# HITZALDIAK

# SESIONES TÉCNICAS

# CONNECTIONIST REPRESENTATIONS FOR NATURAL LANGUAGE: OLD AND NEW

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Connectionist natural language processing research has been in the literature for less than a decade and yet it is already claimed that it has established a whole new way of looking at representation. This article presents a survey of the main representational techniques employed in connectionist research on natural language processing and assesses claims as to their novelty value i.e. whether or not they add anything new to Classical representation schemes.

Connectionist natural language processing (CNLP) research has barely been in existence for a decade (cf. Sharkey & Reilly, in press, for a potted history) and yet it has grown enough to attract criticism from some formidable guardians of the Classical tradition. For example, Fodor and Pylyshyn (1988) claimed that connectionist representations could work for NLP if and only if they were implementations of Classical representations. One of their main arguments was that only Classical representations exhibit the properties of compositionality, and structure sensitivity and therefore only Classical representations can be used for natural language processing. While it is not the purpose of this paper to address the Fodor and Pylyshyn arguments in detail, some of their arguments will be used to examine connectionist representations for their novelty value. The main aim of the paper is to present a critical survey, and the Classical criticisms are discussed in this light of the survey. The stance taken here will be that there are novel connectionist representational types which are compositional (though not in the Classical sense) and which can be manipulated by structure sensitive operations.

Natural language research is normally concerned with two main types of representation: structural or syntactic representation and semantic or meaning representation. The latter is usually divided into the representation of lexical items and the representation of larger units such as phrases or sentences. In much connectionist work it is difficult to separate syntactic and semantic representation. Nonetheless, each of the different types will be discussed in turn and a taxonomy will be proposed.

## 1. The representation of meaning and structure.

### 1.1 Semantic representations.

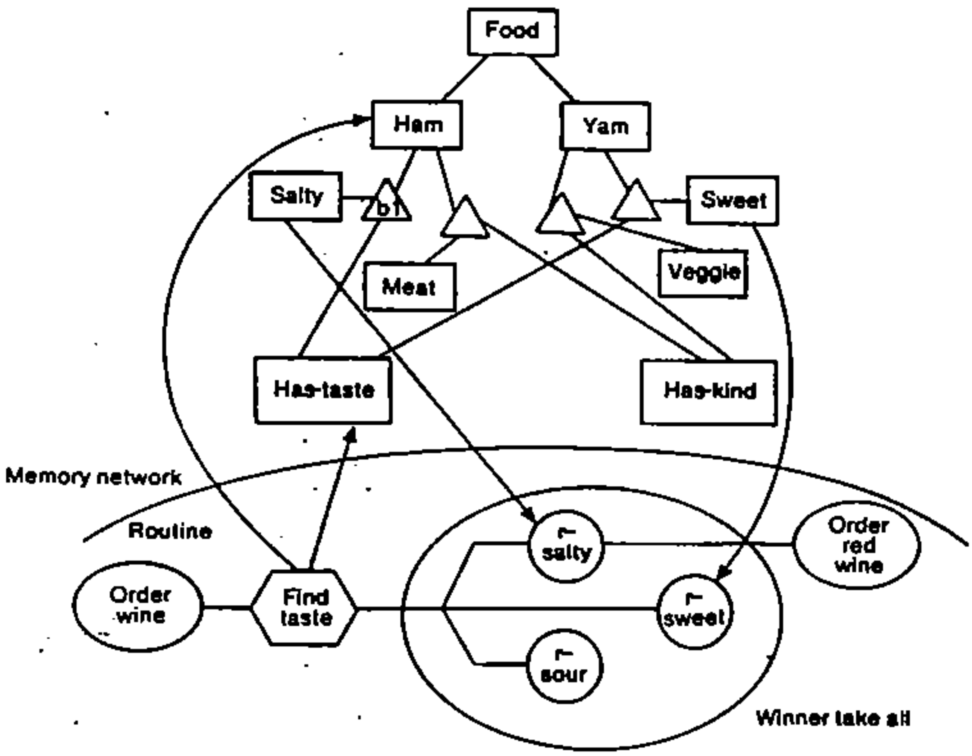
*Localist v Distributed.*

One of the major debates in connectionist research of the early to mid-eighties was concerned with whether or not individual items in a net should be represented by the activity on a single unit in a net - a *localist* representation (e.g. Cottrell, 1985) - or whether their representation should be a *distributed* pattern of activation across a number of units (e.g. Hinton, McClelland, and Rumelhart, 1986). Localist connectionism became almost synonymous with Jerry Feldman's group at Rochester, USA, while the proponents of distributed representations resided in San Diego (UCSD) as Rumelhart and McClelland's Parallel Distributed Processing group (c.f. Feldman, 1989 for a fuller discussion).

Hinton (1989) points out that terms *localist* and *distributed* are relati...

implementation. We can extract two simple defining criteria for distril representations from the Hinton paper. First, an entity that is described by a : term in the descriptive language is represented by more than one element i: connectionist implementation. For example, if the letter 'F' is a term in the descr language, then the distributed elements in the descriptive language may be the features ' ', ' ' and ' '. Second, each of the elements in the connect implementation must be involved in representing more than one entity describec single term in the descriptive language. For example, the features that make u letter 'F' may also be used as part of the representation for the letter 'E'.

Figure 1 shows a fairly typical example of a localist net from the Rochester ; (Shastri & Feldman, 1986). This is rather like the old semantic network idea in · each unit in the net represents a single concept and is linked to other units by · positive or negative weights. In most of the early Rochester work the weights we by hand rather than by a learning algorithm. But there is no reason why lc representations cannot be trained using the same algorithms as those c distributed school.




Both representational types have their advantages and disadvantages. The advantage of localist representation is its transparency. Each unit is clearly la and so it is easy to see what its function is in the network. However, it is diffi see what the novelty value of such representations amounts to. Since eacl represents a single semantically interpretable symbol, there is no new actio does not appear in the Classical tradition. Connectionists using such pu representations must rely on the novelty value of the processing implementat the main thrust of their research[1].

As we shall see later, despite their seeming opacity, there are advanta distributed representation which make them more desirable. Unlike l

[1]We have not discussed here the problems of building a representational theory using p representations for whole propositions. Such a theory would have to make the unlikely assu that mind has a finite number of propositions which can never be unpacked and used to cc novel propositions (see Fodor & Pylyshyn, 1988).

representation, there are number of types of distributed representation. Two broa classes will be discussed here: symbolic and subsymbolic (c.f. Smolensky, 1988). Al other types may be subdivided into these two groups.

*Symbolic v Subsymbolic.*

To understand the distinction between symbolic and subsymbolic representations, w need to look first at the notion of a *microfeature.* This is a term that has not bee used entirely consistently in the literature. All would agree that microfeatures are th atomic elements in a distributed connectionist representation. However, som authors (e.g. McClelland & Kawamoto, 1986) use the term to refer to individu elements which are semantically interpretable on their own without examining the role in the representation e.g. propositional predicates such as *is human, is sof* These sort of microfeatures are symbolic in the sense that they refer to properties i the world. That are much akin to semantic features, and are sometimes called sem localist.

Figure 2 shows some of the microfeatures used by McClelland and Kawamoto (1986 While these are closely related to earlier semantic feature representations, they hav the defining criteria for a distributed representation. That is, a single term in th descriptive language, such as the word 'ball', is represented by a number microfeatures in the connectionist implementation i.e. non-human, soft, neute small, compact, rounded, unbreakable, food. In addition, the microfeature representing the word 'ball' are shared by other words. For example, 'cheese' share non-human, soft, neuter, small, and rounded.

**Feature Dimensions & Values**

| | NOUNS |
|---|---|
| HUMAN | human, nonhuman |
| SOFTNESS | soft, hard |
| GENDER | male, female, neuter |
| VOLUME | small, medium, large |
| FORM | compact, 1D, 2D, 3D |
| POINTINESS | pointed, rounded |
| BREAKABILITY | fragile, unbreakable |
| OBJ-TYPE | food, toy, tool, utensil, furniture animate, nat-inan |
| | **VERBS** |
| DOER | yes, no |
| CAUSE | yes, no-cause, no-change |
| TOUCH | agent, inst, both, none, AisP |
| NAT-CHGE | pieces, shreds, chemical, none unused |
| AGT-MVMT | trans, part, none, NA |
| PT-MVMT | trans, part, none, NA |
| INTENSITY | low, high |

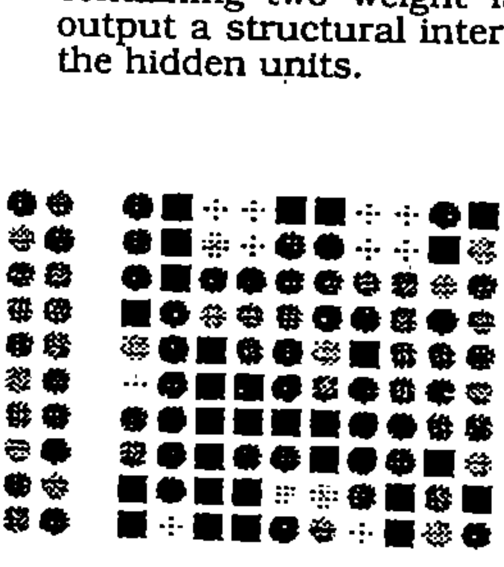
Other authors (e.g. Hinton, 1981; Smolensky, 1988) use the term microfeature refer to individual elements that are semantically uninterpretable (witho participating in further processing) or subsymbolic. By this we mean that no o individual microfeature refers to a property in the world. Rather, reference to su properties emerges from a pattern of activation across several microfeatures. Th style of representation is more like how many imagine information to be encoded the nervous system. Each neuron is an unlabelled unit in a large collective fro which symbolic information emerges.

There are two main ways in which subsymbolic microfeatures have been devel the literature. In the first mention of the term, Hinton (1981) arbitrarily set a g units to represent each word in his system (although a subvector for eac represented type information). A set of arbitrary microfeatures used in Sh (1989a) Lexical Distance model (shown in Table 1) should give the general pict

| | | |
|---|---|---|
| Doctor | 111000000000000 | 111000000000000000000000000000 |
| Nurse | 111000000000000 | 000111000000000000000000000000 |
| Knife | 000111000000000 | 000000111000000000000000000000 |
| Fork | 000111000000000 | 000000000111000000000000000000 |
| Bread | 000000111000000 | 000000000000111000000000000000 |
| Butter | 000000111000000 | 000000000000000111000000000000 |
| Dog | 000000000111000 | 000000000000000000111000000000 |
| Bone | 000000000111000 | 000000000000000000111000000000 |
| Foot | 000000000000111 | 000000000000000000000111000000 |
| Shoe | 000000000000111 | 000000000000000000000000111000 |

Table 1. Arbitrary microfeature sets as used in Sharkey (1989a). Thes were used for a psychological model of word priming. Hence the vector of microfeatures are divided into two fields. The first field represent shared microfeatures between related words, while the second fiel represents unique microfeatures.

Another way in which microfeatures have been developed is through the use ( learning algorithm such as the generalised delta rule (e.g. Hinton, 1986; Miikk & Dyer, 1988). Figure 3 illustrates a set of microfeature activations that were for use in a prepositional attachment task (Sharkey, 1989b). In this instance containing two weight layers was given sentences as input and was requ output a structural interpretation. The learned microfeatures are the activat the hidden units.



thieves stole paintings in museum NPA
thieves stole paintings in night VPA
couple admired house with garden NPA
couple admired house with friend VPA
administrator announced cuts in budget NPA
administrator announced cuts in meeting VPA
report described government's_programs in education NPA
report described government's_programs in detail VPA
I read article in magazine NPA
I read article in bathtub VPA

One disadvantage of using symbolic microfeatures is that the task of choosing a sufficient set of microfeatures is in the hands of the researcher. This can be problematic in that it is difficult to determine, *a priori*, what microfeatures would be required for a given task. At its worst, the use of symbolic microfeatures can lead to the sort of *ad hoc* "tuning" from which much of AI research has suffered i.e run the system and, if it doesn't work, try some different microfeatures (though it may be possible to circumvent part of this problem by conducting an empirical investigation with humans to determine a sufficient set of microfeatures).

With semantically uninterpretable microfeatures, these problems need not occur. It is possible for a net to develop a sufficient set of semantically uninterpretable microfeatures for a required task[2] (e.g. Miikkulainen & Dyer, 1987).

*Some advantages of Distributed representations*

Distributed representations require less memory than localist ones. More distributed items can be represented per vector element (for vectors with more than two elements). A classic example is McClelland and Rumelhart's (1981) representation of the 26 letters of the alphabet with a 16 element vector of visual features. A localist scheme would require a 26 element vector.

Localist networks can encode up to $n$ items, where $n$ is the dimension of the representation space; while distributed networks have the capacity to encode $2^{n}-(n+1)$ items. In Example 1, a comparison is given, of localist representations versus distributed representations using a four-bit vector. Note that the localist vector holds only 4 items while the distributed vector holds 11.

Localist representations
1000 0100 0010 0001

Distributed representations
1100 1010 0110 1110 1001 0101 1101 0011 1011 0111 1111

Example 1. Comparisons of a distributed versus localist representation on a four-bit vector.

The difference in storage capacity becomes more apparent as the size of the representing vector gets larger as shown in Table 2. With only 10 bits, 101[3] distributed representations may be encoded, whereas a localist representation wi[ll] have a storage capacity of only 10 items.

| Nº Bits | Localist | Distributed |
|---|---|---|
| 2 | 2 | 1 |
| 3 | 3 | 4 |
| 4 | 4 | 11 |
| 5 | 5 | 26 |
| 6 | 6 | 57 |
| 7 | 7 | 120 |
| 8 | 8 | 247 |
| 9 | 9 | 502 |
| 10 | 10 | 1013 |

Table 2. Comparisons of the storage capacity for localist and distributed systems.

Another important advantage of distributed representations is that they have built generalisation properties. In localist representations, all of the vectors representi items are, by definition, perpendicular to one another and equidistant (Hamming Euclidean distance). Thus it is difficult to capture similarities and differences betwe items in localist representation space (although it can be done by explicit markir On the other hand, distributed representations can form a denser representat space. For example, for simplicity of exposition, imagine that a set of distribu representation vectors are unit normalised (i.e. are all set to length 1). These vect may then be described geometrically as points on a unit hypersphere as illustratec the sphere in Figure 4.

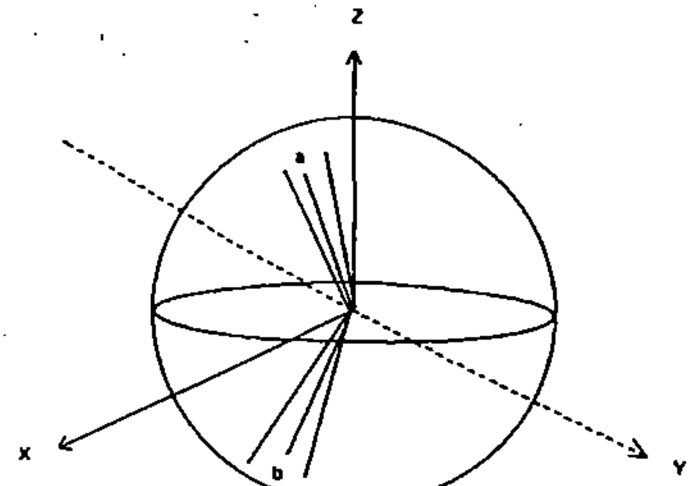



Figure 4. Two clusters of vectors, a and b, are shown on the surface of a unit sph

The point here is that similar items will cluster on the surface of the hypersphere ( clusters are shown at a and b in Figure 4. It is then relatively easy to develc process model in which similar items produce similar or identical results. example, if a net was trained to take microfeatural representations of HORSE, C and COW as input and map them onto ANIMAL in the output, then we would ex a microfeatural representation for DOG, which was not in the training set, to produce the response output ANIMAL. That is, we would expect the ve representation for DOG to be sufficiently close to the vector representation for other animals to have a similar effect.

A third advantage of distributed representations for CNLP is that they provi natural basis for content addressable memory (e.g. Hopfield, 1982). That i network can be trained such that given a partial description (a subse microfeatures), it will complete the pattern. Sharkey (1989c) has taken advanta this property to "fill in" information not explicit in a text. This is the connecti equivalent of default reasoning,but it comes automatically as a standard featu distributed representations.

In summary, the various types of semantic representations for CNLP have examined here. It was also proposed that the most powerful representation, in t of memory efficiency, pattern completion and storage efficiency, was the distrib subsymbolic. But there is another important reason for favouring subsym representations. Their examination represents a research topic that is uniqu connectionism. Distributed symbolic representations have been applied in Classical tradition in areas such as speech recognition. However, as shall be ar later, the study of subsymbolic representation is a new departure.

## 1.2 The Representation of Structure

A distinction can be drawn between those connectionist structures which ar syntactically accessible and those which are syntactically implicit. Syntacticall explicit representations are those in which structural operations rely on the actua spatial layout of theelements in the representations. Syntactically implici representations, on the other hand, are not spatially concatenative and do no contain explicit representations ot their constituent tokens. This distinction wil become clearer as the different styles of structural representation are discussed i turn.

*Syntactically structured representations*

A common form of structural representation in AI is the sentence *frame* (e.g. Minsk 1975)[3]. In this notation, propositions or concepts are described as structures explici containing a number of slots that have constraints on what items may fill them. Fo example, Schank (1972) developed the notion of conceptual dependency in whic there were a small number of action frames (approximately 12). For example,

John drove mary to the station.

would be represented as:

```
                                     ┌──> STATION
JOHN <==> PTRANS --> MARY ───────────┤
                                     └──< ?HOME?
```

where ?HOME? is a default value. This can also be represented as a frame with slots

| agent | action | object | to | from |
|---|---|---|---|---|
| JOHN | DROVE | MARY | STATION | ?HOME? |

Hinton (1981) described a distributed representation for propositions which shares number of properties with these sentence frames. In Hinton's system, binary vecto representing distributed propositional triples are conceptually divided into thr parts. The elements of the $n^{th}$ partition, by analogy with frames, represent all ar only the permissible fillers of the $n^{th}$ slot. Thus the only constraint on what iten may fill a slot is only that the appropriate vector partition has bits for representi the items. There are defaults for filling in missing values in the partitions/slots, b these fall out of the pattern completion process in Hinton's system.

These vector frames are syntactically explicit because the vector partitions slots in a structured frame[4]. Thus it is easy to tell at a glance what are the the constituents. Probably for this reason, vector frames have been used wid McClelland & Kawamoto, 1986; St.John & McClelland, in press; Touretzky & 1988). Their main use is as input and output buffers to make the inputs and comprehensible.

Although very useful, vector frames suffer from three particularly bad pr First, there can be considerable redundancy in the representations. For e most items that could appear in an Object partition could also appear in the partition, and so they have to be represented twice by different elements. The problem relates to the first in that the representation for the same item partitions is entirely different. Thus the system has no way of "knowing" t example, the *book* in the Object partition is the same as the *book* in the position. A third problem with vector frames is that they have a fixed length o number of partitions. Thus all of the input sentences can be only of that lengt

A number of ways have been found to get around this fixed length restriction having a processing window that moves along the input vector (e.g. Sejn( Rosenberg, 1986). Other researchers have taken the alternative appr( employing recurrent networks (e.g. Elman, in press) which accept sequential We shall return to examine these representations in more detail in the se( *Encoding temporal structure.*

The vector frame representation, it could be argued (c.f. Fodor & Pylyshyn, 1 simply a connectionist implementation of symbolic case frames. By being implementational, vector frames add nothing new to the theory of langu: cognition. For a connectionist representation to add something new it r different from classical representations. Nontheless, vector frames are us input and output representations. They can act as a *symbol surface* or connectionist representations can emerge for the researcher to check out w been happening underneath. We now turn to examine distributed represent: structure which are syntactically implicit.

*Syntactically unstructured representations.*

Saying that a representation is syntactically implicit means that it does not *concatenative* constituent structure. The most common form of syntactically representations are those that result from a mapping of an input space onto of lower dimensionality. For example, Hinton (1981) mapped propositiona onto a lower dimensionality PROP assembly using fixed random weights. Th triple, in a sense, recruits a set of PROP units to represent it in a synt implicit form. Through a learning process, it is possible to map the PROP act back onto the higher dimensional Triple space, and thus recreate the st Coarse coding, as Hinton called it, is discussed at length in Hinton, McClell: Rumelhart, (1986).

Variations of this type of compact representation are common in the literat Touretzky & Hinton, 1988; Touretzky and Geva, 1987; Willshaw & von der M 1979; Cottrell, Munro, and Zipser, 1989) and may be set up by a simple algor in conjunctive coding (e.g. McClelland & Kawamoto, 1986), or may be learne

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[4]A similar technique was employed in McClelland and Rumelhart's (1981) model of word re The vector partitions, in that instance, were used to represent positional information of the l

by *supervised* (e.g. Hinton, 1986) or *unsupervised* techniques (e.g. Kohonen, 1982 Regardless of the learning technique used, the representation *encodes* statistic regularities of the input (usually) by reducing the pattern environment to a low dimensional feature space. When required, the lower dimensional coding can b decoded onto the symbol surface again.

To make the notion of compact representations clearer, from the perspective of bot semantic and structural representation, we turn now to briefly analyse one of th learning algorithms in more detail.

1.3 Representation in a back propagation net

In this section, we discuss how the generalised delta learning rule construc representations. This is perhaps the most commonly employed learning algorithm i connectionist natural language research. We begin by discussing its application in feedforward net architecture with two layers of weights (as shown in Figure 5).

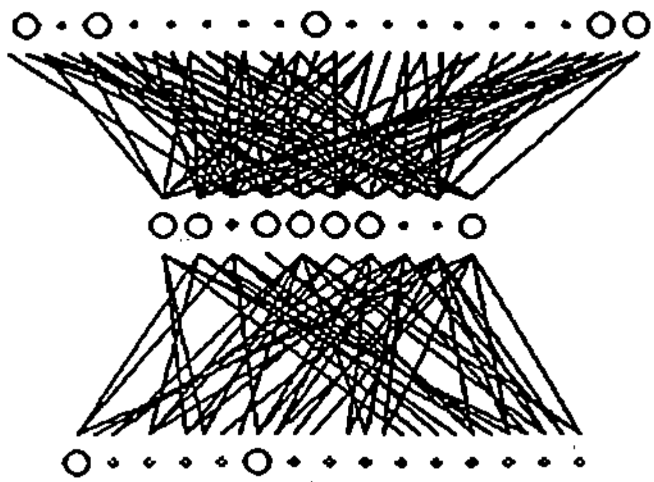

Figure 5. An illustration of a standard back propagation net with 2 layers of weight The circles represent the units and the lines between are partial representation of th weights.

Before running the learning, all of the weights, from the input units to the hidde units and from the hidden units to the output units, are usually set to small rando values in the range -1 to +1[5]. In the forward operation of the net, the input vector is set to the binary states of the first input pattern. This vector is then mapped on the hidden unit vector **h** (normally of lower dimension than **v**) by multiplying **v** b the first weight matrix $\mathbf{W}_1$ and applying the squash function S:$\mathbf{W}_1\mathbf{v}$ -> **h** (where S $1/1+e^{-\mathbf{x}}$ , $\mathbf{x} = \mathbf{W}_1\mathbf{v}$). Then **h** is mapped onto the output vector **o** using the san squash function S:$\mathbf{W}_2\mathbf{h}$ -> **o**

During learning **o** is compared with a target vector **t** to determine its correctness. If > **t** - **o** > 0 then an error correction procedure is set in motion which adjusts th weights matrices $\mathbf{W}_1$ and $\mathbf{W}_2$ such that **o** is closer to **t**. The mathematics ar rationale of the weight adjustment have been given full treatment in many sourc (e.g. Rumelhart, Hinton, and Williams, 1986; Hinton, 1989) and so will not b repeated here.

[5]A smaller range of initial values is sometimes used. Kolen and Pollack (1990) demonstrate the importance of initial conditions to learning in monte carlo simulations and show that under certain

What we are interested in at present is how the representations develop over Our first question must then be: where are the representations. Up until nc concern has only been with representations that are patterns of activation ac set of units. In this sense, the hidden unit activations are the representatio discussed in sections 1.1 and 1.2), while the lower weights are part of the en function (S:$\mathbf{W_1 v}$ -> **h**) and the upper weights, are part of the decoding fu (S:$\mathbf{W_2 h}$ -> **o**).

However, we may also describe the encoding and decoding weights as represent themselves. It is instructive to view the learning process geometrically to ; intuitive grasp of the notion of weight representation. The first step in learnin adjust the upper (decoding) weights so that the weight vectors for output uni want to be 'on' are moved closer to the current vector of hidden unit activation the weight vectors for outputs that want to be 'off' are moved away from the c hidden unit vector. Secondly, the lower (encoding) weights are adjusted to pu vector of hidden unit activations even closer to the weights whose outputs shc 'on' and further away from weights whose outputs should be 'off'.

The upshot of this learning is: (i) input patterns that are required to produce : outputs will learn to produce similar hidden unit activations and thus they wi to have similar 'projective' weights; (ii) similar output patterns will have t similar 'receptive' weights. It is possible to examine this similarity using a Eu distance metric, where the distance between two vectors $\mathbf{v_1}$ and $\mathbf{v_2}$ in $\mathbf{R}^n$ length of $\mathbf{v_1} - \mathbf{v_2}$ i.e. distance $d = ||\mathbf{v_1} - \mathbf{v_2}||$, where length $||\mathbf{v}|| = \mathbf{v}.\mathbf{v}$. Euclidean distances can then be fed into a cluster analysis program which pl similarities on a 2D dendogram.

The point to be made here is that it is not just unit activations that may be : under the representational umbrella. The weights can also be thought representations. It can be argued that the projective weights from the inputs . representations of individual elements and the hidden unit activations a compositional representation of strings of the individual elements.

## 2. Recent issues in natural language representation.

### 2.1 Encoding Temporal Structure

One problem for researchers employing the standard feedforward back prop nets discussed in 1.3, has been how to represent temporal sequences. In readi and speech understanding, the input is structured in time, and thus the beha a system cannot be determined solely on the basis of the current input elemen is required is some sort of memory for previous elements in a sequence (or se to be combined with the current element. Up until now, the input representat have examined involve presenting each whole sequence to the system as a input. This is equivalent to buffering the input stream until a sequence ha completed, before acting on it. The question then reverts to how to struct contents of the buffer.

The main approach examined here has been the vector frame (e.g. Hinton McClelland & Rumelhart, 1981). Another approach is that of Rumelha McClelland (1986). They adapted Wicklegren's (1969) proposal for the represe of words as sequences of context sensitive phoneme units (Wicklephones represent each phone as the phone itself, its predecessor, and its successor ( vowel in the word "cat" would be represented as $_k a_t$). Thus a set of overlappin

Wicklefeature is a single unit that conjunctively coarse codes a feature of the central phoneme, a feature of its predecessor, and a feature of its successor. A different method, employed by Sejnowski and Rosenberg (1986) for their NETtalk system, employed a window containing 7 letters that moved across an input text. The central element of the window, on each successive move was encoded using the three elements on either side of it as context.

An alternative solution to the encoding of sequential structures, without using a buffer, was proposed by Elman (1988) with the introduction of a network architecture for predicting successive elements of a sequence (sentence). This is a variant of the feedforward multi-layer perceptron which allows feedback or recurrent links from the hidden units to the input. As each element of a sequential structure, such as a sentence, is coded onto the input units, the previous hidden unit vector is copied onto memory units in the input stream[6]. In this way, the meaning of an element of a sequence will be shaded by the context of the prior elements. In a sense each input cycle contains a memory of the previous cycles in the sequence.

Elman (1989) has conducted a number of simulations using the simple recurrent net architecture (SRN). He presented short sentences to the net, one word at a time, using the next word as a target. Thus the task for the net was to predict the next word in a sentence. Elman found that the network had developed hidden unit representations for the input patterns that reflected information about the possible sequential ordering of the inputs e.g. the net knew that the lexical category VERB followed the lexical category NOUN. Cluster analyses of the hidden unit activations revealed that the verb category is broken down itno those verbs which require a direct object and those for which a direct object is optional. Furthermore, the analyses showed that the nouns were divided into animates and inanimates with a further subdivision for human and non-human. In a larger scale analysis, Elman also discovered that the tokens of particular types clustered together[7]. Thus, hidden unit representation in the simple recurrent net, after learning, can be shown to exhibit a number of properties needed for a lexical category structure and type/token hierarchies.

Elman (1989) also investigated the representation of grammatical structure in a study which used a phrase structure grammar to generate the input sentences. This grammar allowed recúrsion through the use of a relative clause category that expanded to NPs that permitted further relative clauses. The results suggest that the net had learned to represent abstract grammatical structure. For example, when presented with a subject noun the net correctly predicted a verb which agreed with the number of the subject noun (i.e. singular/plural), even when a relative clause intervened. In addition, given a particular noun and verb, the net was shown to correctly predict the class of the next transition allowed by the grammar, thus demonstrating the representation of verb argument structure. Finally, the results from the recursive representations showed limitations. These representation were found to degrade after about three levels of embedding.

The same type of SRN was employed by Servan-Schrieber, Cleeremans, and McClelland (1989) in a study which involved learning a finite-state grammar. There were many interesting results from this study. But the most important results, for

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[6]Elman's recurrent net is actually a variant of Jordan's (1986) sequencing net. Jordan took his recurrent links from the output units or from the training vector to the input units whereas Elman's recurrent links are from the hidden units to the input units.

[7]The [illegible]

our purposes, are: (a) the net learned to be a perfect recogniser for a finit grammar (at least for the Reber (1967) grammar they used). (b) under conditions, long distance sequential dependencies were exhibited, even embedded sequences. The latter result was best when the dependencies were re at each step. Moreover, performance across embedded strings deteriorated length of the string increased.

In sum, by extending the backpropagation algorithm in a simple recurrent net, been possible to add a number of features to the compact representations tha discussed in Section 1. Primarily, SRNs allow the representation to encode seq information such as the order of the input, and the path from one element to a They also exhibit a certain ability to allow the encoding of long range seq dependencies across embedded sequences.

## 2.2 Recursive distributed representations

One aspect of natural language processing that has been problematic connectionist community is that natural languages are recursive. We have seen, in the last section, how this posed difficulties for SRNs. In this section, w discuss two recent attempts at representing recursive structures.

### *Tensor product representations*

The tensor product system (Smolensky, in press) combines lexical items wit syntactic roles in a way which is mathematically equivalent to *outer product* l (cf. Sharkey, 1989). That is, a vector representing an item (or role filler), **i**, is b a vector representing a role, **r** by the outer product $\mathbf{r}\mathbf{i}^T$. This is a tensor of ra and results in a square matrix of activations. However the formalism goes bey simple outer product in that it enables the construction of recursive represe for, say, syntactic trees by using $3^{rd}$, $4^{th}$, or $n^{th}$ order tensors. A third orde is a cube of unit activation and orders beyond the third are hypercubes.

There are two main problems with tensor products. First, with deep embedd representation could grow exceedingly large. Second, when the input vect fillers for the roles) are not orthogonal the tensorial representations hav constructed by more complex incremental learning methods (e.g. the delta linearly independent pattern sets, or back propagation). This makes th process less manageable as it is not at all obvious how such learning wou place[8]. However, processing and memory considerations aside, Smolensky p an elegant and formally tractable theory of recursive representation. We can to later research to work out how to develop it in real time and how to u recognition.

### *Recursive auto-associative memory (RAAM)*

Hinton (1988) outlined an idea for handling embedded clauses by inserting a *description* of them into larger representations. However, he did not detail a by which such representations could be learned. This challenge has been tak Pollack (in press) who shows how such a reduced description can be lear Recursive Auto-Associative Memory (RAAM). The RAAM architecture is the the standard feedforward net with two layers of weights (for encoding and the hidden unit representations) and the standard back propagation algo employed for learning. Pollack has shown the power of the RAAM system for encodin a sequential stack with PUSH and POP and also for encoding and decoding syntacti trees. The whole trees are represented in a single layer of hidden units and can b decoded in cycles until the terminal symbols appear as the outputs. The differenc between RAAM and the usual back propagation net rests on the method fo presenting the input patterns.

We shall briefly describe the operation of a RAAM system here using the example of simple binary tree: ((A B) (C D)). First the input space is divided into *n* partitions, wit *k* units in each partition. The size of *n* depends directly on the maximum valency c the tree to be represented (in our simple example $n = 2$). Since this is a autoassociative net the output vector is identical to the input vector; both have *n* units and there are *k* hidden units.

The representation of the binary tree would be formed as follows: (i) A and B a presented in the two vector partitions and autoassociated. The resulting hidden un representation $R_1$ is kept to one side (on an external stack or somesuch); (ii) C and are presented and autoassociated and the resulting hidden unit representation $R_2$ put to one side; (iii) $R_1$ and $R_2$ are presented as input and autoassociated. Th resulting hidden unit vector $R_3$ is a representation of the entire tree. $R_3$ can b decoded by presenting it directly to the hidden units and the outputs will be $R_1$ an $R_2$. These are then presented in turn until the terminals have been decoded.

Pollack (in press) presents a range of interesting simulation results which sho RAAM to be a very effective method for encoding and decoding recursive structure The only problem is that the method of presentation of inputs relies on an extern stack and it is not altogether clear what a pure connectionist implementation of th would be. However, regardless of how the representation is constructed, Pollack h demonstrated how unstructured representations can encode recursive representati in a compact form.

### 2.3 Compositionality and structure sensitivity

In Section 1, connectionist representations were classified into different types. Son of these, as we have seen, are very similar to their Classical counterparts in that th contain explicit symbol tokens and/or have concatenative constituent structure (e. localist concept notes, symbolic microfeatures, vector frames), and some are weak (e.g. localist proposition nodes). It is not the aim here to cast doubt on the value the research using these representation schemes, but to consider whether or not t representations themselves (not the research) have novelty value.

From the review above, it should be quite clear that compact subsymbo connectionist representations are different than Classical syntactic structu representation. This style of representation, Fodor and Pylyshyn (1988) argue, is r compositionally structured. However, as Van Gelder (1990) points out, Fodor a Pylyshyn are implicitly discussing only one type of compositionality: *spatia concatenative composition.* In this mode of composition, the spatial layout of t symbols (reading from left to right) is important (indeed crucial) for symb manipulation and inference. Van Gelder states that for a mode of combination to concatenative, "... it must preserve tokens of an expression's constituents (and t sequential relations among tokens) in the expression itself.".

In contrast, to Classical concatenative representation, the type of comp connectionist representation we have been discussing may be considered to hav different mode of combination. That is, "pure" connectionist representations are concatenative, but are functionally compositional nonetheless. It is worth quoting Gelder again on this point. "We have functional compositionality when there general, effective and reliable processes for (a) producing an expression giver constituents, and (b) decomposing the expression back into those constitue: Connectionist models can certainly perform (a) and (b) as well as meet the cri that the processes must be general, effective, and reliable. By *general*, van Ge means that that the process can be applied, in principle, to the construction decomposition of arbitrarily complex representations. We have seen how a si feedforward back propogation net can learn to encode and decode representatic To be *effective* the processes must be mechanistically implementible and to be *rel* they must always generate the same answer for the same inputs. On connectionist net has finished learning it meets both of these criteria.

Given that connectionist representations are functionally compositional, the que is: do such seemingly unstructured representations carry structural informa And a subsiduary, though perhaps more important, question is: do representations allow direct structure sensitive operations? The short answer t first question is obviously "yes". Even in the early Hinton (1981) model of sem nets, the vector frames of structured input represenions were coarse coded o compact representation such that they could be accurately reconstructed ont identical vector frame. To be reconstructed, the coarse coded representation have been carrying structural information. In fact, they were carrying inform about concatenative structure without themselves being concatenative.

The subsiduary question, as to whether connectionist representations allow stru sensitive operations, is partly addressed by the answer to the previous que However, it might be argued that even the functionally compositional connect representation may be a variation on the Classical theme because the connect representations must emerge onto the symbol surface before they can be struct manipulted. For example, Fodor & McLauglin (1990) claim that in order to su structure sensitive operations, compositional representation must contain ex tokens of the original constituent parts. This position has been subjected to a r empirical investigation by Chalmers (in press) which refutes it.

Chalmers constructed compact recursive distributed representations of syntac structured sentences using Pollack's (in press) RAAM system (described in 2.2 a After training the net to develop compact representations for both active and p sentence structures, Chalmers set out to test the structure sensitivity c representation. He did this by attempting to train the transformation of the co active sentences into the compact representation of the passive sentences. experiment was successful in that it demonstrated that connectionist represen can be structurally manipulated (passivisation) without recourse to emergence symbol surface.

## 3. Conclusions

The main classes of connectionist representation for natural language proc have been examined in this paper. For convenience these were divided into se representations (Section 1.1) and structural representations (Section 1.2). In S 1.1, semantic representations were clasified into major types: localist and distri and a number of advantages were pointed out for distributed represent (memory efficiency, content addressibility, and built-in generalisation). In ad two flavours of distributed representation were pinpointed: symboli subsymbolic. On the question of the novelty of connectionist semantic represen the subsymbolic was shown to be the only contender. Distributed symboli representation have a lot of similarities with Classical feature theory.

On the syntactic side, a distinction was drawn between representations which ar syntactically explicit and syntactically implicit. It was argued that only the latte could be considered to be representationally novel. The syntactically implic representations were discussed further in Section 2.3. It was argued that they wer functionally compositional (as opposed to concatenative) and could be sensitive t structural manipulations without recourse to decoding into the original symboli tokens of their constituent parts.

This paper displays optimism about the development and utility of uniqu connectionist representations i.e. subsymbolic, syntactically implicit representation: We have seen only one connectionist study in which these representations have bee shown to be structure sensitive. However, this is just the beginning. We have als seen (Section 2.1) how non-concatenative distributed representations can car information about temporal structure, long distance dependencies, lexical catego structure and the type/token distinction. We have also seen how they can represe finite state grammars. In section 2.2, we saw how research on connectioni representation had begun to overcome one of the hardest problems for CNLP, th representation of recursive structures.

All in all, despite (and to some extent thanks to) Fodor and Pylyshyn's critique connectionist representation, it looks as though the prognosis for CNLP is goo Judging by the explosion of research we have seen up until now, the next few yea are expected to yield many exciting new results.

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