Game Intelligence Analysis by Means of a Combination of Variance-Analysis and Neural Networks

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1 Introduction: knowledge transfer in game analysis

Over the past years there has been an increasing demand for installing interdisciplinary projects which bring institutes from different fields of research into collaboration. This tendency is based on the expectation that new results, even in individual disciplines, depend more and more on a fruitful *transfer of knowledge*.

> *"Vielmehr ist die dauerhafte Institutionalisierung solchermaßen integrativer und technologisch ausgerichteter wissenschaftlicher Arbeitszusammenhänge ebenso erforderlich wie die Institutionalisierung eines solchen Wissenstransfers, der Evaluation und der Implementation von wissenschaftlichen Befunden in die Trainingswirklichkeit."(Daugs, Mechling, Blischke & Oliver, 1991, S. 27)*

It is to be expected that in the case of well-structured and successfully run research paradigms in especially, additional potential is available from interdisciplinary collaboration – particularly by a creative exchange of methods.

Team game research and *game analysis* have played an important role in the field of sport science for a long time (for a review see Hohmann, 2004; Hohmann & Lames, 2004; Hossner, 2004; Memmert & Roth, 2003; Schöllhorn & Perl, 2002). They could be described as well-structured research paradigms. In order to evaluate performance data from games, qualitative and quantitative methods are normally used separately. The aim of this research project is to demonstrate that the combination of net-based qualitative analyses and stochastic quantitative analysis can improve the information output significantly. The stochastic approach reduces the total of recorded data to only a few statistical quantities and checks their significance by means of variance analysis. In contrast, neural networks – considering all available data to be high-dimensional points that correspond to neurons – can be used to extract specific striking features and qualitative trends on all original data.

At the University of Heidelberg, on the one hand, the focus is on the education of beginners and talent development in the area of games, with non-specific *creativity* and *game intelligence* as main points. A BISp-sponsored field experiment generated longitudinally structured data with five different kinds of treatment and convergent and divergent tactical game performance as dependent variables (see Section 2). Appropriate methods for additional differentiated analyses are currently not available.

At the University of Mainz, on the other hand, a type of *Dy*namically *Co*ntrolled *N*etwork ("DyCoN") has been developed, which can be used for the analysis of adaptive processes, among other things. Normally, a Neural Network responds primarily to frequent data and ignores infrequent data. In a next step the DyCoN-concept will be completed by the ability to also react to infrequent but relevant data, such as creative behavioural patterns of players in a game (see Section 3). To this end, a large amount of sufficiently reliable data with a large statistical spread is necessary for validation and calibration.

This research project will make plain that there are a number of synergy effects that can be expected from a combination of both approaches (see Section 4). The initial results are presented, which demonstrate that convergent results obtained using the stochastic approach can be replicated using neural networks. Furthermore, we were able to detect additional interesting aspects that were not open to the stochastic approach (see Section 5). It will be shown that the results of such an interdisciplinary collaboration are not limited to convergent performance attributes, but that they also can be most useful in the intended validation of the creative learning model of DyCoN (see Section 6).

2 Data material: A field study based on game intelligence and creativity

This approach will be demonstrated exemplarily using data from a BISp-sponsored project (VF 0407/06/12/2001-2002) that was run by Roth and Memmert (2003). In this field experiment, sport-specific training concepts were compared with non-specific ones. In addition to the general non-specific basic training (N = 54), a handball-specific (N = 13) and soccer-specific training concept (N = 20) and a mixed training model (N = 16) in the area of mini-hockey – 50 % non-specific and 50 % hockey-specific content – were included. The control group consisted of first-year primary school pupils (N = 17). The starting age selected was relatively consistent at an average of 7.2 years (SD: 0.9).

The dependent variables are non-specific creativity and game intelligence. They are measured at two points over six months. Furthermore, divergent and convergent characteristics are ascertained in the game situations USING GAPS and SUPPORTING AND ORIENTING using concept-oriented expert ratings. *Game test situations* are tasks in which particular tactical behaviour is provoked reliably and regularly by presenting the game idea, the number of players and rules and environmental conditions (see Memmert & Roth, 2003). It is essential that distribution of the positions be changed systematically by rotating the positions twice for each subject. As such, hand, foot and hockey stick are used one after the other in a random sequence. The performance of the children in the game test situations was recorded on video tape and evaluated using a subsequent *concept-oriented expert rating*. This means that (i) fixed characteristic definitions and scalings were given for the experts, (ii) they were trained with special video tapes and (iii) they had to make a final video-based test to check their expert coding qualities. Only those experts with a high reliability as measured against a golden standard of experts in ball games were chosen. The children in the game test situations were each judged by three experts in ball games. These values were later averaged. Extensive preliminary studies validated this diagnosis inventory with regard to the classic quality criteria (see Memmert, 2004).

Only the pattern of results for game intelligence shall be discussed below (see Figure 1, left). In the study, more than 90 % of the objectivity coefficients (intra-class correlations) for the game test situations are above the value of 0.80. The development of the convergent increases in learning determined via the two dependent variables and the three forms of performing motor functions is shown in Figure 1 (left). A general training effect is evident here ($F(1,219) = 10.15$; $p < 0.01$, $\eta^2 = .04$). The various types of treatment caused differing increases or decreases in performance ($F(4,219) = 3.78$; $p < 0.01$, $\eta^2 = .07$). Furthermore, average differences in performance were found between the groups which could not be attributed to coincidence alone ($F(4,219) = 10.46$; $p < 0.001$, $\eta^2 =.16$). However, only the mixed ($p < .0001$) and soccer-trained ($p < .01$) groups made a significantly greater improvement compared with the control group. It must be mentioned here that the performance of the children at the pre-test varies ($F(4,220) = 12.18$; $p < 0.001$, $\eta^2 =.16$). As is only to be expected in a training experiment under field conditions, the varying levels of previous experience complicate interpretation. However, no changes in the results can be identified when the results of the pre-test act as a covariable.

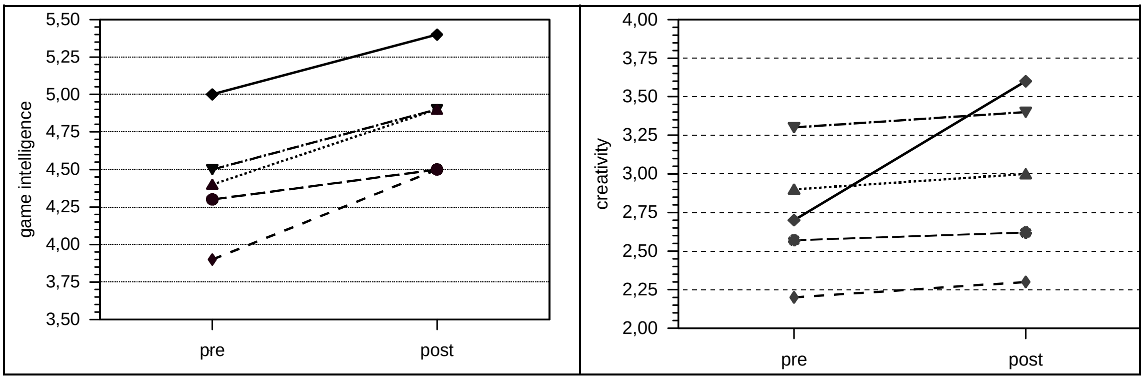

Figure 1. Convergent (left) and divergent (right) non-specific increases in learning between the first and second measuring points (non-specific = – – –; specific handball = ··········; specific soccer = – · – · –; mixed = ———; control group = – – – –)

3 Method of solution: qualitative analyses with DyCoN

The above mentioned DyCoN is a type of Kohonen Feature Map (KFM), the training of which is normally controlled by external functions which guarantee that a final state is achieved (cf. Mc Garry &Perl, 2004). This approach is helpful when training a network statically to be used as a tool. It is not helpful if the aims are to learn dynamically, adapt to changing situations and analyse learning processes. Therefore each DyCoN neuron contains an individual *learning self-control*, which was originally developed as an autonomous model for physiological adaptation (cf. Perl, 2003). In this way, the network is always in a well-defined non-terminal state. The consequences and advantages of this concept are as follows (see also Perl, 2002; Schöllhorn & Perl, 2002):

- *Training steps* and test steps do not have to be separated into different phases but can be combined arbitrarily. Temporary states of the network can therefore be watched during the training process - and can be influenced by appropriate training data if necessary.

- A training process can be interrupted and continued arbitrarily. Data on time-dependent patterns can be trained repeatedly to increase the quality of *pattern recognition* adaptively.
- In the case of small amounts of data, which are not normally sufficient for network training, the network can be *pre-trained* with an unlimited amount of Monte Carlo-generated data, the structure or distribution of which follow that of the original data (Perl, 2002). The training is then completed by a second phase, in which the network is specifically moulded using the original data. This method has been used successfully in several projects when the structure of the data was well-known, but the amount of original data was too small (cf. Lippold, Schöllhorn, Perl, Bohn, Schaper, & Hillebrand, 2004; Perl & Weber, 2004).

In order to study interactive learning processes and develop training strategies (e.g. completing learning vs. replacing learning), different patterns can be trained to the same net in different phases. Moreover, there are four reasons that make clear why neural networks should be used and developed in order to analyse particular aspects of divergent performance.

- Neural networks of the KFM-type are of importance if data have to be classified without any *a priori information* on the given cluster structure – as is typically the case with data from convergent or divergent tactical game performance.
- As has been pointed out by projects, neural networks of the DyCoN-type are of specific importance if the *amount of data* is small and data profiles and/or cluster structures change dynamically in time – as is the case with the available project data, which is recorded from only a medium number of subjects over a time interval of six months.
- In addition to the advantages mentioned above, neural networks – unlike stochastic methods – allow for *qualitative evaluations*, which can be deduced from spatial (topological cluster representation) or temporal (trajectories) structures of the network.
- In particular, the intended completion of DyCoN with regard to associative clusters, bridging neurons and semantic relevance (see Section 6) enables us, in addition to quantitative stochastic methods to analyse qualitative phenomena, such as *creative performance*.

4 Research strategy: "win-win-situation"

In addition to a replication of the results of the BISp-project, the application of neural networks to the BISp-data from Section 2 allows for a deeper understanding and yields new intuitions. As will be made clear below, there are *advantages* in both directions: On the one hand, the BISp-data builds a valuable basis for the development of the adaptive network concept. On the other hand, networks can to provide a more differentiated interpretation of the BISp-data. Moreover, they can produce additional information, which can help to structure new experiments. Firstly, the reasons as to why the *BISp-data* serves as a good basis for *developing neural networks* are listed below:

- One central point is the fact that specific research into divergent learning behaviour yields data, which is excellently suited to the particular purpose of *validating* the intended creative learning model of DyCoN (see Section 6). As far as we know, a sufficient amount of such data is only available from our project. In this paper, however, the data initially serves only to replicate the convergent results of the BISp data (see Section 5).

- Moreover it should be mentioned that the necessary conditions for the applicability of those networks – namely that the *characteristic attributes* are scaled relative to a not too large scale – in the case of the BISp-data are given in an excellent way.
- As is shown in Section 2, there are 6 pieces of data available for each tactical performance and child (i.e. 3 experts × 2 player rotations per tactical behavior and child), which means a 12-dimensional attribute vector for both measuring points in time. These vectors form the patterns that have to be learned and, later on, recognized by the network. The vector dimension "12" on the one hand is large enough to spread a sufficiently differentiated pattern space during the network training. On the other hand, the dimension is small enough to guarantee a sufficient representation of the original patterns by the network. Therefore the *data configuration* fits the demands of a successful network analysis perfectly.
- A further advantage regarding the application of DyCoN is the *statistical spread* of the BISp-data. This spread enables – particularly when only a small amount of original data is available – the DyCoN method of pre-training with stochastically generated data, followed by a specific moulding with the original data (see Section 3). Due to the study design described in Section 2, a sufficiently large variance regarding the dependent variables (four tactical performances) and independent variables (five different kinds of treatment) is given.

Furthermore, *networks* present possibilities for *qualitative evaluation* of the data material, which conventional variance analyses offer only restricted form, if at all:

- Simultaneous processing of 12-dimensional attribute vectors (2 measuring points × 3 experts × 2 rotations) – instead of the 2-dimensional vectors of the aggregated values – creates a data situation which permits more information on the divergent and convergent tactical development of the children. Aggregate indicators are no longer actually included in the calculations, but rather three experts' evaluations for each of the two measuring points at both rotations (see Section 5 for more detailed information). Increasing the dimensions from 2 to 12 enables a more *complex interpretation* of the pattern of results (see Section 5).
- In short, this allows for qualitative interpretation that completes quantitative evaluations. This means that an additional gain in knowledge is not limited to the recognition of *basic principles*, but moreover and in particular that it can be most useful for practical applications.
- For example, the graphical representation makes it apparent that the spectrum between very good and less good performances can be represented almost in its entirety (see Section 5). In this way the neural networks can illustrate *mean variations* in the behavior data.
- It is possible that neural networks could be used to visualize the *time-dynamic development* of learning processes and – not least through the aforementioned reduction to 2-dimensional trajectories (see Section 5) – make these processes accessible for further analyses investigating inter- and intra-individual correspondences.

To sum up, by means of visual evaluation of data distribution projected onto the network structure and analysis of inter- and intra-individual correspondences, useful information made available, which can rarely be obtained from variance-analyses, if at all. First of all, the use of neural networks for the replication of convergent tactical performances is considered. Checks are made to ascertain whether further information on the data material can be gleaned using this method (see Section 5). Not until a second stage are networks conceived that can evaluate divergent performances (see Section 6).

5 Exemplary implementation: game intelligence with DyCoN

Initial tests and plausibility approaches suggest analyzing the convergent tactical behavior separately with regard to the types of execution. Figure 2 below shows the *advantages* of combining the network approach and the variance-analysis approach. The top left section of Figure 2 shows a set of typical original data. Three experts, two player rotations and two measuring points in time give a 12-dimensional attribute vector.

Firstly, the dependent variable SUPPORTING AND ORIENTING (convergent tactical behavior; motor performing "hockey stick") shows a *result pattern* similar to that obtained using conventional methods. As can be seen from the increased frequencies in the green areas, the network approach indicates an improved formation of game intelligence in the case of the non-specific trained model (see Figure 2, top right). This result corresponds to the significant (percentage) increase of convergent tactical performance, which is maximal in the "mixed" training group ($F(1,53) = 9.732$; $p < 0.01$, $\eta^2 =.16$; see Figure 2, top right and below). In contrast, the control group – for both methods – shows a small decrease in the convergent tactical performance ($F(1,16) = 4.548$; $p < 0.05$, $\eta^2 =.22$; see Figure 2, middle and below). A decreased performance is represented by high frequencies in the red areas.

Secondly, the graphical representation of the neural networks for the non-specifically trained group illustrate that larger *mean variations* in the twelve behavior data are present here (see Figure 2, top right). This can be seen from the distribution of "hits", which build a large number of small centres of low frequencies spread over the whole network, apparently representing the spectrum between very good and less good performances almost in its entirety. Interestingly, however, the tactical development of the non-specific trained children proves to be much more heterogeneous than that of the mixed trained children – although the percentage of improvement is almost equal (see Figure 2, middle left). So size and distribution of the neurones together with their correspondences to the clusters give an idea of the quality of the training results and help to detect striking features, such as specific similarities or differences.

Thirdly, Figure 2 shows a trajectory that represents a training process (middle right). Starting with "**o**", the time-steps of the training process move through the areas of the network, indicating successful (green areas), unsuccessful (red areas), or indifferent (yellow areas) phases of the training. In the example given, the subjects' performance decreases at first (which could be interpreted as a super-compensation effect), then improves (green areas, above left and middle right), but in the end at step "×" is worse than at the beginning. Such a process-oriented presentation of the result might help to detect problems and find reasons. In this particular example, this could be due to the fact that that the whole training process was not optimal, only temporarily resulting in improved performance. This way, clusters together with *trajectories* can help to recognize qualitative features and analyse process dynamics.

6	2	2	2	3	3	4	5	5	5	1	4
7	3	3	7	3	3	1	2	5	3	7	3
1	2	6	2	1	1	4	4	4	4	4	4
1	3	3	1	3	3	3	6	6	5	4	5
1	1	3	3	3	3	4	1	3	3	1	6
1	1	1	2	2	2	1	3	6	3	4	7
2	2	6	2	2	2	4	4	4	6	5	6
6	3	3	3	1	1	2	5	7	5	3	3
1	2	3	3	3	3	7	2	3	3	6	2
2	6	6	3	5	5	5	5	5	5	5	5
3	3	2	7	5	5	5	3	3	6	3	3
3	3	3	3	4	2	6	4	4	5	5	4
6	2	6	6	4	5	4	6	6	6	4	6
5	7	7	7	3	7	5	3	7	7	7	3
3	2	6	3	5	6	7	3	3	7	2	7
2	2	6	6	4	2	6	4	5	2	4	4
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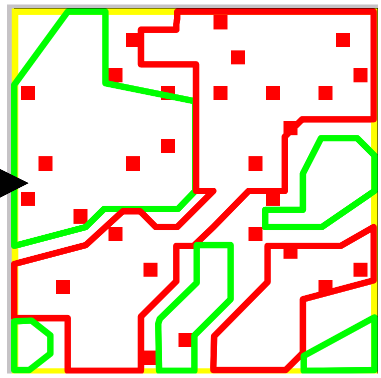

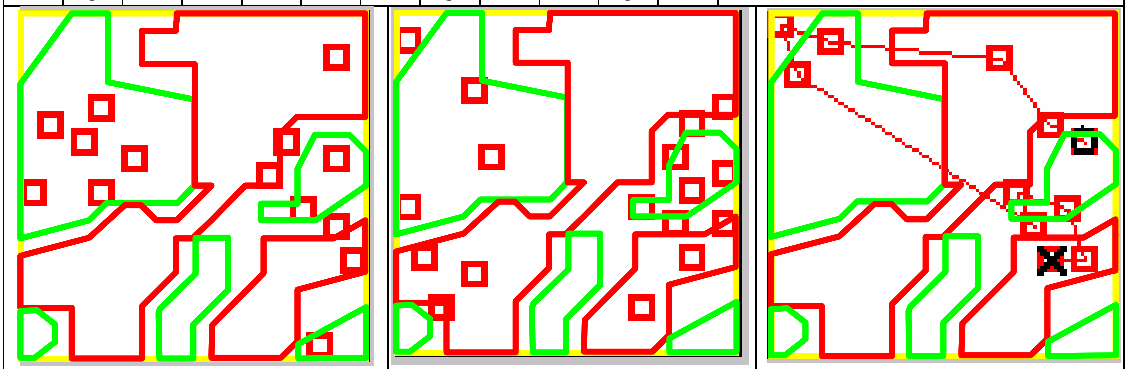

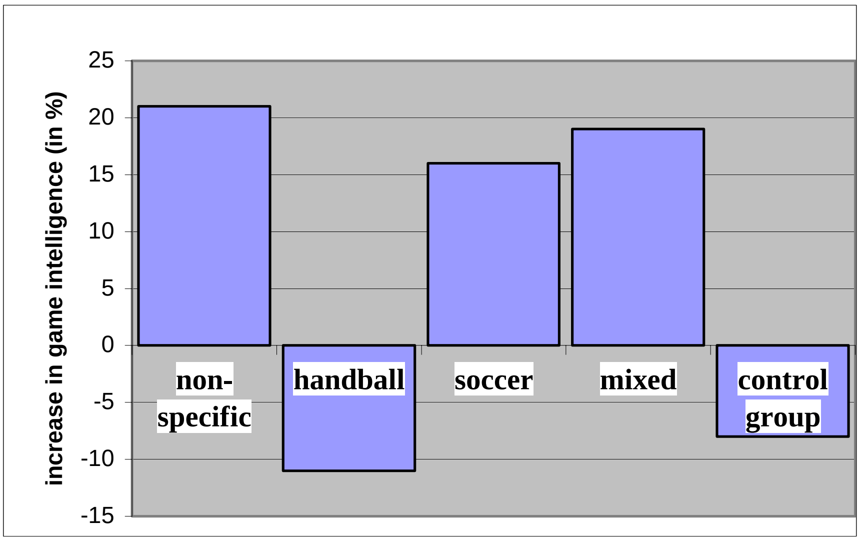

Figure 2. Data matrix of the learning behavior and its mappings to the network: "non-specific" (top right), "mixed" (middle left), "control group" (middle) a representation of a trajectory (middle right). Below: Percentage increases of the convergent tactical behavior SUPPORTING AND ORIENTING with the motor performing "hockey stick". The sizes of the neurons in the network representation map the frequencies with which the corresponding constellations appear in the test data.

To sum up, the neural network was able to replicate the BISp-results mentioned above and demonstrate the advantages of network-based qualitative analysis in addition to quantitative stochastic analysis. The stochastic approach reduces the totality of recorded data to a very small number of statistical parameters, which moreover are not necessarily data-specific. Variance analysis can, however, be used to check the *significance* of changes in the data. In contrast, it should be pointed out that network-based analysis allows for mapping the 12-dimensional time-dependent process structure to 2-dimensional trajectories without destroying topological and qualitative structures such as *similarity* and *connectivity*. This enables interpretable representations of time-dependent learning processes as well as improved visual judgement of distributions. The mapping of the complete data set to the type structure of the network allows for recognition of specific data structures and striking features, which can also be helpful in developing new ideas and theories.

Further studies have to prove whether the *individual* convergent results of the subjects produced by the neural network agree with the ANOVA results. For example, you could use kappa coefficients to compare declining, unchanged and improving subjects according to the network-based qualitative and quantitative stochastic analysis. Another way to analyse the correctness of individual improvement of subjects is to generate quantitative network-based data and compare them to the ANOVA results. You could use 95% limits of agreement on the two sets of data to assess systematic bias and random errors.[1]

The results obtained in this project suggest that, like the case of convergent performance attributes, properly adapted versions of DyCoN may also be successful in divergent cases (see Section 6).

6 Further Research: DyCoN next steps – creativity

Based on the activities presented so far, a *new approach* will be developed, which – besides the quantitative relevance of situations and actions (e. g. frequencies) – also takes the qualitative relevance into consideration, which can help to make "creativity" an object of analyses and learning strategies. Two main aspects of opening the network approach to "creativity" are those of "association" and "relevance" (Perl & Uthmann, 2002).

The first aspect deals with *association*. Let us assume a behavioural process to be a sequence of situations that have to be recognized and corresponding activities that have to be selected. In a net-based simulation, KFM or DyCoN type networks are responsible for the recognition of situations, which are encoded and presented by the clusters. Network learning is normally described and handled by means of "if then" rules – i.e. if the recorded data belong to a certain cluster then the corresponding situation is unambiguously determined, and so is the activity that corresponds to that situation (see Figure 3, above graphic). Using this concept there is no room for associations like "The data belong to cluster A but have a strong affinity to cluster B. Therefore let us try the activity corresponding to B instead of that corresponding to A". In turn, a concept that takes into account aspects of association has to connect clusters by associative bridges instead of strictly separating them (see Figure 3, below graphic).

A second aspect that is normally used in network training is that of frequency-based *relevance* – i.e. data are more relevant and the corresponding clusters are bigger the more frequently they appear in the set of training data. This concept contrasts with that of information theory where the information of an event decreases with the number of its appearances – i. e. a frequent event is not surprising. Transferred to behavioural processes, the consequence is that even seldom situations can be of high semantic relevance because they can trigger spontaneous and/or unexpected activities.

[1] Thanks to an anonymous reviewer for pointing out this further analysis method.

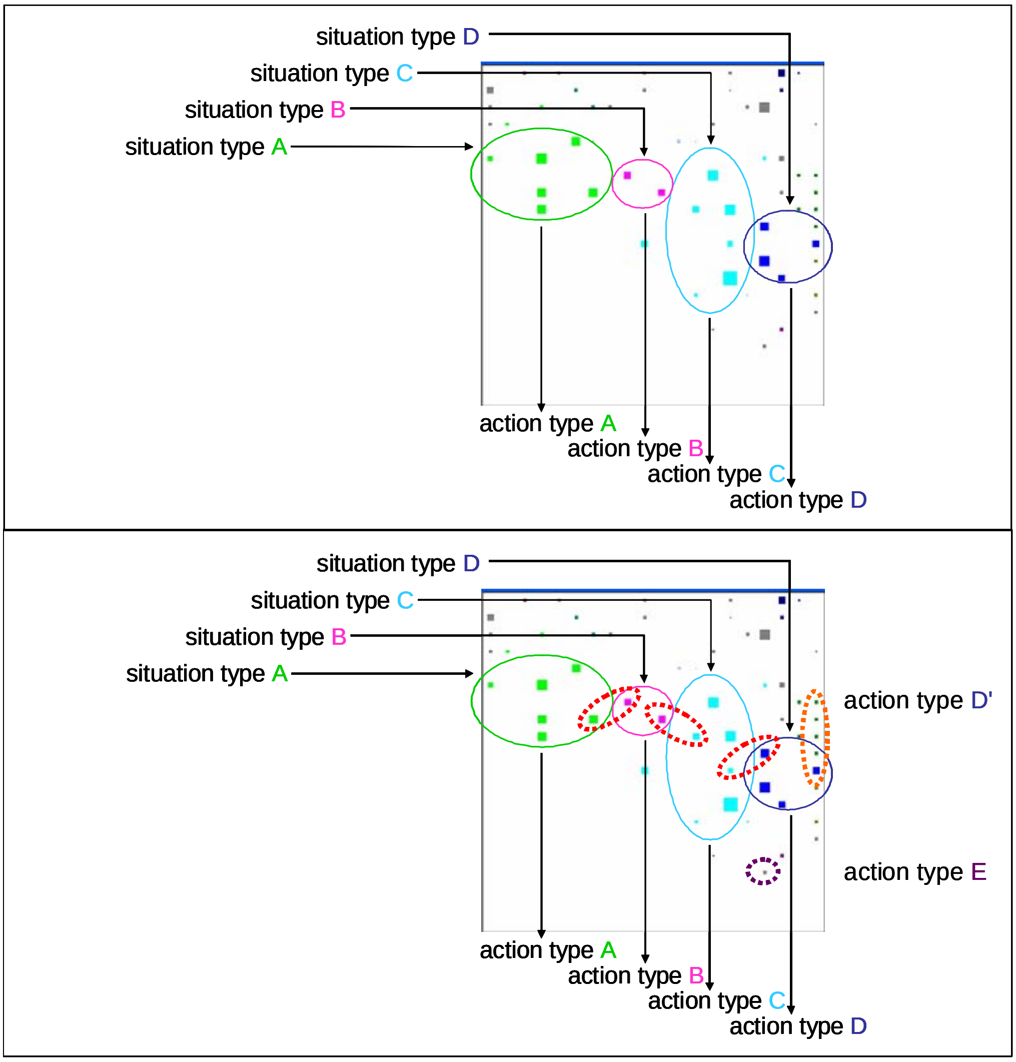

Figure 3. Normal convergent behaviour (top graphic) compared to divergent creative behaviour (bottom graphic): Associative bridges (dotted ellipses) allow moving between clusters, causing unexpected activities. In particular, small but semantically relevant clusters can become important. (The horizontal and vertical edges symbolize the correspondences between situations, clusters, and actions; see explanations in the text below).

The question is how "association" and "relevance" as aspects of creativity can be transferred to an appropriate network model. This approach is not currently in use but is only projected. The main ideas of how it should work are sketched in Figure 3. In the top graphic, the usual method is shown as described above – i.e. in a first step the situation is recognized by its characteristic data corresponding to a specific cluster, which it is connected with by a horizontal edge. In a second step, the recognized cluster can trigger the corresponding activity, which it is connected with by a vertical edge.

In the bottom graphic, different ways of making "creative" decisions are shown. The first is that of *associative bridges* (dotted red ellipses), which connect clusters with each other and so allow for moving between clusters and changing decisions regarding the appropriate activity (see action types A', B', C', D'). The second is that of associations from frequency-relevant clusters to semantically-relevant ones (dotted orange ellipse), causing unexpected activities (see action type D'). The third method is that of spontaneously jumping to a semantically-relevant cluster or neurone without having any associative bridge (dotted violet ellipse), causing unexpected and surprising activities (see action type E). This could finally help in deeper analyses of divergent tactical behaviour in the BISp data similar to that dealt with the results in Section 2 (see Figure 1, right).

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