not be familiar to most persons. We will try to give a brief but hopefully understandable summary here, with the promise of more elaborate presentation later for those interested in details.

This correlation analysis is based on the use of a binning system which is varied in scale (bin size) e and phase ϕ and applied to the space in which the distribution is presented. For each instance (e, ϕ) of the binning system a set of Renyi entropies $S_q(e, \phi)$ is calculated. These quantities are then phase averaged to eliminate aliasing effects from the binning. From the entropies a set of scaled dimensions $d_q(e)$ is determined. The degree of correlation is measured relative to some *reference distribution* which reflects the macroscopic constraints of the system (this is closely related to the partition-function approach in statistical mechanics). Thus, the *scaled dimension lowering* $\Delta d_q(e)$ with respect to some reference distribution is the final and most general descriptor of the degree of correlation in the distribution of interest. We go through the analysis steps in a little more detail below.

3.1 Binning

If the space in which the distribution resides is of integer dimension D then for each scale value (linear bin size) e we construct a system of D-dimensional bins which covers the space. In each bin we determine the contents: bin counts $n(x_i, e, \phi)$ (or $n_i(e)$) for a hit distribution or (energy) density value $E(x_i, e, \phi)$ (or $E_i(e)$) for a density distribution, where x_i represents the i^{th} bin by indices or coordinates. It is also sometimes useful to employ normed quantities $p_i(e)$ where $p_i(e) = n_i(e)/N_{tot}$ for a hit distribution or $= E_i(e)/E_{tot}$ for a density distribution. However, this approximation breaks down at small scale for hit distributions.

These elementary quantities are used to calculate the entropy or other topological measure for that binning system. Then the process is repeated with the binning system shifted by a fraction of the bin size (a shift in 'phase'). All derived quantities are then phase averaged over the ensemble of shifted binning systems to eliminate any anomalies due to a specific relationship between the binning system and the distribution. From this is derived for example a phase-averaged value of the rank-q Renyi entropy $S_q(e)$ at a particular scale value e.

3.2 Scaled Renyi entropies

Entropy is nothing more than an exponential parameterization of volume in some representational space. Thermodynamic entropy parameterizes the representational volume of a dynamical many-body system in phase space. There is a countably infinite number of entropies which can be defined, and these are called after the Hungarian mathematician who formalized the system. The most familiar entropy, called the Gibbs entropy in thermodynamics and the Shannon entropy in information theory, is the rank-1 Renyi entropy. Most distributions can be well characterized by several lowest-rank entropies.

If we use the normed representation $p_i(e)$ of the i^{th} bin contents, and assume that a proper phase average has been carried out (and so ignore that aspect) we can write the scaled rank-q Renyi entropy as

$$S_q(e) = \frac{1}{1-q} log[\sum_{i=1}^{M_q(e)} p_i^q(e)], \tag{1}$$

where $M_q(e)$ is the number of bins containing at least one q-tuple in the case of a discrete hit distribution. The first few entropies can be written explicitly as

$$\begin{aligned} S_1 &= -\sum_i p_i log(p_i) \\ &= -< log(p) > \\ S_2 &= -log < p > \\ S_3 &= -log < p^2 >^{1/2}, \end{aligned} \tag{2}$$

and so forth, where $<>$ here represents an average over the bin system with respect to the normed weight set $\{p_i\}$. Volume is the fundamental set measure in this approach. It is the q-weighted volume $V_q(e, \phi)$ which is phase averaged, and the derived quantity $S_q(e)$ is then the logarithm of that phase-averaged volume.

3.3 Scaled dimension

The nature of dimension has been a central issue in topological research over the last hundred years. The popularization of so-called fractals, fractal dimension, and multifractal analysis by Benoit Mandelbrot and others since 1975 has been only a part of the struggle to understand the metrical and dimensional properties of distributions. This work emphasized that dimension is not restricted to the integers, that for all but a 'small' class of distributions noninteger dimension is the rule.

We find that the dimension of a distribution is itself a distribution in space and scale. For our present application we consider only a 'simple' manifestation of the general dimension question. We restrict to the overall scale dependence of an entire bounded distribution. We define the scaled rank-q set dimension in terms of the corresponding Renyi entropy as

$$d_q(e) = -\frac{dS_q(e)}{dloge}. \tag{3}$$

These quantities are illustrated in fig. 1 for $q = 0$. L represents the size of the bounded space in which the distribution is contained, and the scale is represented by e. The scaled dimension is zero at large scale because the bounded distribution appears point-like. At very small scale the dimension again approaches zero because the individual points of the distribution are resolved at these scales. Over some scale interval the dimension approaches that of a uniform distribution in the 1-D embedding space. This interval depends on the size of the boundary L and the number of points N.

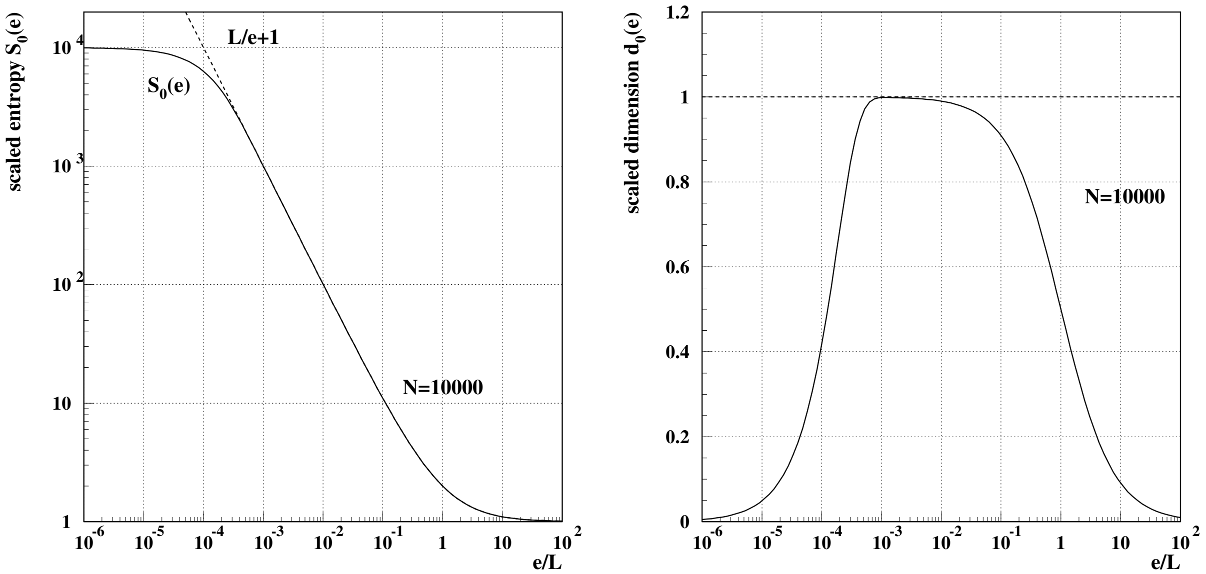

Figure 1: Scaled rank-0 entropy and dimension for 1-D Poisson distribution

We can shed further light on the relationship between entropy and dimension in the following way. As we said, entropy is an exponential parameterization of volume. Thus, for some definition of volume V we can write

$$S = log(V). \tag{4}$$

Now the nature of the volume depends on the way the distribution is being examined. For a point distribution the rank q of a particular Renyi entropy refers to a representation of the set by all the possible q-tuples that can be formed from the points of the set. Thus, a distribution is also represented by a countable infinity of scaled volumes V_q (we will not elaborate on the scaled volume concept here). If we look again at the dimension definition in eqn. 3 we can interpret a rank-q dimension as the proportionality between a *relative* change in the scaled volume V_q of a set and a *relative* change in scale.

$$\frac{dV_q}{V_q} = -d_q(e) \cdot \frac{de}{e} \tag{5}$$

This interpretation works quite well when considering the simple case of integer dimensions and standard objects such as lines and planes in a 3-space. However, the concept is much more general and adequately describes arbitrarily complex situations.

The new definition of dimension developed for this work is a departure from previous definitions because it is by construction *scale local*. By this we mean that the definition admits of an arbitrary degree of *variation with scale* of the dimension of a point set or distribution. This is analogous to the role of the derivative in analysis as a *space-local* measure of slope on a curvilinear locus. Previous definitions of dimension, including definitions associated with fractal sets, contain by construction the assumption that dimension is a global scale invariant, or is homogeneous in scale. Our new scale-local approach is the basis of the correlation analysis that we present here. It is the *scale variation of dimension* and its departure from the scaled dimension of a reference system that best measures the correlation content of a distribution.

4 Dimension lowering as a measure of correlation

4.1 Information

The concept of information as a quantitative measure has its origins in the work of Claude Shannon and Norbert Weiner in the nineteen forties and early fifties in connection with optimization of electrical signal propagation and servomechanism design. Shannon adopted as a measure of information the Gibbs entropy (rank-1 Renyi entropy). The information concept today continues to suffer from ambiguity, as does the concept of entropy. Part of this ambiguity derives from not considering these as scaled quantities. We give here an explicit definition in terms of scaling. To proceed we need to recognize that information corresponds to a *change in the representational volume* of a system. Thus, information can be defined clearly as a change in system entropy or a difference in entropy with respect to a reference system. Information is 'acquired' if the representational volume of a system is reduced. For instance, if one receives one 'bit' (binary digit) of information one's 'conceptual volume' has been reduced by a factor of two ($log_2(1/2) - log_2(1) = -1$ bit). Thus, we can write for the scaled rank-q information

$$I_q(e) = S_q(e) - S_{ref}(e), \tag{6}$$

where $S_{ref}(e)$ is the prior or reference entropy for the system - prior to receipt of information or representing an idealized reference distribution. The accurate determination of S_{ref} in a given circumstance is a critical and sometimes difficult task.

Note that the fully scaled picture presented here makes it possible to describe quantitatively how in the same transaction one can receive information at one scale while losing information at another scale. This reflects situations intuitively described by such aphorisms as "... can't see the forest for the trees" and "penny wise and pound foolish."

The terms information and entropy are sometimes used interchangeably or in combination, as in 'information entropy.' We prefer to maintain a clear distinction. Entropy is an exponential measure of volume. It is scale dependent. For a given scale value, binning system and distribution the entropy has a unique value. Information on the other hand is a relative quantity, like potential energy. Information is a measure of difference between two entropies, and depends critically on the definition of a reference or *prior* entropy. It is a measure of *volume ratio.*

4.2 Dimension lowering

With scaled information defined we proceed to a definition of *dimension lowering* (in scale) as a measure of correlation. To motivate this we consider the 'condensation' of a maximally uncorrelated distribution to a highly correlated one. Consider a bounded 2-D embedding space (e.g., a square) of some size represented by L. This space is initially filled with a uniform distribution of N points - a Poisson distribution. The scaled entropy of this distribution is maximal at all scale values, given the total number of points N and the size of the space L. We take this as the reference distribution for the problem. This distribution is represented, e.g., in fig. 2

Now consider that for some reason the N points condense onto some more correlated structure. We calculate the information corresponding to the reduction in volume and hence entropy of the point set as a result of the condensation. We also calculate the scaled dimension of the distribution before and after the condensation, and note that corresponding to the entropy change or information there is a change in the scaled dimension distribution, which we denote by $\Delta d_q(e)$. We assert that the scaled dimension lowering $\Delta d_q(e)$ is a sensitive measure of relative correlation for a distribution. It has the further advantage of being model independent. It is therefore a general measure of relative correlation. We define dimension lowering in terms of scaled information as

$$\begin{aligned} \Delta d_q(e) &= -\frac{dI_q(e)}{dloge} \\ &= -\frac{dS_q(e)}{dloge} + \frac{dS_{ref}(e)}{dloge} \\ &= d_q(e) - d_{ref}(e). \end{aligned} \tag{7}$$

The expression 'dimension lowering' as used here is a compact reference to the more general problem of dimension transport, which is outside the scope of this paper. Dimension lowering can be considered as a small-amplitude approximation to the general problem, and thus appropriate for detection of small degrees of differential correlation as it is applied here.

The process of dimension lowering of a distribution in a representational space by acquisition of information is a good model for the learning process. It provides a description of learning in artificial neural nets and biological organisms.

5 Examples: scaled entropy and dimension

To illustrate some of these concepts graphically we apply them to simple systems, some of which are also essential as reference distributions.

5.1 The Poisson distribution

This distribution uniformly fills a bounded region of size L (=1) in an embedding space of dimension D (=2). At large scale the scaled, dithered rank-0 entropy S_0 follows a simple $log(L/e+1)$ dependence. This expression can be derived by elementary considerations. At lower scale, for an everywhere-dense set the dependence would continue as $log(L/e+1)$. However, for a Poisson distribution with *finite* point number N (=10,000) the scaled entropy turns over and approaches asymptotically the value $logN$. This is shown in fig. 2. The corresponding dimension behaves qualitatively just as we described above.

In this figure (and others) the solid curves represents the theoretical expressions for the scaled reference quantities, whereas the dashed curves represent the results of a full dithered binning analysis of the object distribution. Because the object distribution in this case *is* the reference distribution the analysis result agrees very well with the theoretical expression, and the dashed curves are barely visible. The Poisson distribution is often used as a reference distribution.

If the forgoing point set is dilated to a smaller scale we expect the scaled entropy, and all other scaled quantities, to simply translate down in scale by the dilation factor. This behavior is an excellent check on coding and other errors in the implementation of the formalism. This behavior is shown in fig. 3. Here the dashed curves show the result of a scaled entropy analysis of the dilated Poisson distribution of 10k points. The result of the analysis is seen to be equivalent to a translation of the scaled quantities with respect to an undilated reference distribution as expected, and the scaled information I_0 is now nonzero and represents the volume reduction of the dilated point set.

5.2 Condensation

5.2.1 Clusters and hierarchy

As an illustration of dimension lowering and other alteration of scaled quantities by the onset of correlation we show a series of point distributions which contain *clustering.* The total point number is held fixed (=10,000), but the point locations are determined by a hierarchical random procedure, in which a certain number of primary sites is distributed randomly throughout the bounded embedding space, and then at each of these primary sites a secondary population of hits is generated within a local region of a specified size.

In fig. 4 each of three hierarchical distributions is labeled by the number of primary sites (2000), the size of the primary distribution (1), the type of the primary distribution (P), the number of secondary hits at each primary site (5), the size of the secondary distribution (0.01) and the type of the secondary distribution (P), where numbers from the top distribution in fig. 4 have been used as an example. Fig. 5 shows a more subtle clustering sequence.

In the three dimension graphs the actual scaled dimension of the distribution (dashed) is compared to the expectation for a uniform reference distribution (solid). The degree of correlation corresponds to the degree of 'transport' of the dimension distribution to lower scale.

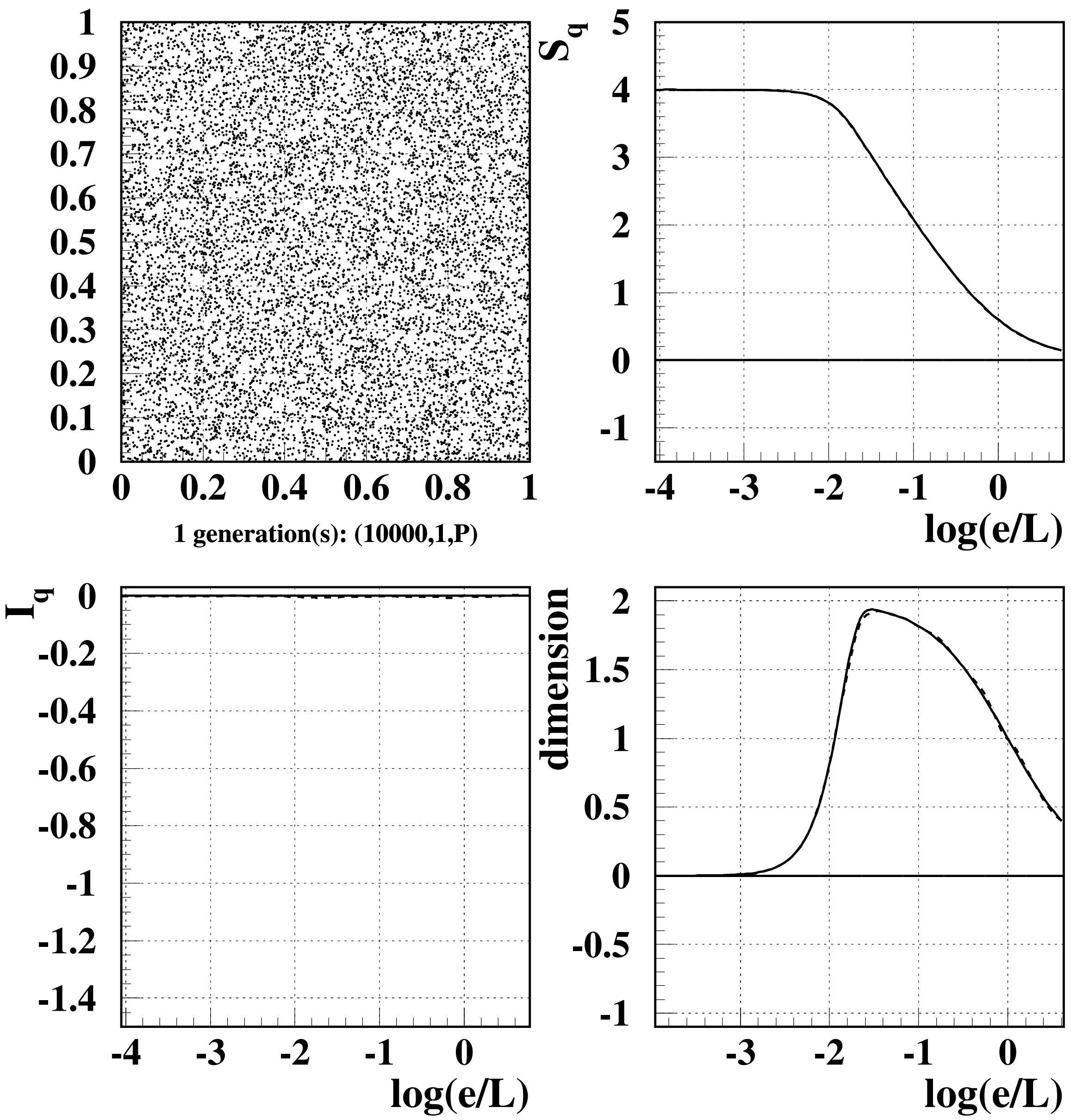

Figure 2: Scaled entropy and dimension for Poisson distribution.

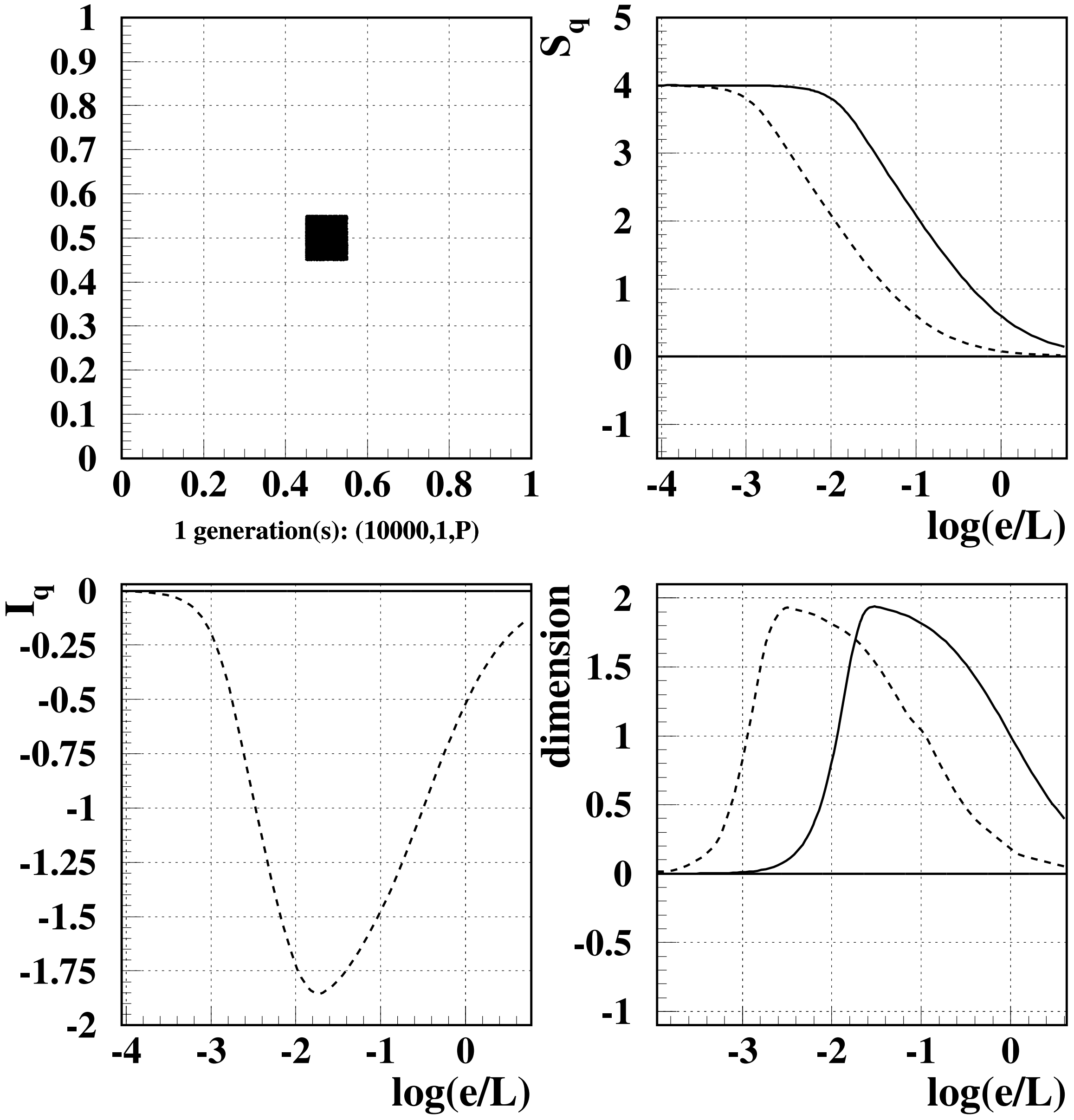

Figure 3: Scaled entropy and dimension for dilated Poisson distribution.

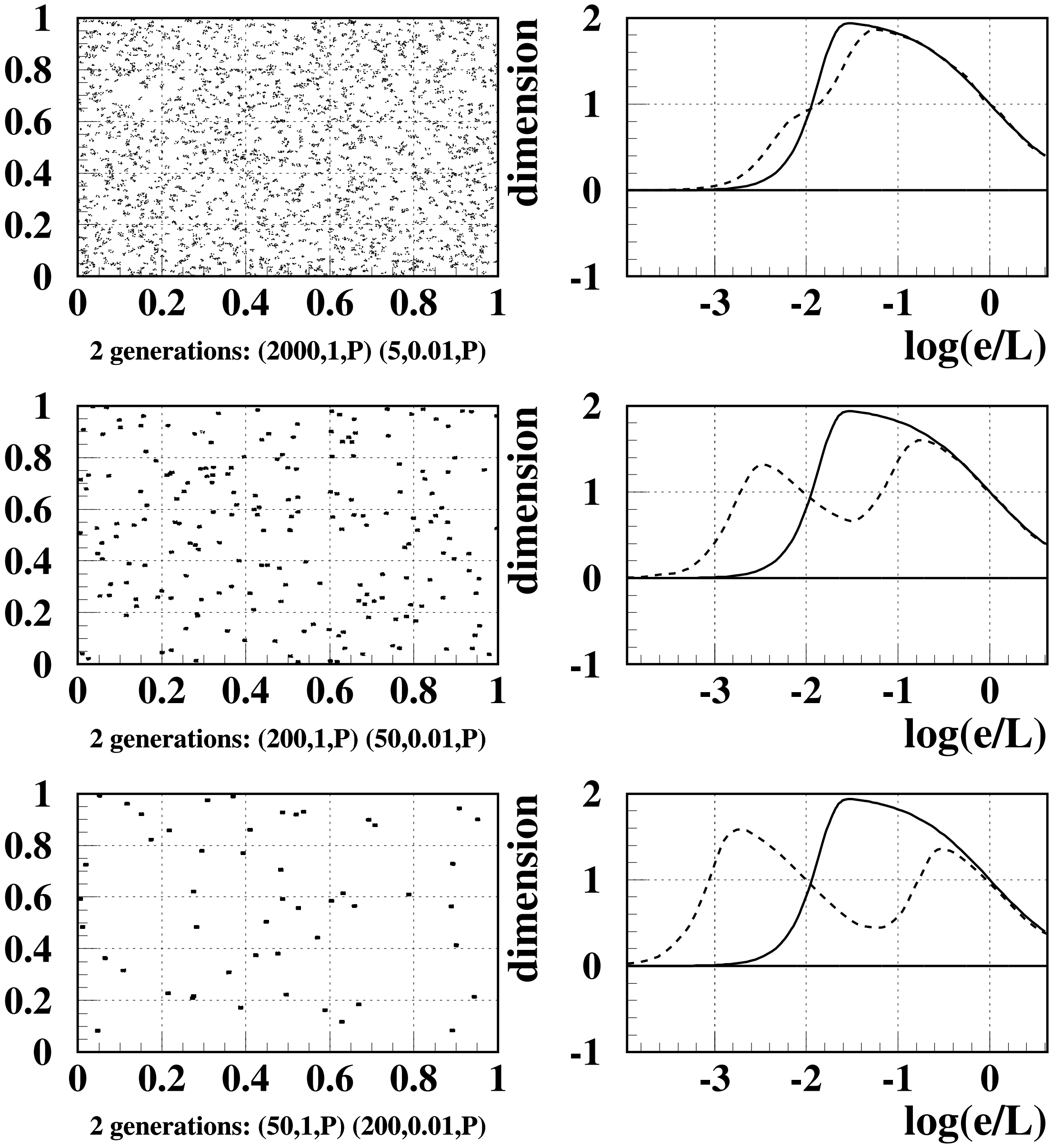

Figure 4: Condensation to clusters - coarse.

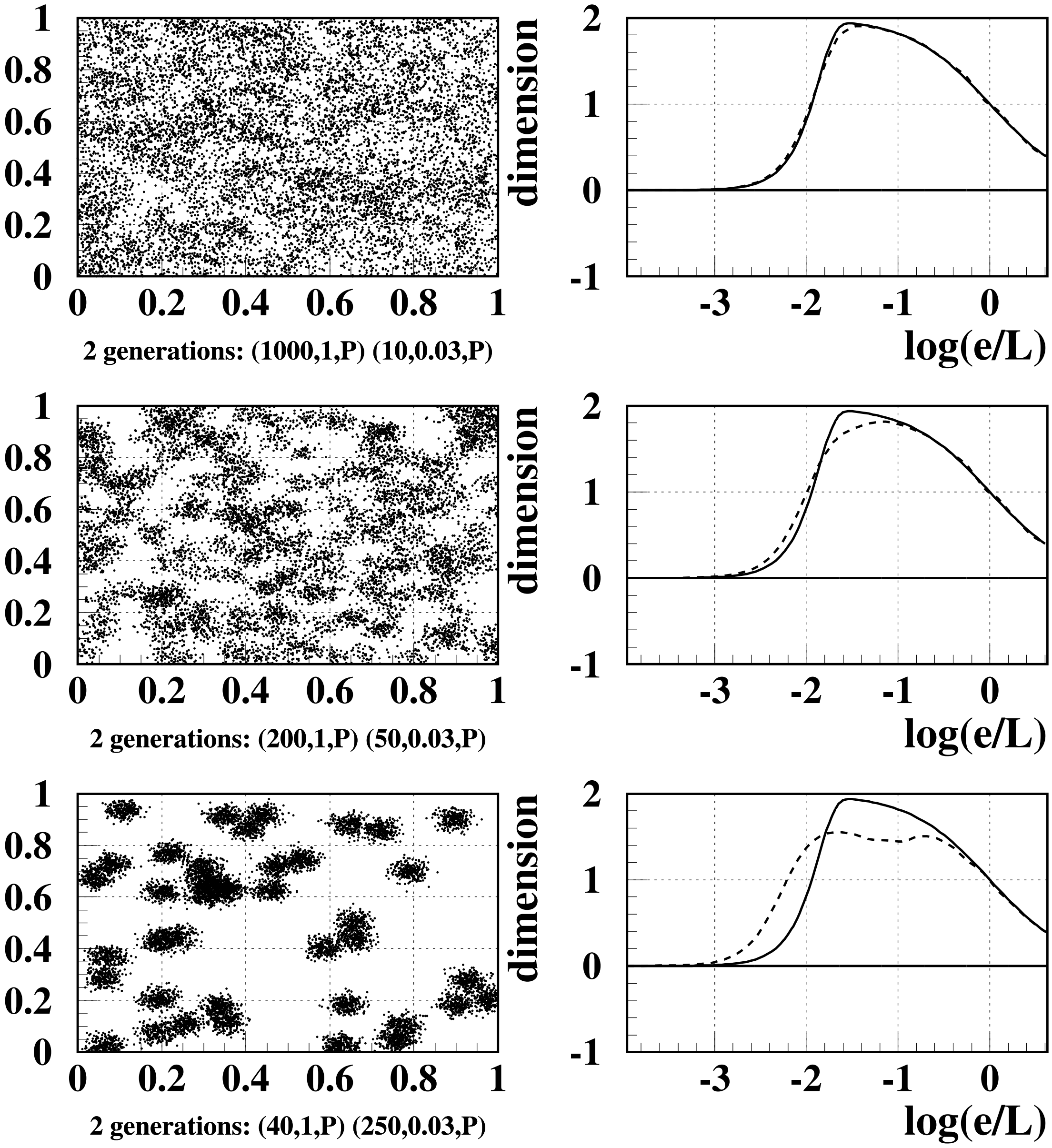

Figure 5: Condensation to clusters - fine.

5.2.2 Curvilinear locus - line segment

In this second example, shown in fig. 6, of the onset of correlation three distributions are generated with varying degrees of linear correlation. This was done by locating primary sites at random along a straight-line locus, and then relative to these primary sites generating a certain number (1000) of secondary hits within a local region of specified size. When this size parameter is of order the size of the bounded space (top section) the correlation is negligible. One approaches the Poisson limit. When the size is very small (bottom section) one approaches asymptotically the properties of the straight line locus.

Note that in the dimension distribution for the bottom section the dimension is approximately unity over some range of scale, as one would expect for a linear correlation. Toward the bottom of this scale range the dimension exceeds unity over a small interval. This is the region in which the finite size parameter (0.001) of the secondary distribution and the resultant *finite width* of the locus are detected by the analysis.

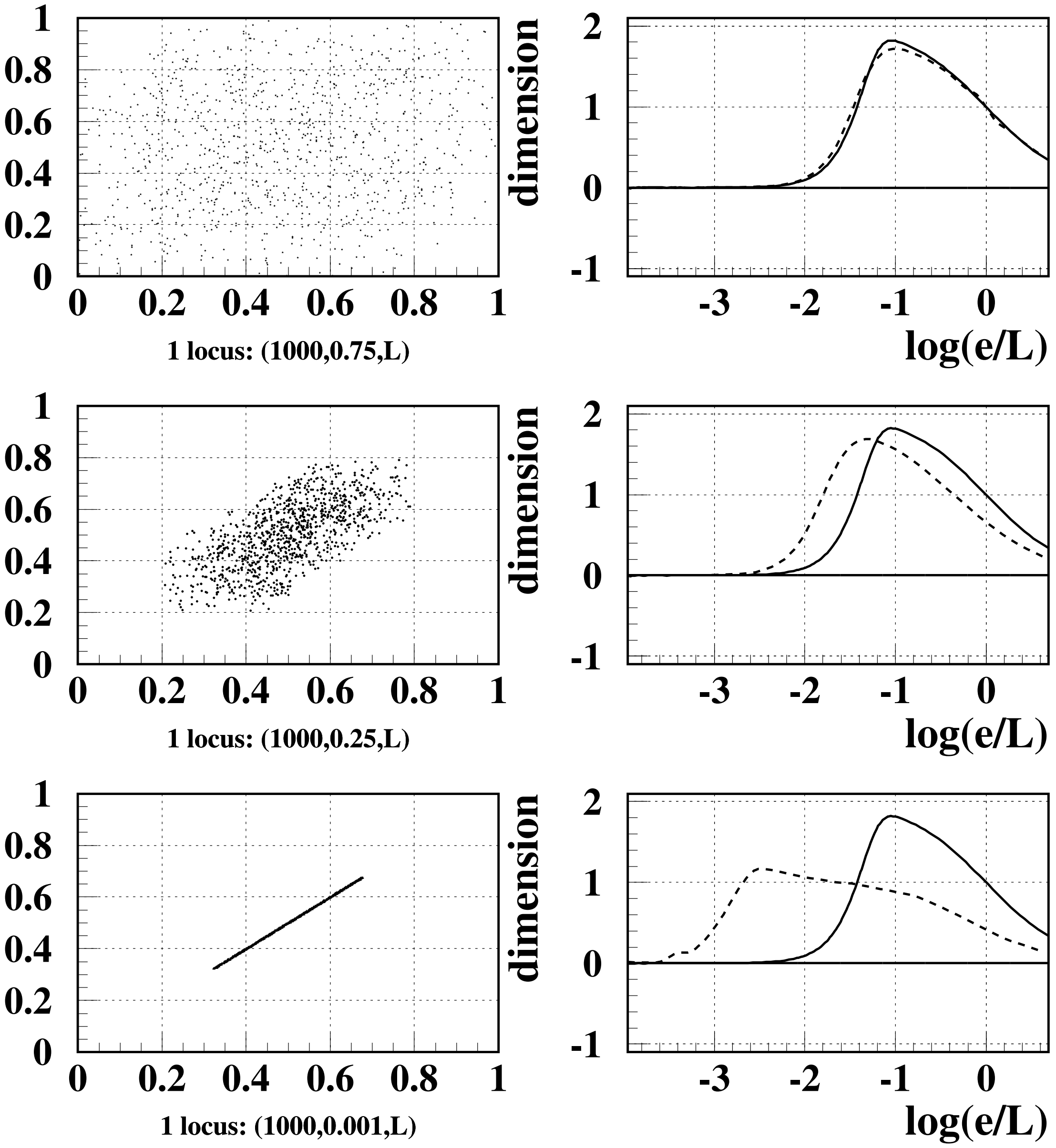

Figure 6: Condensation to curvilinear locus.

5.3 Condensation to clusters and EMCAL distribution analysis

In fig. 7 we show a sequence of three point distributions which represent increasing correlation due to condensation onto two point sites, and crudely model two-jet EMCAL distributions. These are not meant to be detailed models of EMCAL distributions. Such detailed modeling is the subject of ongoing research to be reported later. We use these distributions merely to sketch the relationship between the correlation analysis developed here and the jet analysis that we describe below.

The distributions shown in fig. 7 depart from typical EMCAL distributions in several ways. Most importantly they are not tower energy distributions, which are prebinned with a specific (20x60) binning model. They are point distributions in an unbinned space. Furthermore, they don't have the detailed structure of jets in light collision systems, which are grainier, and have more of a hierarchical nature to the distribution. These distributions have the minimal correlation structure needed to explain the gross features of the actual EMCAL distributions that we will show in the next section.

The quantity of interest is the dimension lowering $\Delta d_q(e)$. This quantity obviously increases in magnitude as the degree of correlation increases. Also, the interval of significant dimension lowering increases in scale as the distributions approach a two-point distribution. We will find behavior like this in the MC simulations to follow.

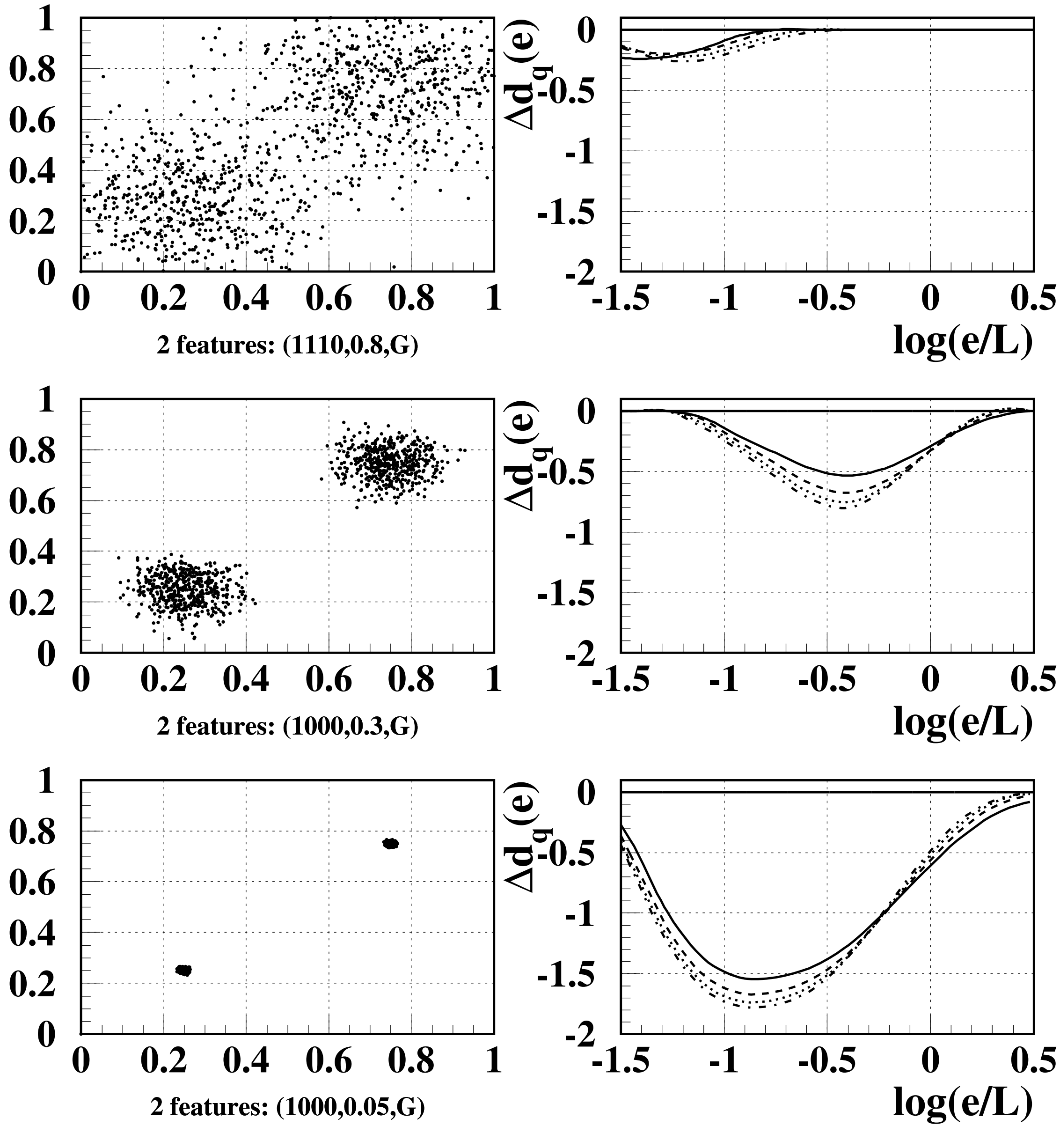

Figure 7: Dimension lowering to two points.

6 Application to specific collision systems

Using the definitions and examples above we now carry out scaled entropy analyses on simulated EMCAL tower energy distributions from specific collision systems.

6.1 p-p collision system

Fig. 8 shows a complete scaled analysis on a single p-p collision event produced by the Monte Carlo code HIJING [7]. This particular event was chosen because it illustrates very nicely a clean jet pair with minimal background. There is also shown a distribution of tower energies. In this correlation analysis there is no background subtraction. The tower energies as given by HIJING and GEANT are used without modification.

The middle two figures show the reference and actual distributions for $S_1(e)$ and $S_2(e)$. The lower left figure shows the scaled informations for ranks 1-4. The lower right figure shows the scaled dimension lowering also for ranks 1-4.

In fig. 9 we show the scaled dimension lowering separately for each of ranks 1-4 for an ensemble of ten p-p collision events. This figure and others like it help us to decide at what points in scale the scaled dimension lowering is most discriminating among events. These points are candidates for forming a level-2 trigger space.

For the p-p collision system we form the preliminary opinion that scaled dimension lowering values at log(e/L) = 0.0, -0.35 and -0.70 are candidates to form the three coordinates of a trigger space.

If we compare the gross behavior of these distributions to the simulations in fig. 7 we see that something intermediate between the middle and bottom distributions in this figure correspond well to the general behavior in the p-p case. This is the first step in optimizing the scaled correlation analyis for use as a trigger system in level 2.

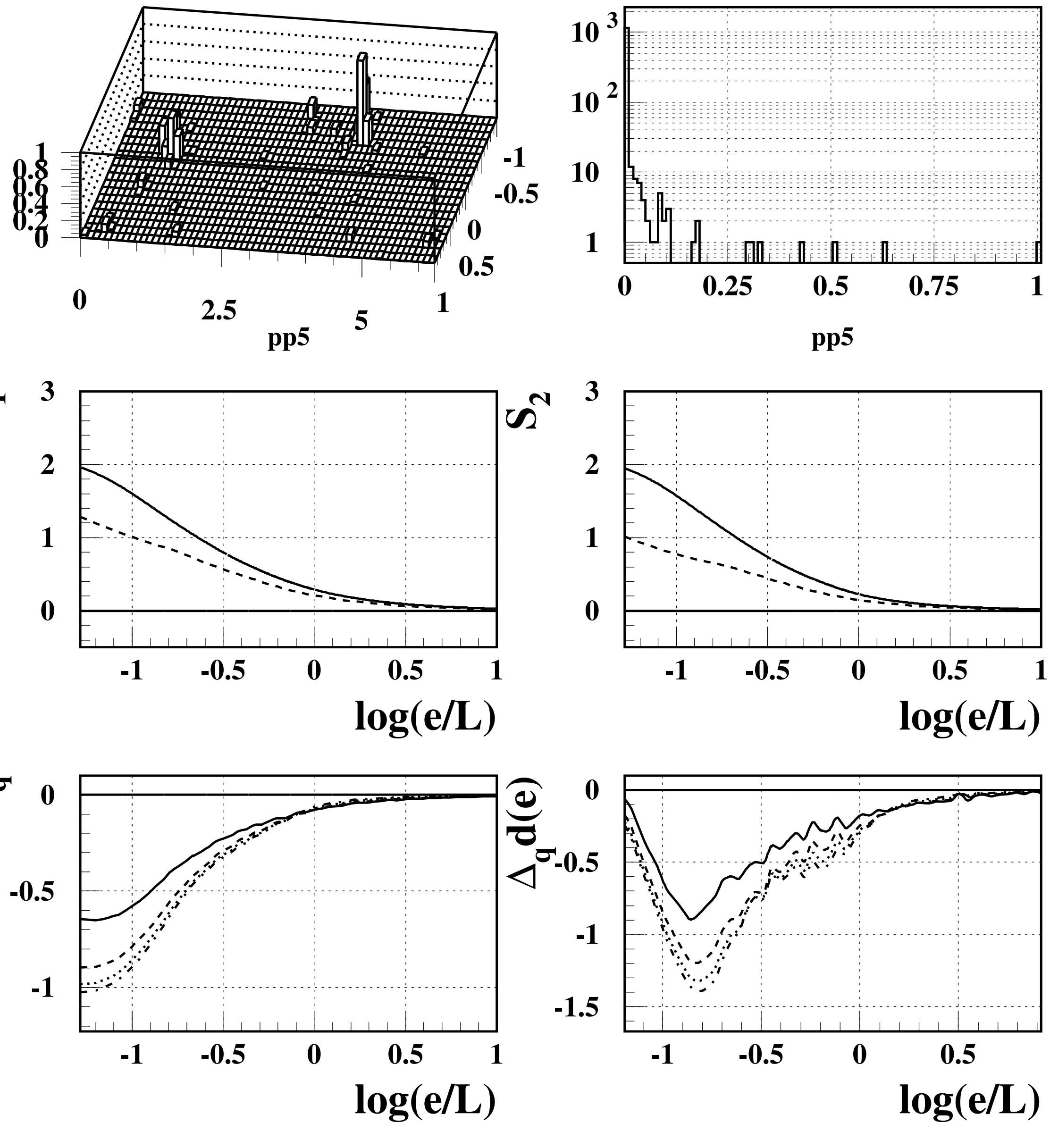

Figure 8: Scaled entropy analysis for p-p system.

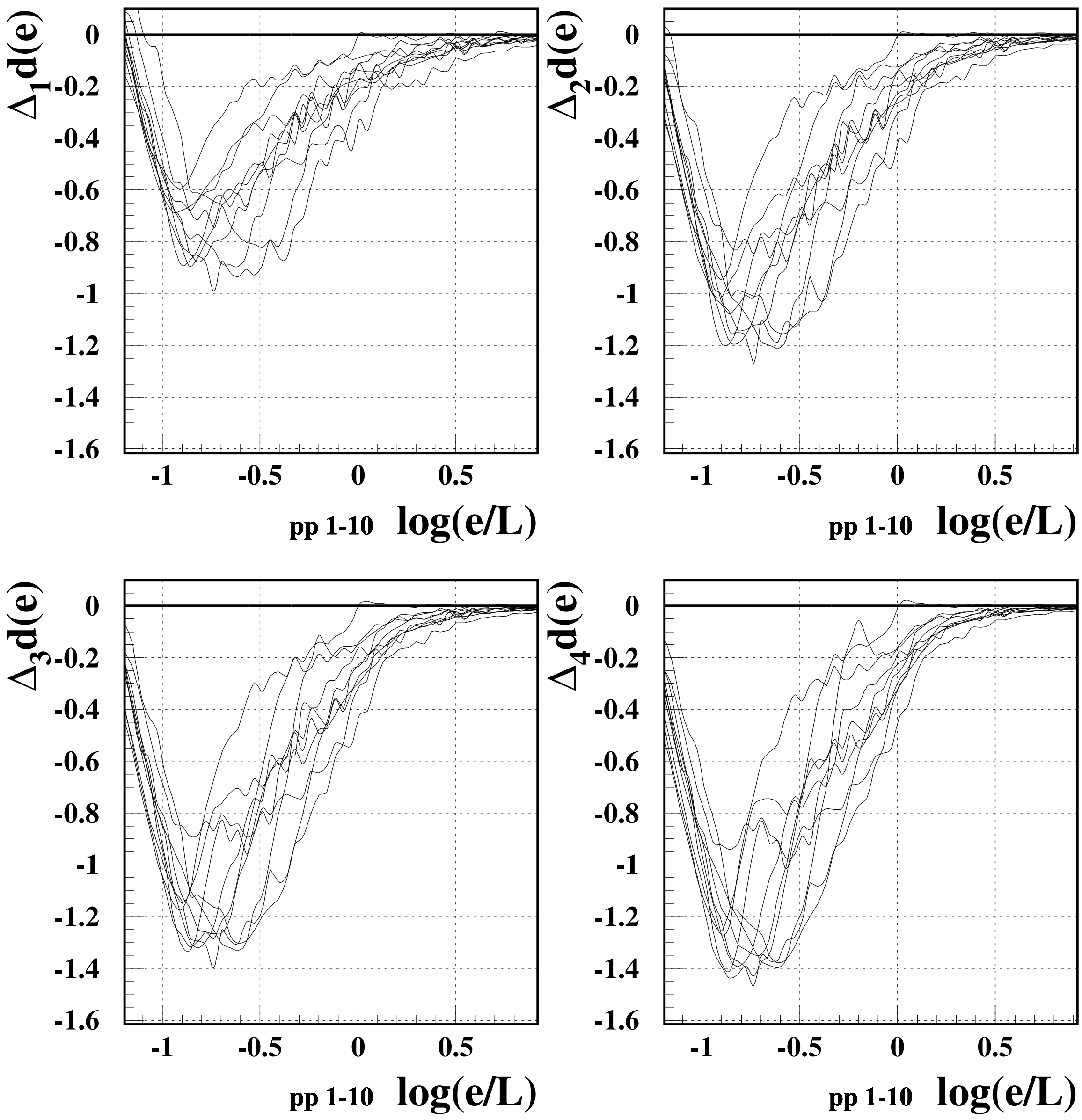

Figure 9: Dimension lowering for p-p system, ten events.

6.2 C-C collision system

Here we have multiple jets more likely, and a more substantial background. The dimension lowering is significantly reduced in magnitude at the larger scales and also overall, as one might expect.

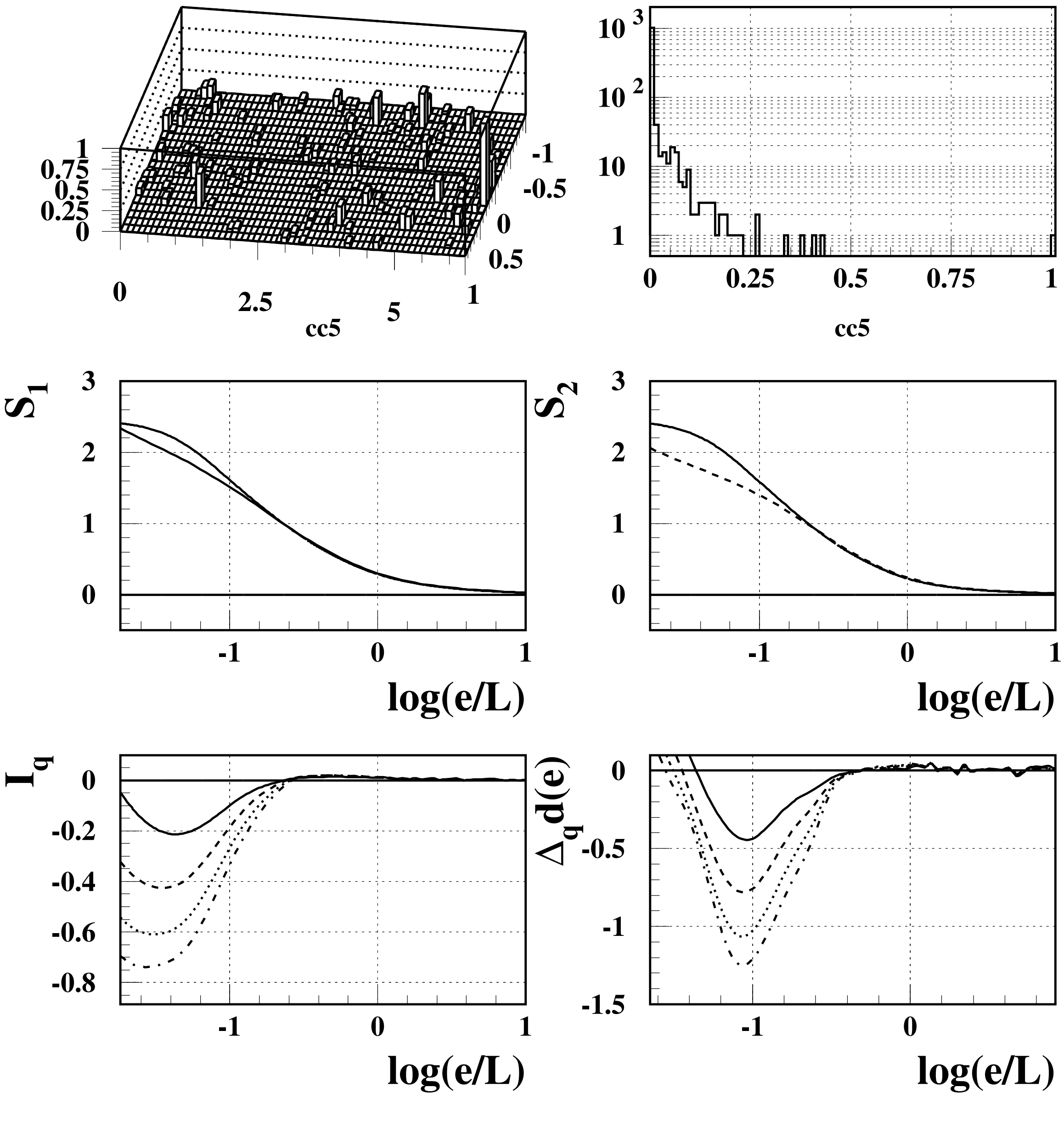

Figure 10: Scaled entropy analysis for C-C system.

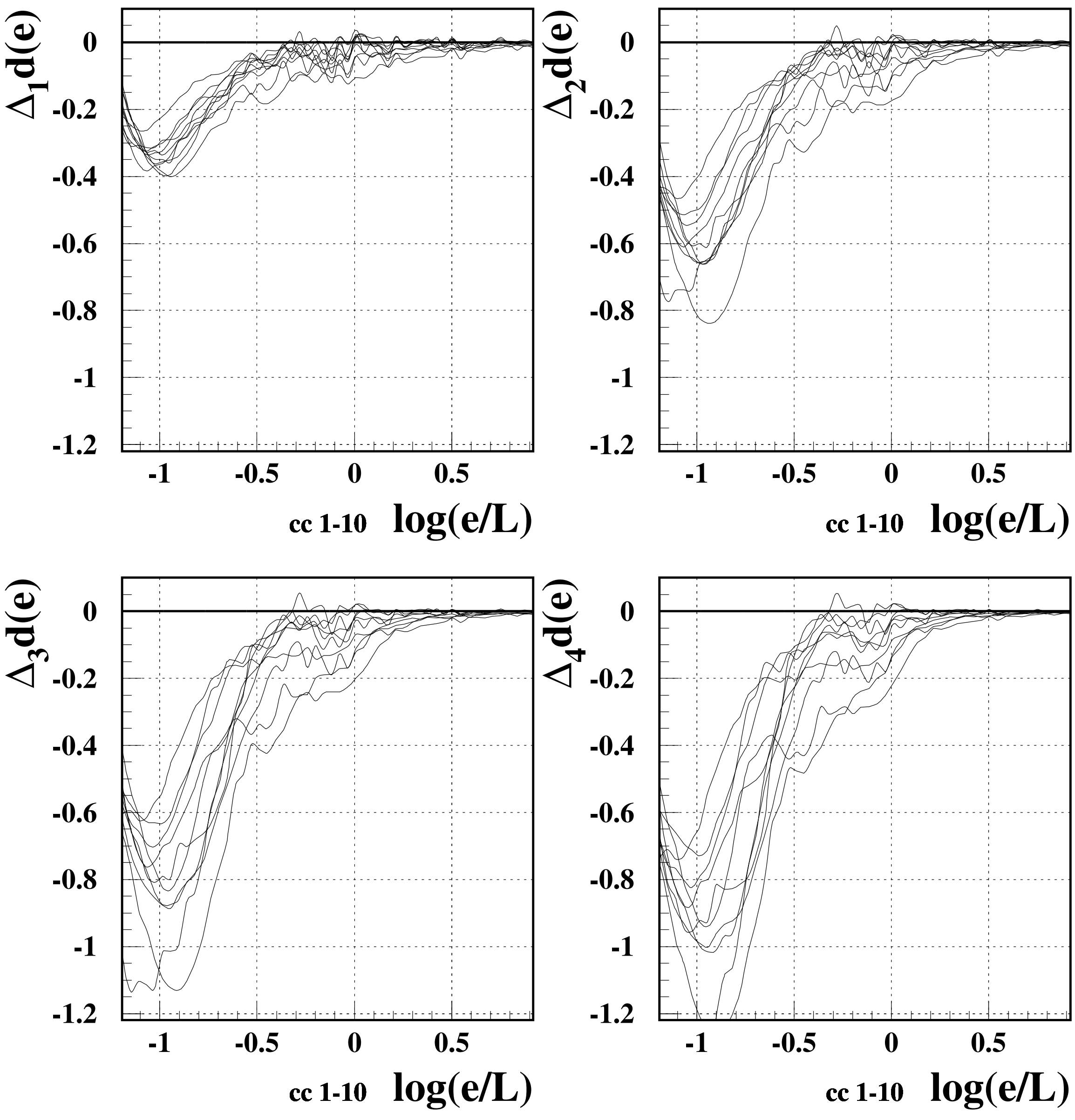

Figure 11: Dimension lowering for C-C system, ten events.

6.3 Au-Au collision system

In this case the dimension lowering is sharply reduced to near zero at all but the smallest scales for most events. However, there is still substantial correlation content to the events at the smaller scales, and one from this particular set of events contains a large amount of structure.

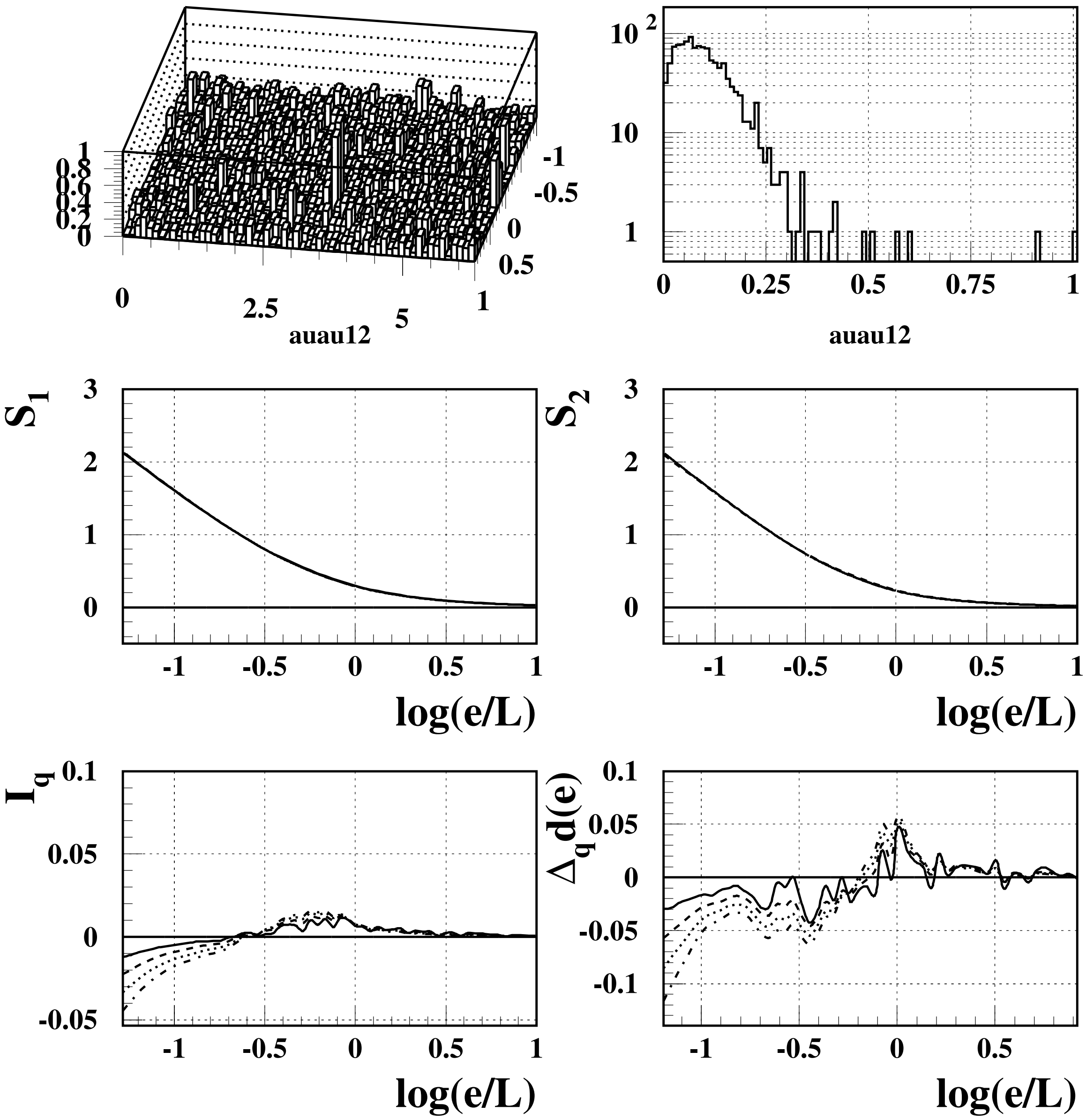

Figure 12: Scaled entropy analysis for Au-Au system.

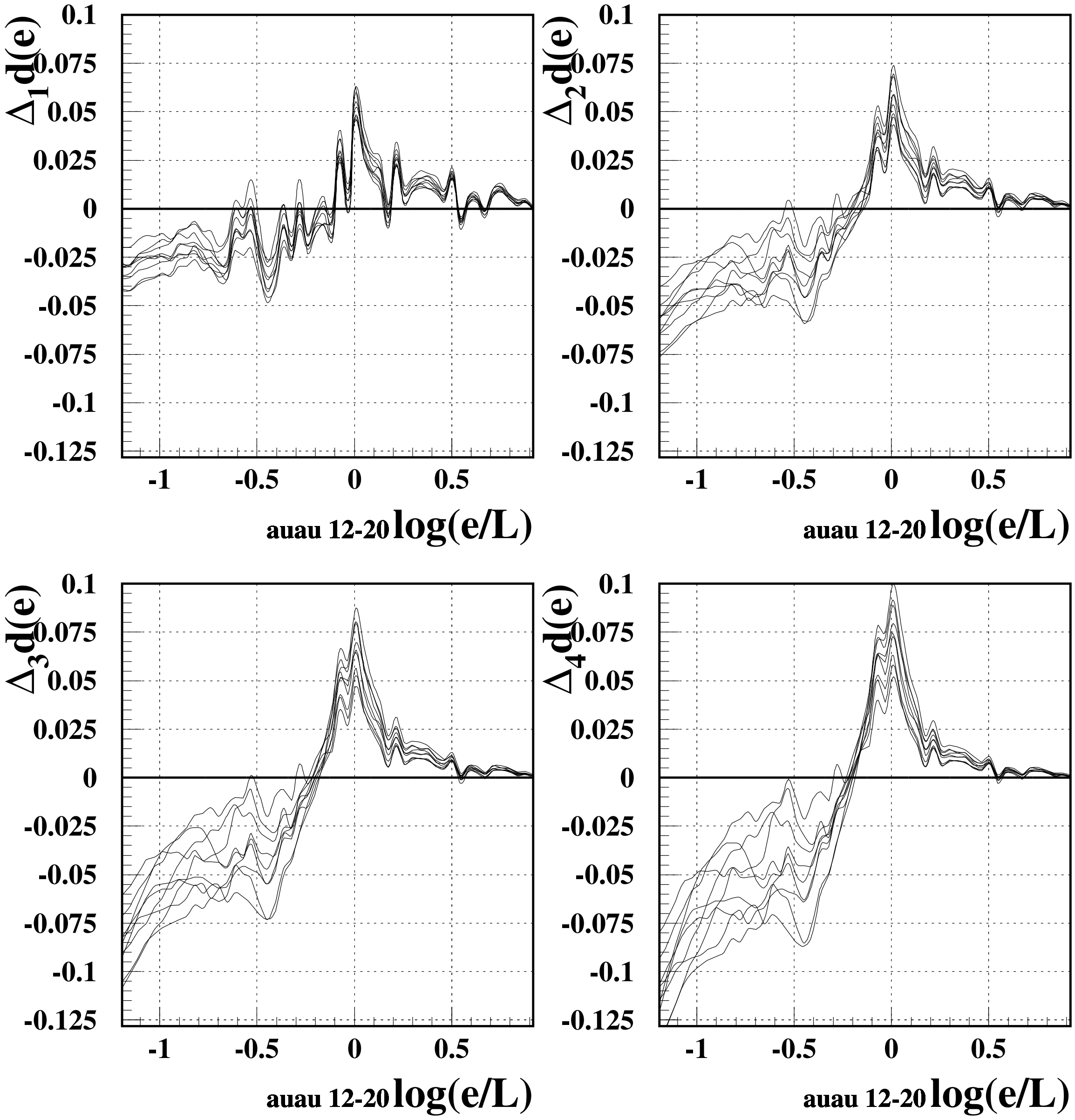

Figure 13: Dimension lowering for Au-Au system, ten events.

6.4 p-Au collision system

We can compare the results in fig. 14 with the top sections of fig. 7.

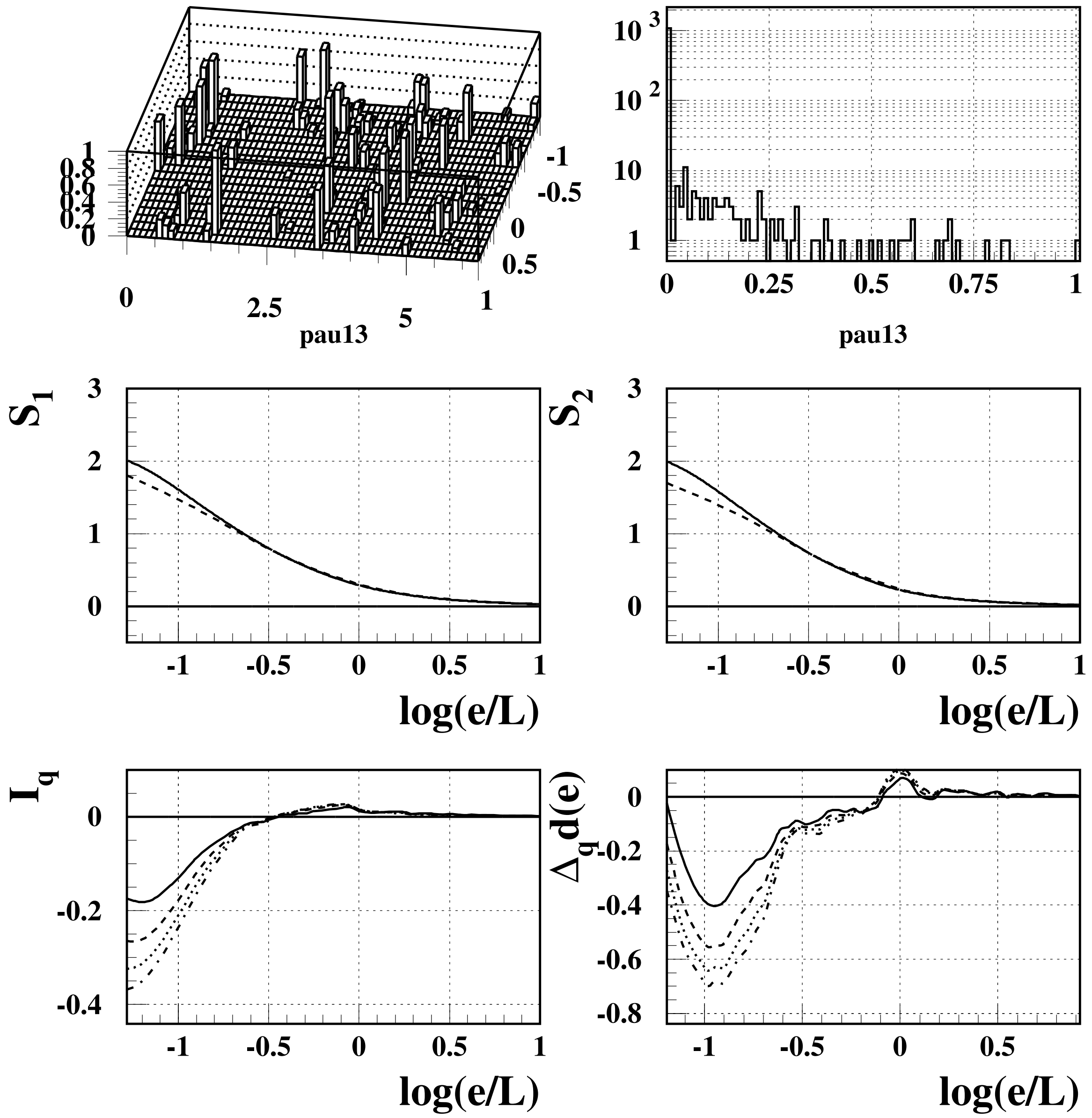

Figure 14: Scaled entropy analysis for p-Au system.

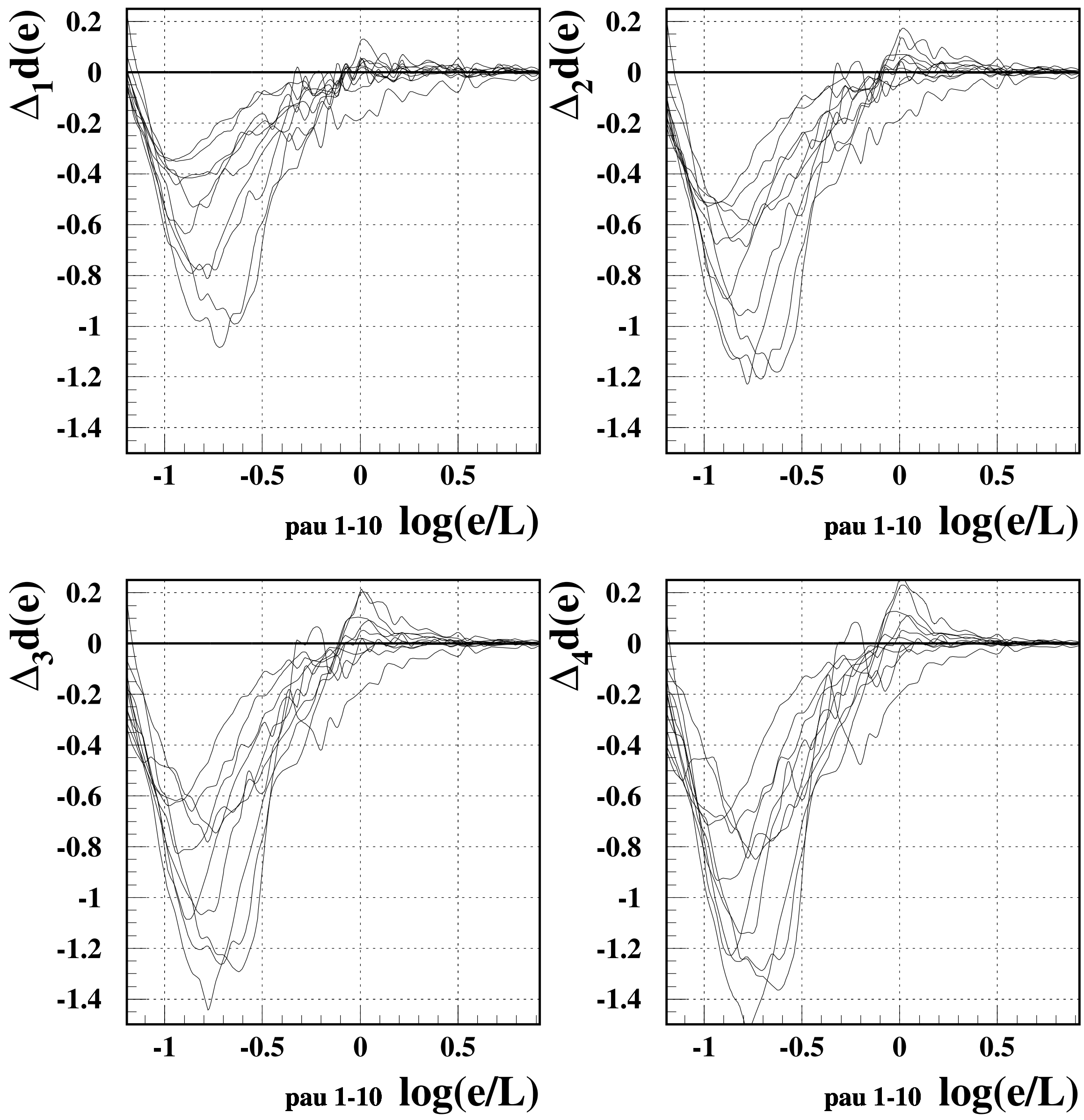

Figure 15: Dimension lowering for p-Au system, ten events.

7 Scaled correlation analysis and trigger algorithms

A full correlation analysis as illustrated above takes between 10 and 50 seconds for each event using a 66 Mhz processor. We need processing times per event that are 1000 times shorter than this to provide effective trigger algorithms at levels two and three. How is this to be accomplished?

First, we anticipate the use of approximately 10 processors at level 2 with a speed ($\sim$ 200 Mhz) at least 3 times our current processor speed. Second, the full correlation analysis is not required in order to formulate an effective trigger algorithm. The full analysis allows us to see the complete picture of the correlation contained in typical EMCAL distributions. After extensive study of simulated events with the full analysis it becomes clear at what scale values and for what rank the bulk of the correlation is concentrated. Simplifying the analysis by restricting scale ranges, limiting dithering and carrying out the analysis at a single optimum rank will further reduce the run time by of order 50 fold. This brings the *effective* process time per event down to roughly 10 ms, which is consistent with the level-2 trigger requirement.

For example, from an analysis of p-p events we see that the differential correlation is concentrated at scale values corresponding to log(e/L) $\sim$ 0, -0.35 and -0.70 (factors of 2 removed in scale). Also, the responses of the $S_q(e)$ are very similar above rank 4. This suggests that quantities $S_q(log(e/L)) = S_4(0)$, $S_4(-0.35)$ and $S_4(-0.7)$ may form the coordinates of an efficient trigger space. Each event would be represented by a point in this 3-D space, and we would expect different classes of events to accumulate in different regions of this space. Then, as with the trigger space for level 1 autocorrelation analysis, we can select event classes by means of cut surfaces in this space. Similar arguments apply for other collision systems.

While we must use a reduced or simplified correlation analysis for level-2 trigger operation due to finite processor capacity we still expect to do a full correlation analysis on a subsample of minimum bias triggered events from the data stream. In this way we can monitor various aspects of trigger function and look for rare event types that may suggest a reconfiguration of the trigger space. Thus, the level 2 trigger system should be thought of as a hierarchy of related algorithms, with varying degrees of generality and taking more or less processor time, and blending smoothly into the offline EMCAL data analysis.

8 Other trigger simulation issues

When we begin a detailed comparison of the correlation analysis technique with jet-finding methods we have to ask when is a found jet not a jet? That is, when reporting efficiencies we must consider false positives as well as false negatives. This is currently an open area, but of critical interest for heavier collision systems. Also, if a jet finder is 85% efficient, this may be exactly what is expected given the fragmentation function. Thus, a determination of the jetfinder efficiency must take into account what is actually findable by any reasonable means. For this reason a parallel study of scaled correlation and jet-finder methods may be mutually beneficial.

9 Conclusion

We have reported here the essential elements of a scaled correlation analysis of EMCAL energy distributions which may serve to extend and complement standard jet-finding techniques for heavier collision systems. We have also shown analysis of specific HIJING-simulated events to give an idea of how this technique might be applied to real data. We are now examining more closely the relationship between jet-finding results and the correlation analysis, and developing from the general analysis specific trigger algorithms which coincide with the computational bandwidth of the STAR level-2 trigger system.

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