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CONCAT - Connotation Analysis of Thesauri Based on the Interpretation of Context Meaning

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Abstract–Knowledge acquisition constitutes the bottleneck for the creation of legal expert systems. Legal language must be formalised to such a degree that it can be processed automatically. We deal with this problem by supporting the process of creating a selective thesaurus for a legal information system which can be seen as prerequisite for further knowledge processing. This selectivity is obtained by means of connotation analysis of the individual descriptors which makes it possible to detect hidden word meanings and to distinguish between precise legal terms and words with fuzzy meaning. Within the prototype system CONCAT we applied both a statistical and a connectionist approach to connotation analysis and performed a comparative evaluation of the achieved results.

1 Introduction

Advanced use of information technology in the legal field requires formalisation of the legal data (e.g. statutes, treaties, court decisions or literature). Two main approaches are concerned with this situation. On the one hand, laws are rewritten as logic programs, a harsh simplification of the complexity of legal systems leading to severe limitations (e.g. open texture problem, appropriate deontic logic). On the other hand, the focus is put on the linguistic structure of legal language. Due to the arduous nature of linguistics, so far only partial analysis can be performed efficiently.

Our aim is the automatic representation of the expert knowledge about legal language. As the central subject of the lawyer's work a special vocabulary has been developed by jurisprudence which is clear, simple and pithy. Lawyers have formed definite concepts of human beings, objects, and processes by use of methods of abstraction and logic thinking.

The main hypothesis in the design of the prototype CONCAT is the assumption that legal thesauri can be used as tool for knowledge acquisition if the applied descriptors are selective. Intellectually created thesauri cannot be matched against document descriptors by means of Boolean retrieval logic because of their missing selectivity. Therefore, our attempt to overcome this deficit is to analyse automatically each descriptor with regard to its connotations. By that we can capture all distinct dimensions of word meanings as well as determine the feasibility to a certain domain.

The connotation analysis is based on the interpretation of the contexts of the individual legal terms which are represented as vectors. To calculate the similarity between descriptor occurrences we applied statistical techniques as well as neural networks. Both methods were evaluated on the basis of a small test database leading to a comparative analysis of the quality of results.

2 Related work

The traditional approach to legal knowledge representation was the use of intellectually produced thesauri or classifications providing a simple form of conceptual search. Due to cost reasons it has been often substituted by Boolean information retrieval. However, the formulation of Boolean queries in order to cover the underlying concepts turned out to be a tedious task [4].

An important improvement is represented by conceptual information retrieval systems. They make use of knowledge representation techniques in order to encode the semantics of legal concepts [5], [3]. The legal domain is mapped to a knowledge scheme. A great variety of representation techniques has been applied: semantic networks [16], conceptual graphs [6], concept frames [7], diagnostic expert systems [12] or object-oriented programming [14]. Although the obtained results were superior to Boolean logic, with respect to the high development costs only small systems have been built which are not applicable for commercial use within the legal field.

Neural networks seem to be an interesting tool for legal knowledge representation but their application has been restricted so far to conceptual information retrieval [1] and open texture [2], [15].

The approaches mentioned above suffer from the same shortcoming, the lack of automatic knowledge acquisition which is indispensable for the conceptual representation of the existent huge databases in the legal domain. A promising direction to overcome this deficiency was the application of statistical analysis. Most work within this area is based on the vector space paradigm which represents similarities as distances between vectors [20]. The similarity values are the basis for subsequent clustering resulting in improved precision and recall with regard to the retrieval results. Interesting adaptions of the standard model are the Generalized Vector Space Model (GVSM) [23] and Extended Boolean Logic [19]. Statistical methods for the representation of legal concepts have been introduced by Schweighofer and Winiwarter [21].

3 Generation of descriptor vectors

As basis for the computation we first transform the document texts to sequential word lists and remove all occurring stop words. By making use of a lemmatising module these sequential lists are then converted to a word index. The lemmatising module was designed to take care of important morphological phenomena, namely *spelling errors vowel-gradation*, *inflexions*, and *suffixes*.

In the same way, the documents are indexed by use of the thesaurus entries which results in an index containing the postings for the individual descriptor occurrences. The user is not restricted to the use of simple descriptors but can also apply synonyms and compound descriptors to the representation of the domain knowledge.

By merging the word and the descriptor index, the contexts of the descriptor occurrences are extracted and represented by vectors D_i according to the vector space model of information retrieval [20]: $D_i = (TERM_{i1}, TERM_{i2}, ..., TERM_{in})$.

As weighting function we used binary indexing so that $TERM_{ik} = 1$ if the word k ($1 \le k \le n$) is present in the context of the descriptor occurrence and $TERM_{ik} = 0$ otherwise. Thus, the vectors D_i capture the context meaning as a function of the absence or presence of certain words. Figure 1 summarises the individual steps of the applied process model.

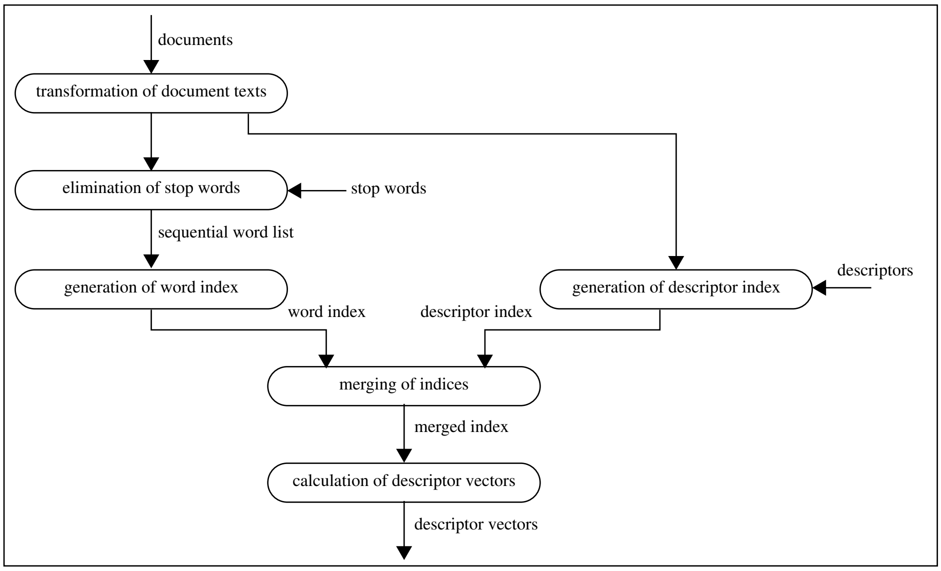


Figure 1. Process model

4 Connotation analysis of descriptors

4.1 Statistical approach

The similarity between two different occurrences of a descriptor is expressed by the number of words that are present in both contexts, that is, the number of vector components which equal 1 in both descriptor vectors. We used the symmetric *coefficient of Dice* as the similarity measure [20].

The coefficient represents exactly the percentage of words which the two contexts D_i and D_j have in common. Therefore, the value range is the interval [0, 1], the value equals 0 if the two vectors are completely different and equals 1 if they are identical.

According to the similarity values the descriptor occurrences are clustered by use of a quick partition algorithm that creates non-hierarchical disjunctive clusters [17]. The similarity value of each pair of descriptor occurrences is compared with a given threshold. If the similarity exceeds the threshold and one of the two occurrences is already a cluster member, the other one is appended to the cluster in question. Only if both participants of a similar pair are not yet included in any existing cluster, a new cluster is created.

In a second run duplicate cluster entries are removed by joining the concerned clusters. Finally, all descriptor occurrences not captured so far by the clustering process are added as single element clusters.

To simplify the interpretation of the results of clustering, the created clusters are supplemented by descriptions which represent the descriptor connotation and are created from the ten most frequent words that are part of the concerned contexts.

4.2 Connectionist approach

Artificial neural network models are specified by the network topology, i.e. the arrangement of units and connections, by the unit characteristics, i.e. the activation function and the output function, and finally by the learning rules. Learning rules specify the way in which the weighted connections have to be adapted in order to improve the performance of the artificial neural network.

With regard to the learning process we identify at least two different paradigms. The first paradigm is commonly referred to as *supervised learning*. In this paradigm learning is performed by reducing the error between the computed output of the neural network and the desired output with respect to a given input. Thus, in this learning paradigm pairs of input and desired output data have to be specified. Learning completes when each input is mapped correctly onto its desired output.

The second paradigm is known as *unsupervised learning*. In this learning paradigm the artificial neural network constructs internal models which capture the regularities in the input domain without any additional information as, for example, a desired output. For a more detailed description of neural network basics and learning paradigms we refer to [8], [18].

Within our approach we utilise an artificial neural network adhering to the unsupervised learning paradigm, namely self-organising feature maps [9], [10], [11]. The architecture of self-organising feature maps consists of a layer of input units and a grid of output units. The output units are arranged in some topological order. In the case of our application we used a two-dimensional plane of output units. Each output unit is connected to its topological neighbours and is assigned a so-called weight vector which is of the same dimension as the input data.

The learning process of self-organising feature maps can be described as follows. Firstly, an input is randomly selected out of the set of possible inputs. This input in terms of a vector is mapped onto the input units where each input unit receives exactly one component of the input vector. The input units propagate the components as they are onto the output units. Secondly, the state of every output unit is computed. The state of an output unit is determined by the activation function which is the Euclidean distance between the unit's weight vector and the input vector currently under consideration. Thirdly, the output unit with the highest state is selected. This unit is further referred to as the best-matching unit or the winning unit. Finally, the weight vector of the winning unit as well as weight vectors of neighbouring units are adapted in such a way that the state of these units gets even higher with respect to this input vector. Thus, the learning process is a generalisation of the winner-takes-all rule. These four learning steps are performed repeatedly until no more changes to the weight vectors are observed.

More formally, the crucial steps of the learning process can be described as follows.

(1) Random selection of one input vector x.

(2) Selection of the winning unit i by using the Euclidean distance measure. In this formula w_i (w_j) denotes the weight vector assigned to output unit i (j).

$$i: \|w_i - x\| \leq \|w_j - x\|, \text{ for all output units } j$$

(3) Adaption of the weight vectors w_j in the neighbourhood of the winning unit i at learning iteration t. The strength of the adaption is determined with respect to a so-called learning rate $eps(t)$ which starts with an initial value in the range of [0, 1] and decreases gradually during the learning process to 0. The scalar function $delta_{i,j}(t)$ determines the amount of adaption dependent on the neighbourhood relation between the winning unit i and unit j which is currently under consideration. Generally, the weight vectors of units which are in close neighbourhood to the winning unit are adapted more strongly than weight vectors which are assigned to units that are far away from the winning unit. This so-called neighbourhood function has to guarantee that at the end of the learning process only the weight vector which is assigned to the winning unit is adapted. Obviously,

with these two restrictions on the learning rate and the neighbourhood function the learning process will terminate.

$$w_j(t+1)=w_j(t)+eps(t)\times delta_{i,j}(t)\times[x-w_j]$$

(4)Repeat steps (1) through (3) until no more changes to the weight vectors are observed.

The outcome of the learning process of self-organising feature maps results in a clustering of related input data in topologically near areas within the grid of output units. This is due to the fact that during the learning process the weight vectors of the winning unit as well as weight vectors of neighbouring units are moved towards the current input vector. The repetition of this adaption during the numerous presentations of input vectors makes the formation of areas possible which consist of output units specialised to regularities in the feature vectors of the various input data.

To conclude, the self-organising feature map preserves the distance between the input vectors as faithfully as possible. However, some distortion is unavoidable since a very high dimensional input space is projected onto a much lower dimensional output space. Yet, the most important neighbourhood relationships between the input data are preserved in the output space. Furthermore, these relationships are made geographically explicit in terms of the neighbourhood of the various units. This is confirmed as can be seen in the examples which are presented below.

5 Evaluation

As a test environment for our approach we used a database consisting of 41 text segments of documents from the European Community law database CELEX. The text material - terms with context windows - was produced as retrieval result from a search in the CELEX database for the term *neutralit*y which is a very good example of a term with several meanings.

By intellectual separation we achieved clusters of the various context related meanings of the term *neutralit*y which represented the comparison module for our automatic analysis. Due to space restrictions we can present only the various groups and the CELEX numbers of the documents.

In Figure 2 we provide the result of the intellectual document analysis. We specify each document by its CELEX number. Furthermore, each cluster is labelled by a short descriptive term which is given in parentheses in Figure 2. Note that several segments of one document are designated by using capital letters, e.g. /A, /B, etc.

In the next subsections we will compare the results which have been produced by the statistical and the connectionist approach with this very time consuming intellectual analysis.

5.1 Statistical approach

The efficient clustering algorithm of CONCAT produces good results. The clusters can be seen as types of the concept which are described automatically. A shortcoming of CONCAT is the sensitivity to the correct adjustment of the parameters (i.e., list of stop words, threshold value). However, multiple clustering with different parameters can be a useful support for the analysis of a term. More detailed evaluation results can be found in a recently published paper [22].

The outcome of the clustering algorithm is represented in Figure 3. For each cluster we give the consecutive number of the text segment as well as its corresponding CELEX number. Furthermore, we provide the cluster description which consists of the ten most frequent words that are contained in the respective contexts.

- Neutrality of States (STATE): 992E2408, 990H0306, 989H0195, 987H0184, 987H0183, 982H0240
- Fiscal neutrality:
  - Neutrality of the value-added tax system (VAT): 389L0465, 385L0361, 381Y0924(10), 367L0227/A, 367L0227/B, 690C0097, 690C0060, 690C0035
    - deduction of residial VAT (RES_VAT): 689J0159/A, 689J0119
    - import turnover tax (IMP_VAT): 689C0343
    - parent companies and subsidiaries of different member States (SUB_VAT): 390L0435
  - spirits (SPIRITS): 689C0230
  - $C0_2$/energy tax (EN_TAX): 392D0180
  - sugar sector (SUGAR): 390B0354
  - non-discrimination in matters of taxation (NON_DISC): 689J0159/B, 689J0011/A
- Neutrality of competition:
  - Neutrality of common rules for the allocation of slots at Community airports (SLOTS): 393R0095/A, 393R0095/B, 393R0095/C, 393R0095/D
  - Neutrality of the Community eco-management and audit scheme (ENVIRON): 393R1836, 392R0880
  - Neutrality of the tariff structures in the combined transport of goods (TRANSPORT): 393D0174/A, 393D0174/B, 393D0174/C
  - Neutrality of computer reservation systems for air transport services (AIR_SERV): 391R0083, 388R2672
- Neutrality of the research programmes of the Joint Research Centre (RESEARCH): 392D0274
- Neutrality of anti-dumping duties (ANTI_DUMP): 392R0738
- Chemical neutrality:
  - oil seeds (OIL): 386R2435
- Neutrality of the customs valuation system:
  - customs value of goods (CUSTOMS): 689J0011/B
- Conjunctural neutrality (CONJUNCT): 385D105.1
- Cost-neutrality (COST): 385D105.3
- Budgetary neutrality (BUDGET): 380Y1231(06)

Figure 2. Intellectual analysis of the text segments related to the term *neutrality*

5.2 Connectionist approach

During our experiments self-organising feature maps are trained with the descriptor vectors as input data. The length of these vectors is about 500 components. Obviously, the length is dependent on the stop word list. Thus, we perform a projection from a very high dimensional input space onto a two-dimensional output space by means of the self-organising map.

The most obvious difference to the statistical approach is that the neural network did not produce clusters but maps. The advantage of such maps is a better description of the relationship to the various connotations of a concept which can be described by using well-known geographical terms:

- *Hills*: Strong concentration of document segments with the same meaning,
- *Plateaux*: Loose set of document segments with similar meanings,
- *Valleys*: Document segments with meaning elements of several groups,
- *Region*: Neighbourhood relationship between hills and plateaux.

A note on the graphical representation of the final maps which are given in the figures below is in order. The graphical representation contains as many entries as there are output units in the artificial neural network. Thus, every entry corresponds to exactly one unit of the self-organising feature map. Each entry is further assigned either the CELEX number of a text segment or a dot. The appearance of a label denotes the fact that the corresponding unit exhibits the highest activation level with regard to the input vector corresponding to this CELEX number. Thus, this unit is the winning unit. Contrary to that, a dot appears in the final map when none of the input vectors is

1 41 NEUTRALITY

/1/11/ *393R1836*, *392R0880*
MEMBER, STATES, COMPOSITION, COMPETENT, BODIES, INDEPENDENCE, PROVISIONS, THIS, REGULATION, CONSISTENT

/2/3/4/ *393D0174/A*, *393D0174/B*, *393D0174/C*
APPLICATION, TARIFF, STRUCTURE, PRINCIPLE, INCOME, RAILWAY, COMPANIES, CERTAIN, ROUTES, ADJUSTMENTS

/5/15/18/21/22/27/ *992E2408*, *990H0306*, *989H0195*, *987H0184*, *987H0183*, *982H0240*
QUESTION, NO, COUNCIL, AUSTRIAN, COMMISSION, BONDE, IRISH, UNILATERAL, DECLARATIONS, WRITTEN

/6/7/8/9/ *393R0095/A*, *393R0095/B*, *393R0095/C*, *393R0095/B*
MEMBER, STATES, AIRPORT, PRINCIPLE, NO, RESPONSIBLE, TRANSPARENCY, DISCRIMINATION, CERTAIN, REQUIREMENT

/14/20/ *391R0083*, *388R2672*
PARTICULAR, NO, BASIS, CONDITIONS, ORDER, DISCRIMINATION, SUBJECT, REGARDS, SYSTEMS, CO-OPERATION

/19/30/31/33/ *389L0465*, *367L0227/A*, *367L0227/B*, *690C0060*
TAX, VALUE, ADDED, SYSTEMS, PRODUCTION, DISTRIBUTION, MEMBER, STATES, PROVISIONS, SERVICES

/28/35/36/37/38/ *381Y0924*, *689J0159/A*, *689J0159/B*, *689J0119*, *689J0011*
MEMBER, STATES, TAX, COMPETITION, VAT, REMISSION, EXPORTATION, GOODS, COMMON, RESPECT

The other remaining clusters consist of only one single document:
392D0274, *392R0738*, *392D0180*, *390L0435*, *390B0354*, *386R2435*, *385L0361*, *385D0105/A*, *385D0105/B*, *380Y1231*, *690C0097*, *690C0035*, *689J0011/B*, *689C0343*, *689C0230*

Figure 3. Clusters obtained by using a statistical approach

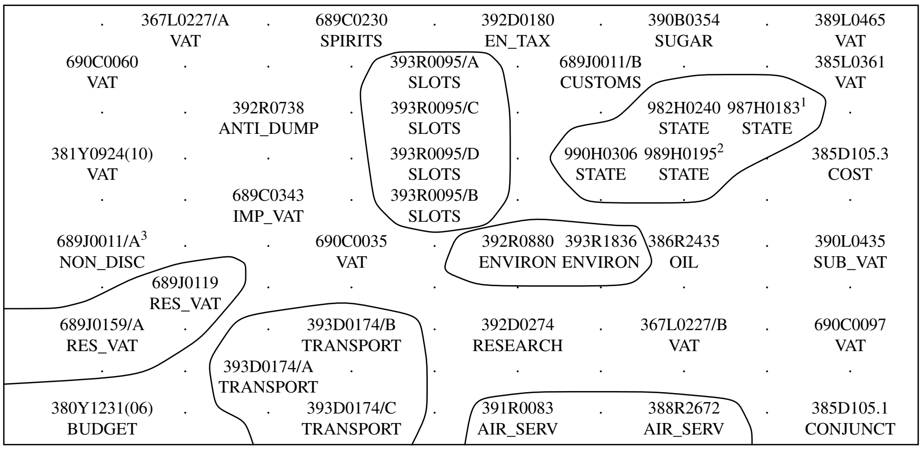
assigned to the corresponding unit. In other words, the respective unit does not exhibit the highest activation level for any input vector. Due to the limited space in the figures the CELEX number of only one text segment is shown even in the case where more than one text segment is assigned to an output unit. The other text segments are given as footnotes. In order to ease comparison we give the short mnemonic description for each CELEX number as they are introduced in Figure 2.

Note that the topological arrangement of the labels is an indication for the similarity of the corresponding text segments. However, the distance of the labels in terms of the two-dimensional surface cannot be used as an exact metric of semantic similarity.

Figure 4 contains the final arrangement of the various text segments based on input vectors which are reduced from stop words. The neural network has produced good hills (e.g. neutrality of the common rules for the allocation of slots at Community airports, neutrality of states) but also some interesting plateaux (e.g. fiscal neutrality or neutrality of competition). An example of a valley is the combination of the meaning elements of environment and competition. A region can be seen including the meanings fiscal neutrality, cost neutrality, budgetary neutrality, and conjunctural neutrality. The results of the neural network are the same in the hard core when compared to the statistical approach, i.e. the good clusters and hills but the interpretation is more difficult. However, the self-organising feature map describes weak relationships between the various meanings better.

A necessary prerogative of the statistical method is a good adaption of the model to the problem. The choice of the stop word list and the threshold value always represents a tricky issue. The neural network overcomes this problem because both parameters are not necessary as the following examples will show. In these experiments we utilized input vectors which are not reduced from stop words.

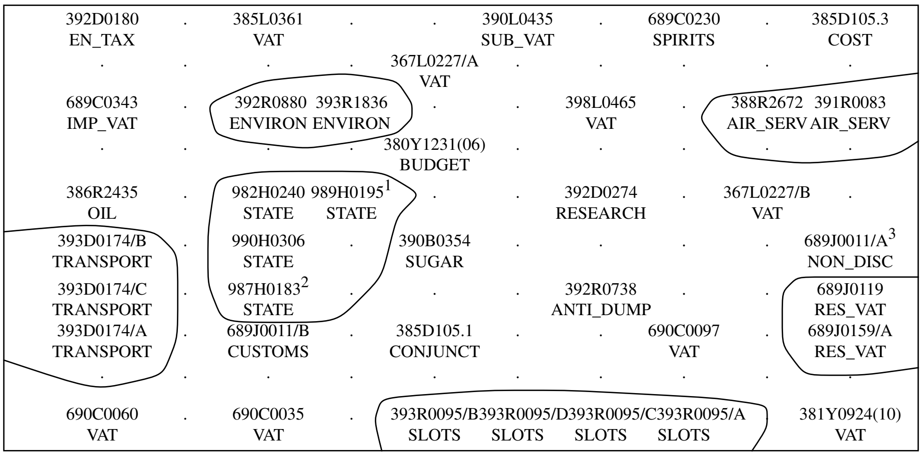
The final map in Figure 5 is different in terms of the geographical location of the



1. 987H0184 (STATE)
2. 992E2408 (STATE)
3. 689J0159/B (NON_DISC)

Figure 4. Final map (with elimination of stop words)

various text segments but in the hard core the result is the same. The plateau concerning neutrality of competition has disappeared but a good new plateau has been created concerning the meaning of neutrality and environment.

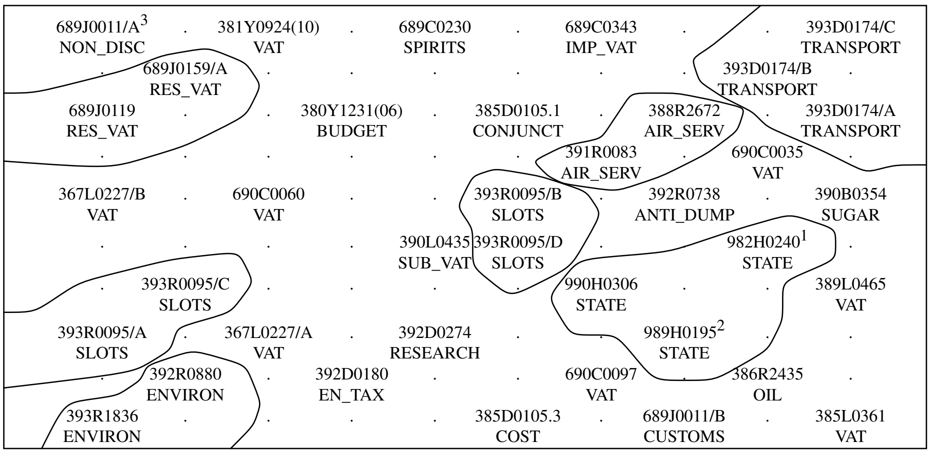


1. 992E2408 (STATE)
2. 987H0184 (STATE)
3. 689J0159/B (NON_DISC)

Figure 5. Final map (without elimination of stop words)

In our last example we used a slightly modified version of self-organising feature maps, namely we adapted the learning rule to capture lateral inhibition of output units. Lateral inhibition may roughly be described as follows. Weight vectors which are assigned to units in close neighbourhood to the winning unit are moved towards the current input vector whereas weight vectors which are assigned to units far away from the winning unit are pushed away even farther. Such a learning function produces an earlier establishment of the final clusters as well as a better approximation to the input vectors. A more detailed description of this learning function can be found in [13]. The final map is depicted in Figure 6.

Without some emphasis on clustering the modified learning function produces not as obvious hills as they are found in the previously presented maps. Nonetheless this experiment proved to be useful because some meanings are better represented, namely the neural network detected similar patterns within the text segments. For example, in the lower left corner of the final map we find four text segments concerning the composition of bodies, i.e. 393R0095/A, 393R0095/C, 393R1836, and 392R0880. Contrary to that, in Figures 4 and 5 clustering stresses on the same meaning, i.e. the allocation of slots at Community airports and the Community eco-management and audit scheme.



1. 987H0184 (STATE), 987H0183 (STATE)
2. 992E2408 (STATE)
3. 689J0159/B (NON_DISC)

Figure 6. Final map (lateral inhibition of output units; without elimination of stop words)

6 Conclusion and future work

The main contribution of this paper is the comparison between two approaches both aiming at data classification. The first approach adheres to statistical clustering whereas the second one applies artificial neural network technology. At first sight both approaches produced quite similar results. At a closer look, however, the neural network turned out to be paramount since it proved to be able to produce its results without the need of the time consuming tasks which are related to stop word elimination and threshold selection. Yet, the interpretation of the final maps demonstrated to be more laborious because of the different paradigm of presentation. Furthermore, the results of the neural network lack a declarative representation comparable to the cluster descriptions. The outcome of the experiments are encouraging and constitute a basis for further research using larger test data material with regard to the number of documents as well as the size of the thesaurus. The results achieved so far are useful for automatic knowledge acquisition within the legal domain.

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