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The Power of the Links

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Zusammenfassung: *Relationen in Graphen – ein mächtiges Werkzeug*. Wissen ist eine sehr nützliche Metapher bei semantischer Kognition und Bildverstehen. Die in diesen Bereichen entwickelten Verfahren basieren meist auf einer einzigen, geschlossen Methodik und vernachlässigen die Synergie bei Nutzung verschiedener Ansätze je nach Aufgabe. Im Zusammenhang mit Wissensrepräsentation sind verschiedene Verfahren vorgeschlagen und auf ihre Eignung hin untersucht worden, wie neuronale Netze (implizit) oder semantische Netze (explizit). Die Vorstellung, dass der Erfolg in der Kombination verschiedener Methoden liegen könnte, ist bisher noch nicht weit genug erforscht worden. Jedoch gibt es eine Gemeinsamkeit vieler Modelle, welche Wissen repräsentieren wollen: Der Graph. Der Grund dafür ist, dass ,,Wissen“ mit seinen beiden Basiskomponenten, den Fakten und den Regeln, charakteristischerweise die Fakten den Knoten und die Regeln den Relationen zuordnet.

Auf diesem Hintergrund zeigt die Veröffentlichung die theoretischen Gemeinsamkeiten von zwei expliziten Modellen, welche sich als effektive Standardverfahren erwiesen haben, semantische Netze einerseits und Bayesnetze andererseits. Beide geben eine sehr allgemeine Struktur vor, welche die Formalisierung von vielerlei Arten Wissen erlaubt. Da gibt es gemeinsame Elemente, wie die Ablage von Deterministik in den Knoten (geometrische Primitive, Objekte, Koordinaten, Begriffe . . .). In den Relationen bieten beide Modelle unterschiedliche Möglichkeiten: Da gibt es Begriffe in semantischen Netzen (,,Teil von“; ,,Spezialisierung“; ,,Instantiierung“ . . .) und stochastische Eigenschaften in Bayesnetzen – zusammen mit einer großen Zahl von Optionen.

Wie die Literatur zeigt, erscheinen die meisten Wissenschaftler von Faktenwissen fasziniert (welches sich in den Knoten findet) und erkennen weniger die Bedeutung des Regelwissens (welches in den Relationen enthalten ist). Aus diesem Grunde versucht der Aufsatz das ,,mächtige Werkzeuge der Relationen in Graphen“ herauszustellen (WOODS 1975, BRACHMANN 1977), und zwar anhand von semantischen und Bayesnetzen als Bei-

Summary: “Knowledge” is a very useful metaphor in cognitive semantics and image understanding. The developed procedures in this field are mostly conveyed by a single methodology neglecting the benefits of synergy when interrelating different approaches. In knowledge representation, for instance, different algorithms have been suggested and validated like Neural Nets in the implicit domain or Semantic Nets in the explicit domain. The awareness of the power lying in the combination of different methods has not yet been studied to the necessary extent. However, there is a common feature in many of the models which try to represent knowledge: the graph. The reason for this is that knowledge with its two basic components, facts and rules, characteristically assigns the facts to the nodes and the rules to the links.

With respect to this, the paper shows the theoretical relationship between two explicit models which have proved to be two effective “standard” models, the Semantic Nets on the one hand and the Bayesian Nets on the other. Both give a very general structure which allows the formalisation of many kinds of knowledge. There are common elements like the representation of deterministic features in the nodes (geometrical primitives, objects, coordinates, terms). In the links, both models offer different opportunities: there are semantic expressions in Semantic Nets (part, specialisation, instantiation) and stochastic properties in the Bayesian Nets – including a large variety of options.

As literature shows, most scientists seem to be fascinated by factual knowledge (which is in the nodes) and fail to see the importance of inferential knowledge (which is in the links). Therefore this paper is intending to point out the power of “what is in the links” (WOODS 1975, BRACHMANN 1977) given for both Semantic and Bayesian Nets as examples. Starting from the analysis of results which have been attained in recent research general findings of the potential of interrelations will be given. Nodes without links literally make no sense and vice-versa. With relation to image understanding, an object without its context is not fully described. It is not surprising that the metaphor “un-

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spielen. Ausgehend von einer Analyse neuerer Forschungsergebnisse werden allgemeine Einsichten über das Potential von Relationen vermittelt. Knoten ohne Relationen machen offensichtlich keinen Sinn. Bezogen auf Bildverstehen ist ein Objekt ohne seine Umgebung nicht vollständig beschrieben. Es ist nicht verwunderlich, dass die Metapher „Verstehen“ aus der natürlichen Sprache entlehnt ist. Auf diesem Felde ist das Argument noch klarer, da ein isolierter Begriff strenggenommen ohne Sinn ist: Die Bedeutung eines Begriffes liegt in seinem Kontext. Dies gilt gleichermaßen für die Sprache wie für ein Bild.

derstanding” has been taken from natural language. Here the matter is even more evident as a term in isolation does not exist in reality. The meaning of a concept is in its context. This holds true for both language and image.

1 Introduction

Makato Nagao (1990) defines knowledge by means of the following equation: „KNOWLEDGE = COGNITION + LOGIC“ where knowledge comprises two very different and apparently antagonistic components.

COGNITION, which refers to “truth” (in the sense of the “true/false dicotomy”) can occur in quite different forms. It implies a-priori knowledge (a “model”) that combined with further cognition instances (“data”) leads to new understanding (“results”). Therefore, acquisition of knowledge requires “intelligent reasoning”.

LOGIC, on the other hand, has to be understood bearing in mind that knowledge can only exist in structured form. The ordering principle applied may be constructed following quite different criteria since cognition is not equal for all human beings, which is particularly evident for *spatial* cognition (Mark et al. 1999).

The acquisition and the representation of knowledge through computer technology is based on metaphors. What underlies the concept of metaphor is the fact that expressions used to describe ideas in a given context are taken out of such context and applied to a given situation within a new context (Lakoff & Johnson 1984, Landes 1999). Due to this transformation, the original conceptual content undergoes modifications, a condition that has to be taken into account in subsequent work.

The transference to the computer of these eminently human mental activities which comprise what was formerly known by the unfortunate term “artificial intelligence”, occurs almost simultaneously in many disciplines, and always in discrete steps.

In what follows, we are going to devote our attention to image analysis, knowing that similar developments are in progress in other areas of knowledge. It would be desirable to look for natural relationships between image analysis, cognition science and theoretical linguistics since in all these fields concepts are the central subject of study. Unfortunately, possible synergy has so far deserved little attention.

2 Models (Examples)

Man defines knowledge. He tries to transfer his understanding (his models) using the structures given by the computer, his tool. Such effort can lead to implicit (“heuristic”) solutions or to real explicit (knowledge-based) systems. In the latter, knowledge acquisition and knowledge processing are separated. In the case of implicit solutions, the system is trained by man, and in such a case we speak of systems capable of learning.
It is important to point out that in both cases the elements of knowledge acquisition are

established by man. In the case of implicit solutions, the object model is less complete than in a-priori object models, which are explicitly formulated. The requirements as to structuring posed by logic are considerably higher in the second case than in the first.

The procedures of image analysis that have been developed and have found worldwide applications are uncountable and diverse. It is the aim of this paper to point out common grounds in different existing models, taking as examples four well known procedures.

2.1 Neural nets

To describe this alone there exists enormous quantities of literature (PRECHTELT 1995). To copy physiological functions of the human brain constitutes a typical implicit procedure. The empty structure of the given net comprises input and output nodes and, depending on the approach chosen, different intermediate layers. The underlying principle is that all input concepts are related to all output concepts whereas the instantiation of each net depends on learning based on real data driven by a human operator and quantified by weights and distributions.

Fig. 1 shows the structure of a Neural net to recognize and store land use classes (SEGL 1996). In opposition to traditional multispectral classification in this case not only the spectral signatures but also further object features like size and shape were taken into consideration. Like the system of the Neural net and different from the maximum likelihood classifier, man can easily fuse and process simultaneously different features like color, texture, shape, size, compactness, etc.

Each node contains object classes and object attributes while the links contain the trained relations between these concepts, given by weights or stochastic distributions.

2.2 Delaunay nets

In contrast to the purely implicit procedures of Neural nets, those based on Delaunay nets already show features of an explicit a-priori object model. The example given below, however, is an object model at a very elementary stage.

Fig. 2 shows the net of isolated pixels which had been assigned with high likelihood to the class "sealed". It is the result of a Landsat-TM image classification corresponding to a settlement area (SCHILLING & VOEGTLE 1996). The structure of the sealed surfaces in the given context can be derived from the shape and size of the triangles. For example, shape may be numerically expressed by a compactness factor $C = P^2/4\pi A$, where P is the perimeter and A the area of the triangles. Thus it is possible to segment the outline of settlement areas. Streets out-

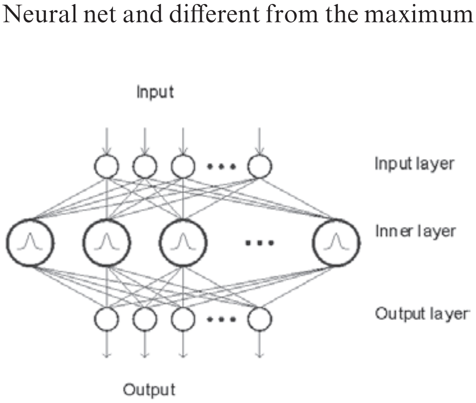


Fig. 1: Neuronal network (taken from SEGL 1996).

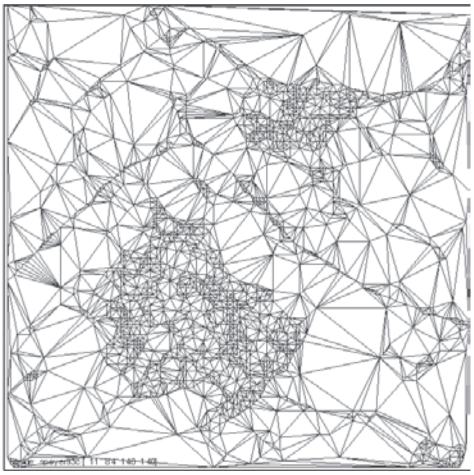


Fig. 2: A Delaunay net composed of pixels assigned to „sealed surface" (SCHILLING & VOEGTLE 1996).

side the enclosed settlement areas are shown by characteristically long stretched chaines. It is also possible to segment surfaces within settlement areas representing vegetation or different concentration of buildings located within the sealed areas.

The procedure applied by Delaunay net has gone beyond implicit methods since the object model given through the assignment of the different types of triangles to different object classes is an a-priori set.

Nodes always contain values of one and the same class ("sealed surface"). Although links as such do not convey information in themselves, the resulting triangles support the meaning of the object nodes. The meaning is given by the geometry, the "Gestalt" of the net.

2.3 Bayesian nets

These are classical representatives of the explicit case and give the a-priori modeling of the occurrence of object components, their relationships inherently including their probability.

Fig. 3 shows a dynamic Baysian net for the recognition of buildings (KULSCHEWSKI 1999, KOCH 2000). The letters mark random variables of the corresponding objects, in this case related to the recognition of buildings. All significant features were described, like, for example, parts of aspect (At), aspect (A), occlusion (V), buildings (G), frequency of aspects (H_A), angle of view (Z), for the regional elements, and attributes of the lines (R, N, P, S) for local primitives.

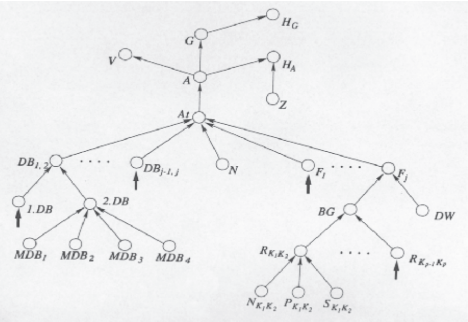


Fig. 3: Baysian net (see KULSCHEWSKI 1999).

The components are written as random variables ($X_1 \dots X_n$) at the nodes. Between random variables exist densities which point towards that random variable for which the density is given. Thus, the Bayesian net establishes a system of uncertainties which is represented as a closed graph.

For Bayesian nets, the random variables are in the nodes and their relationships is given by densities. The Bayesian net models the probability for random variables including their relationships.

2.4 Semantic nets

Here objects and their semantics (meanings) are modeled. This also occurs explicitly since both relationships and their meaning are given a-priori. Fig. 4 is a simple example of a semantic net. Concepts are connected by meaningful relationships like "part link" (bst), "specialization link", and "instancing".

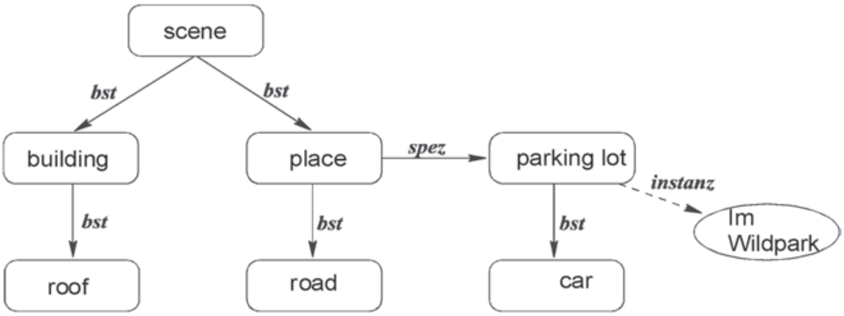


Fig. 4: A semantic net (from QUINT 1997).

Depending on the motivation, both objects and their relationships may be expanded as necessary. QUINT (1997) has been the first to apply semantic nets to aerial image interpretation showing that it is possible to assign an initially random series of graphic primitives to a given semantic net and that in this way it attains meaning. Since meaning is modeled in semantic nets, it goes much beyond the iconic level. This leads to the possibility to establish comparisons at high level image processing for different representations of the real world, like e.g. maps and images.

In the semantic net displayed, objects are found in the nodes similar to the other examples given. However, the links between the concepts are expressed by semantic relations. This introduces meaning, a main feature in image understanding, which we shall investigate more deeply in the next paragraph.

3 The Meaning in Graphs

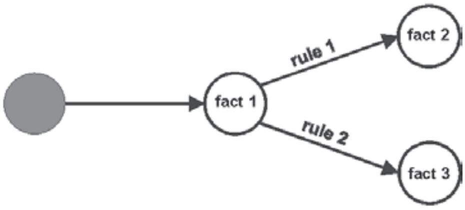
In all the examples previously given, knowledge was structured as graphs. It is indeed evident that both fundamental components of knowledge (facts and rules) can be extremely well represented by nodes and links (BÄHR 1998). We find therefore objects, the concepts, in nodes and their relationships, the context, i.e. the meanings, in the links. This explains inherent capability of nets to generally represent these two basic components of knowledge.

In Tab. 1, the starting point is always "fact 1" which stands for the object (the concept) "sealed surface". Two different rules relate node 1 to node 2 and to node 3.

In the case of NEURAL NETS, the system is trained by means of exemplifying data in such a way that the rule "small and compact" leads to the concept "house" (fact 2) and the rule "large and linear" to the concept "street". Rules can be established in a primitive way by just weights or else by setting parameters in distributions.

In the case of DELAUNAY NETS we can see in Tab. 1 that rules are represented by only the two alternatives: "near" and "far". Consequently this leads in the first case to "same object" and in the second to "different object". As explained in chapter 2, the geometry of Delaunay triangles may be interpreted more widely than the example given in Tab. 1. The *geometric* nature of reasoning becomes evident here.

Tab. 1: Comparison of properties for net-based knowledge representation.



	Neural net (trained)	Delaunay net (given)	Bayesian net (given)	Semantic net (given)
Fact 1	Sealed surface	Sealed surface	Sealed surface	Sealed surface
Rule 1	Small, compact	Near	$p(x, C)_1 = 0{,}1$	Part of
Rule 2	large, linear	Far	$p(x, C)_2 = 0{,}9$	Instance
Fact 2	House	Same object	Changed	Street
Fact 3	Street	Different object	Unchanged	Gildestraat

In the case of BAYESIAN NETS there are objects (concepts) in the nodes: in the example given in Tab. 1, this is the class "sealed surface". In the links there are densities. Rule 1 assigns a low probability (0,1) for the case that the class of node 1 had changed. Correspondingly, a high probability (0,9) corresponds to the case of no change of that class. This example shows the way in which uncertainties are dealt with in Bayesian nets.

Finally, the example for SEMANTIC NETS also starting with sealed surfaces, shows the relationship between nodes 1, 2 and 3 as "part of" and "instantiation". In the case of link 2, instance corresponds to the Gildestraat while the "part of" link leads to the object "street" which has not been instantiated.

These four examples show common features as well as differences. The nodes of the graphs represent deterministics like graphic primitives, coordinates, concepts, classes, objects, instances or whatever name might be chosen. However, segmentation of the image into such classes or objects is the final aim of image interpretation in almost all situations. By doing this it is often forgotten that an object taken out of its context literally "makes no sense". When analyzing a group of trees, for example, it is of utmost importance to know whether they are in semantic relation to the concept forest, park, garden or to that of arboretum.

The contextual information is given by the links. The individual realisation may be of semantic, stochastic, geometric nature or be trained. A single relationship can obviously only model context at an elementary level. Only the analysis of more complete net makes it possible to represent more sophisticated relationships.

An example was given for Delaunay nets where contextual information was limited to geometrical features, like distances and shape. These geometrical features, however, represent knowledge that is being modeled for further image interpretation. In the case of Bayesian nets, the relationships between the nodes connote densities about the existence of concepts of the following nodes. Together with their modeling in form of random variables, this leads to a system of evaluations of inherently uncertain messages for the whole Bayesian net. When speaking of Semantic nets, the importance of context between objects of the nodes is more directly recognizable. The meaning is given "expressis verbis". Finally, Neural nets show in the links weights or distributions, which are characteristic for the occurrence of certain associations. In these nodes there may be a combination of very different types of objects; but their association through links must set meaning, quantitatively given by numbers. Weight and distribution show similarities with densities of the Bayesian nets but they are generated in a quite different way.

Nevertheless, it is necessary that the relationships for image interpretation must be quantified in all cases. This constitutes the greatest problem in modeling, since rigorously speaking it is often a mere estimation. It is at this point that the a priori knowledge of the human operator acquires its relevance. The estimation can be drawn in as implicit training like in Neural nets or it can be incorporated in other cases from a priori knowledge like the information driven from the form of the triangles in the Delaunay nets, the densities in Bayesian nets and the associations of concepts in semantic modeling.

4 Modeling Semantic Neighbourhood

The representation of knowledge by means of graphs has lead to quite different results as has been shown throughout the examples above. Although both nodes and links do not "make sense" in an isolated domain, in image processing attention has traditionally centered in the nodes, for example, in the segmentation of objects, in land use or environmental monitoring. The task is then "deterministic", that is to say that the problem lies in finding a clear answer to a clearly stated question the same way in which traditional cartography had to assign unique types of land use for classes out of a given land use catalogue.

However, a complete description of objects during image interpretation requires in addition the description of relationships between objects.

In graph theory, we generally write an undirected attributed graph in the following way

$$\mathcal{FAG} = (\nu, \varepsilon, \gamma, \varrho)$$

(see KULSCHEWSKI 1999)

where nodes are represented by ν and the relationships by ε with their corresponding list of attributes γ and ϱ. The relationship between an ordered pair of nodes v_i, v_k is

$$e_{ik} = (v_i, v_k)$$

Geometrical or topological relationships lead to the concept of neighbourhood. Neighbourhoods are in general but not necessarily free of contradictions according to the laws of Euclidian geometry and may be visualised in clear correspondence with the „real world". For instance neighbourhoods N of binary surface elements yields

$$e_{ik} = N(f_i, f_k).$$

Expanding geometrically modeled neighbourhoods, we now introduce "semantic neighbourhoods" SN, taking g as binary semantic primitives:

$$e_{ik} = SN(g_i, g_k)$$

In opposition to N, this equation represents a semantic relationship between two elements. Semantic (conceptual) properties differ due to their very nature from geometrical properties in the way that they are not "factually" describable. The fuzziness incorporated by SN , however, is a necessary property of the "real world".

An example from image classification shall make this clear: classes of land use not only overlap with their spectral signatures – they are not only *spectral* neighbours (which leads to the well known problems in multispectral classification) but they are *conceptual* neighbours as well. For instance, the conceptual contents of "deciduous forest", "coniferous forest", "water", "swamp", "hyacinth" and "grass" may share similarities depending from the context in which they are found.

For example, in Fig. 5 the problem is to compose the land use class "swamp". The five subclasses do give completely different semantic concepts but they share the property of being "part of" links pertaining to swamp. The attributes corresponding to the classes in the nodes are, for example, coordinates, spectral signatures, size of areas, compactness, texture, etc. Thus, it is possible to describe sufficiently the concepts involved in Fig. 5 with exception of the concept "swamp" which also suffers variation in the common language since it may contain scientific, pedologic, phytogeographic, or genetic meaning.

The problems arising from this situation can only be solved through context, i.e., by establishing the relationship to its semantic environment. Part of this is also the information contained in the list of attributes for the relationships ϱ_{ik} in Fig. 5. The double indexes show the associations between each subclass (h, d, c, w, p) to the class "swamp" (s). These contain properties of the semantic neighbourhood, SN, by means of which it is possible to recognize the subclasses as "part of swamp" and to assign them to that class.

The required information does not purely consist of semantic components; geometrical components like distance between nodes and size of the area involved are necessary too, as well as statistical data referring to occurrence and distribution of the different "parts of class" corresponding to the concept "swamp".

The analysis of semantic neighbourhood in the given example shall show the possibility and, moreover, the necessity to combine different models of knowledge representation. This is possible by means of attribute lists of both nodes and links. In these lists appear side by side associative, geometrical, topological, physical and statistical attributes.

The example evidences e.g. similarities of semantic and Bayesian nets. The "part of"

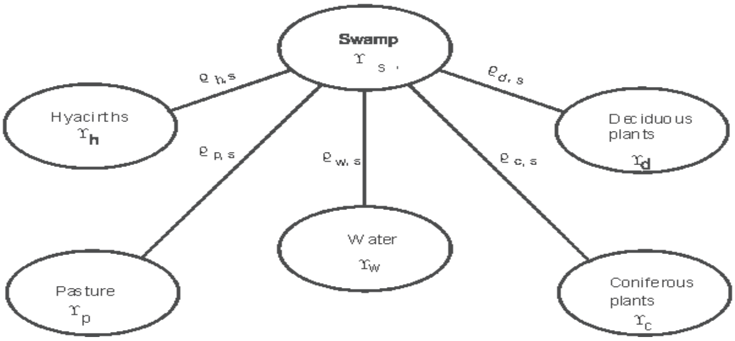


Fig. 5: Explaining semantic neighbourhood; Υ, ϱ are attributes of nodes and relations, respectively.

link among the nodes in Fig. 5 has to list certain conditions. When the concepts in the nodes are written as random variables and the links as densities, the original semantic land use structure is transferred to a Bayesian net. Thus a directed graph is generated in which the arrow points towards the node "swamp".

It is obvious that Bayesian nets model knowledge in a more general way than semantic nets do, because it is clear that the semantic components can be straightforwardly integrated to them.

5 Conclusion

It is the aim of all modelling approaches, whether spatial or not, to structure "knowledge" in the sense of MAKATO NAGAO. It therefore should be clear that all the examples given show common features. This is an insight which may not be immediately evident. The concepts "facts" and "rules" – which play a central role because of their clear simplicity – lead logically to graphic representation. It was shown that different modeling approaches have common roots and may be combined.

In all cases we find neighbourhoods of different kinds, for concepts in the nodes and for relationships in the links. This occurs both in the geometrical and in the semantic domain. Agreement ("fitting") in the sense of "neighbourhood" leads to the concept of "Isomorphism" (HOFSTADTER 1979). This does not require a perfect identity of the graphs but acceptable geometrical and semantic neighbourhood within tolerable ("error") limits.

Isomorphism is also an important concept in theoretical linguistics where it designates "identity of form" (words) in language. It might be helpful to analyse in more detail and take into account findings in linguistics – more precisely, in psycholinguistics (LAKOFF 1988). One of the modern theories is that although a word (good, for example) seems to be self-understanding, in different contexts its co-text is liable to modify its meaning in such a way that it becomes quite a different concept. Compare:

a good boy	good weather	good company	a good student
Good boy!	Good bye!	Good morning!	a good price

Concepts and concept interpretation are a core issue of image analysis. To quantify and find mathematical equivalents for semantic contents in imagery is a challenge we are facing.

In order to understand (decode) a sentence, it is necessary to know its individual context, because the meaning is in the context. This insight can be fully transferred to image understanding (decoding). In graphs representing spatial knowledge for both language and imagery, the context comes out at the relations. This constitutes the role, the power of the links.

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