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Guillaume Touya, Quentin Potié, William A Mackaness. Incorporating ideas of structure and meaning in interactive multi scale mapping environments. *International Journal of Cartography*, 2023, 9 (2), pp.342 - 372. 10.1080/23729333.2023.2215960 . hal-04115095

**HAL Id: hal-04115095**

**<https://hal.science/hal-04115095v1>**

Submitted on 2 Jun 2023

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# INCORPORATING IDEAS OF STRUCTURE AND MEANING IN INTERACTIVE MULTI SCALE MAPPING ENVIRONMENTS

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[HTTPS://DOI.ORG/10.1080/23729333.2023.2215960](https://doi.org/10.1080/23729333.2023.2215960)

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June 2, 2023

## ABSTRACT

Web-based, slippy, scalable maps are commonplace. Interacting with such digital maps at varying levels of detail is key to interpretation, and exploration of different geographies. The process of abstraction remains key to the immediate and successful interpretation of their many structures and geographical associations found at any given scale. Meaning is derived from such recognizable structures and map generalisation plays a critical role in communicating an entity's most characteristic and salient qualities. But what are these structures? How (and why) do they change over scale? Why are such questions relevant to automated mapping? In this paper, we reflect on the value of perceptual studies and reconsider the context in which map generalisation now takes place. We review developments in pattern recognition techniques and the role played by machine learning techniques in identifying high level structures in abstracted maps. The benefits of their application include derivation of ontological descriptions of landscape, identification and preservation of salient landmarks across scales. We argue that a 'structuralist-based approach' provides a more meaningful basis for measuring success and achieving more meaningful outputs. Ultimately the ambition is greater levels of automation in map generalization, particularly in the context of web-based solutions.

**Keywords** map generalisation and web based mapping and Gestalt theory and structuralism and pattern recognition and machine learning and ontology

## 1 Introduction

[1] argue that maps are 'as fundamental to, and successful in, human development as writing, language, culture, religion, and architecture' p331. The power of maps lie in their abstraction, and their utility is enhanced by providing representations of the world at multiple levels of detail (at different scales).

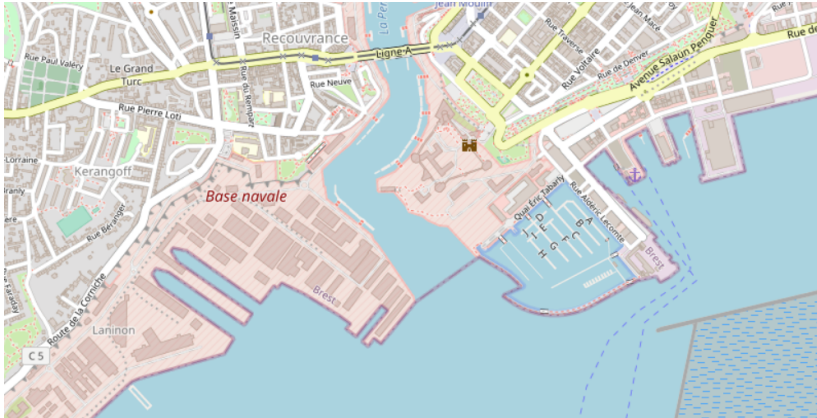


Figure 1: The port area of Brest, France, a functional structure composed of building, roads, docks, or seawalls (©OpenStreetMap contributors).

We can illustrate this idea through a simple example. Figure 1 is an example of a port structure at the large scale in which we can see the detail of the artificial coastline, the buildings, docks, and seawalls; at a broader scale, we will be interested in how the port forms part of the city that lies around it; and at a more regional scale, we would be able to look at the connections of the port with other ports and therefore its role in connecting cities. For the human cartographer the challenge was in finding compromise among a competing set of design constraints (not too cluttered, and with sufficient context to interpret and convey the map message). Early efforts at automation focused on mimicry of the human hand (a computer assisted approach), and then shifted to a vision of deriving smaller scale maps from a single, highly detailed database [2, 3]. Partial success led to eager consideration of a wider choice of thematic maps rather than just conventional topographic maps. But the move to greater levels of automation was inhibited by weak evaluation methodologies and a failure to model the complex interplay of entities and to understand how the representation of entities changes with scale. Essentially the map generalization process was seen as a data reduction exercise whereas it is more meaningful to think of map generalization as seeking to convey different information through changes in scale (not less information at smaller scales, but pertinent information portrayed according to scale).

All these developments focused around production of paper maps but the advent of the digital, mobile world ushered in a paradigm shift in how maps were used. The context moved away from the static paper map towards digital, slippy, interactive and multi-scale web-based thematic maps. Such environments allowed greater exploration whereby the user was able to pan and zoom, overlay secondary data, query, derive new products, and undertake multiple tasks (such as route planning and following).

The immediacy of maps became the imperative with greater emphasis on exploration through intuitive interface design. This changing context brought with it the need to address issues arising from the growing diversity and quality of source data (particularly volunteered geographic information) [4]. So in addition to a set of unanswered questions relating to the automation of traditional approaches to map use, the scope and context of map generalization was widened further by developments in web-based mapping.

This changing context has led to a rethinking of the goals of map generalization and to examine again just what it is we are trying to automate. We need to consider more closely the link between the user and the design, and also how task and environment of use connect with ideas of design. We need to have a deeper understanding of how the map is perceived, and how map generalization can be used to minimise cognitive effort. And we need to model the efficacy of a given map design.

Away from the simpler ideas of geometric simplification, we argue that there is real benefit in seeing map generalisation as a way of modelling the interactions between entities rather than the entity itself; it is the means by which we characterise the map space according to scale which in turn requires techniques that suppress those elements that disturb a 'good reading' of the key structures, whilst giving emphasis to qualities most relevant to the task at hand. In the context of web mapping, a second set of challenges revolve around minimising the cognitive effort associated with navigating across different scales; this involves giving emphasis to salient landmarks and structures that act as 'anchors' across scales, seeking to minimize the disorientation caused by the zooming process [5].

If the goal is to understand things at different scales, map generalisation needs to focus more on the idea of the map as a caricature – one that intentionally sacrifices locational accuracy in order to give emphasis to portraying caricature (meaning). With this in mind, we argue that increased levels of automation require algorithms that:



Figure 2: Generalisation of the Seine River in OpenStreetMap multi-scale maps (with all other themes removed for more clarity) between zoom levels 7 and 6. The meanders of the Seine are no longer recognizable after application of a smoothing algorithm.

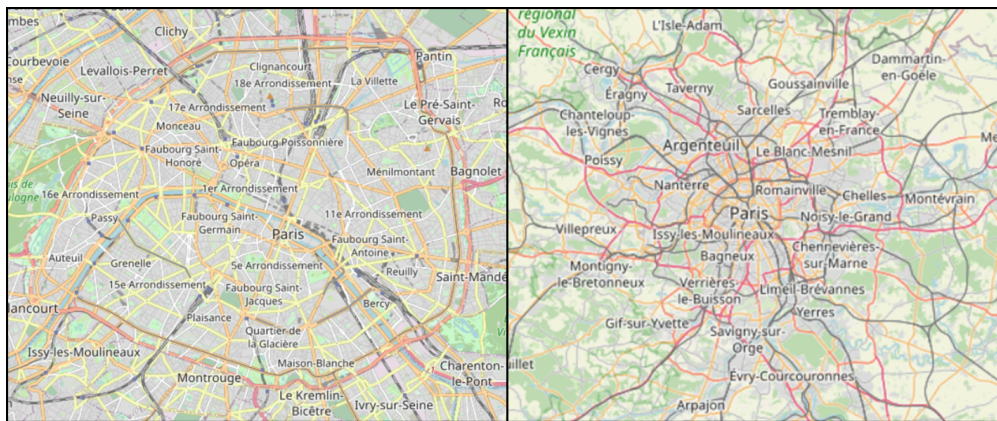


Figure 3: Generalisation of Paris in the OpenStreetMap multi-scale map between zoom levels 12 and 9. The Seine and the ring road are no longer recognizable although they are major features that characterise Paris.

1. take account of the geography contained within the map,
2. can identify and preserve the characterising qualities of entities in order to make them recognizable at different levels of detail.

We can witness these challenges by looking at an example. Figure 2 illustrates how the Seine River is generalized in OpenStreetMap (in this case between zoom levels 7 and 6). The meanders are removed, and the line is smoothed. The result is a simple line that does not have the symbol coalescence and clutter that would otherwise have arisen. But we have also lost its geography: we have lost the meanders (which one might deem the most prominent property of the Seine in its final section to the sea). As a result, map readers may not recognise the river anymore. Moreover, from a dynamic perspective, the rendering of the river is so different between the two consecutive scales that we risk losing our place on the map. As a result, greater cognitive effort is required to see the two renderings as one and the same thing. Figure 3 offers an additional example of what we consider an unsuccessful map generalization. Here the Seine River and the ring road have become lost in the clutter of roads and place names, making it much harder to recognise Paris and thus appreciate that these two maps represent the same thing. Thus interactive mapping requires a more user-centred approach [6]; one in which thematic content changes dynamically according to the task in a way that minimises cognitive effort and maximises the efficiency with which the content is 'consumed' or perceived.

In this review paper, we re-examine the motivations of map generalization first by revisiting some of the thinking on perceptual cartography and reflecting on what a user-centred approach means in the context of map generalization in dynamic, web-based environments. The paper begins by revisiting ideas of perception (section 2), highlighting the relevance of Gestalt theory in the perception of maps. Section 3 reviews various pattern recognition techniques, with an

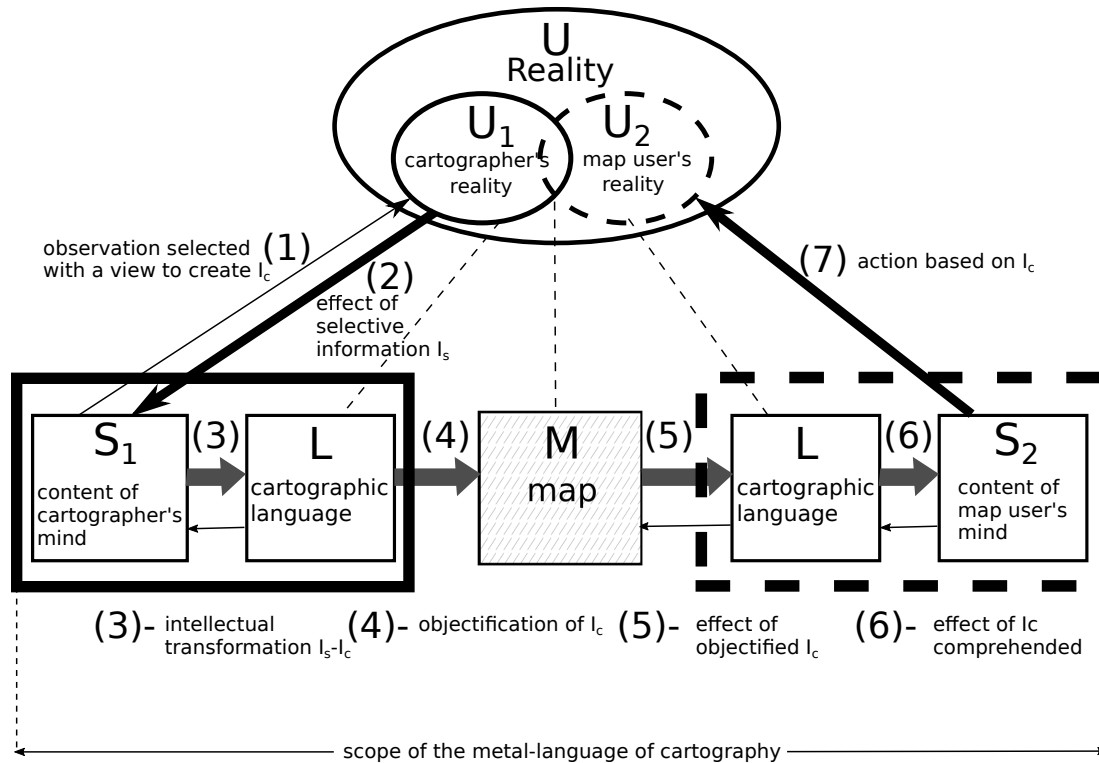


Figure 4: The idea of communication through a shared language [12].

emphasis first on the classical approaches to cartographic spatial analysis, before reviewing more recent developments in machine learning and their relevance to automated design. In the article we use fairly loose definitions of pattern and structure, using the terms interchangeably.

## 2 Perceptual Studies and Gestalt Theory: Their Role in Understanding Map Design

Mental perception (a sub-topic of psychology) is concerned with how the brain gains meaning from sensory inputs. The process is critical to how we interact with our environment. As one form of sensory input, cartographers have always sought to design maps that are effective and efficient in conveying geographical meaning with the least cognitive effort. This is typically achieved through emphasis and suppression of patterns and structures through the manipulation of the symbolised entity – a process that is governed by the map task and the environment of use. It is the connection between task and map design that has been the impetus behind psychological research that seeks to join the dots between the design of the map, and the perceptual skill and cognitive style of the map reader [7]. This idea of the map as a conduit through which information is conveyed led to the development of the field of perceptual cartography [8]. Studies in perceptual cartography have been hugely influenced by the cartographic communication concept (dominant in the 1970s and 1980s), which explicitly acknowledged the role of the map user in the process of design. Influenced by Shannon and Weaver's communication model [9], the map has, and continues to be seen, through the lens of communication science [10]. However, efforts at a unified theory have proved elusive despite various attempts; of note are the efforts of [11]; [12]; [13] and [14].

Figure 4 (the communication model of [12]) examines the notion of a cartographic language in map communication; a language of transfer and communication that he defined 'as a system of map symbols and rules for their use' (p48), the permutations of which can be used to potentially generate an infinite variety of messages [15]. The idea is that a cartographic language enables an encoding of the map, subsequently decoded by the map user, the success of which depends upon both a shared reality, and a shared understanding of the symbols used. Some argue that communication models are now less meaningful given the paradigm shift in how maps are created, used and shared, as the user is more and more a prosumer [16]. The criticism being that they emphasize a linear transfer of knowledge rather than a cyclic and iterative use, typical of interactive web-based mapping [17]. Others have questioned the pursuit of a single optimal map in environments where the user can always resolve any ambiguities by simply zooming into the map [18].

We argue that the benefits of various communication models is that they encourage a user-centred approach (highly pertinent in the context of interactive thematic map design) and remind us that map design cannot be captured merely as a set of map default settings. Frustratingly, the development of a cartographic language (or even an alphabet) continues to be elusive [19].

## 2.1 Semiology in Map Design

Kolacny's idea of an encoding and subsequent decoding of a map translates over to ideas of semiotics and semantics. It was De Saussure (regarded by many as the creator of the modern theory of structuralism [20]), who coined the term 'Semiology' (or semiotics), defining it as the study of signs, a field of research focused on how meaning is created through signs. Within the field of semiotics, there is the study of the relationship between signs and the things they stand for (semantics). Semiotics is also concerned with the structural relationships between signs (syntax). From an automated cartographic perspective, the ambition is to alter the symbology and representation of entities without altering what they signify. We know that the spatial and topological arrangement of those symbols is what conveys meaning which explains the many efforts to construct a map syntax that formalises descriptions of space and topology. The use of Graph theory [21], Space Syntax [22], minimum spanning trees (for example [23]) and many other cartometric measures [24] are all examples of efforts to make formal and explicit, the meaning implicit among an arrangement of symbolised geographic entities. But more than the 'how' of map syntax is the 'what', since a map is comprised of many symbolized entities covering regions, networks and discrete objects. There are a multitude of interactions and meanings that we might want to give emphasis to. The challenge in automated cartography is in linking a set of cartographic processes that take account of the various meanings inherent among those symbolised entities. One means by which we might explore the behaviour of these structures at changing levels of detail is to consider how humans perceive structure - something that continues to be explored through eye-tracking studies.

## 2.2 Eye tracking Studies

Research interests in perceptual cartography have ebbed and flowed since its popularity in the 1960s and 70s [16, 25, 1] but recently interest in perceptual cartography has been revitalised through eye-tracking studies (for example [26, 27]). After the pioneering work in eye movement studies by [28] and the cartographic-specific work of [29], there has been a recent resurgent interest in this challenging field [30]. Easy to use eye tracking technologies [31] are helping to unravel our understanding of various cognitive processes [26] particularly when used in combination with mixed methods such as sketching, or think-aloud techniques [32, 33]. Eye-tracking devices look at different possible eye movements (saccades, fixations, smooth pursuit), and allow us to record the path of the eye resulting in trajectories made up of these different movements [34, 35].

In eye-tracking experiments, the map is seen as a conduit through which the cartographer's encoding passes. Experiments are based on the assumptions that fixation rates and the ordering in eye movement vectors are indicative of perceptual processing [36] and that for a given task, the efficiency with which the message is then decoded by the map reader is a measure of its success [37]. The efficiency of processing depends upon the task, geographical complexity, prior map experience, aesthetics and the efficacy of the design and its layout. From a semiological perspective, the challenge in any perceptual experiment is in unearthing the linkages between syntax and semantics. Some experiments have highlighted how Bertin's visual variables [38] can be used to differentiate map content, thus facilitating the recognition of a particular form over another (e.g. [39]). But the geographical complexity inherent in a map, coupled with the varying cognitive styles of map users and the multi-scaled nature of those interactions has led some to question the veracity of such experiments [17]. Other research has attempted to detect in real-time the task the map user wants to perform in order to modify the map [40], but this is beyond the scope of this paper.

From an automated perspective, there have been few experiments that have unpicked the complex decoding process in a way that enables the formalization of design rules. Except in overly simplistic experiments, it is unclear what 'units' of geography a map reader is perceiving or how different designs impact the effectiveness with which various geographies are conveyed. It is unclear whether the eye fixates on an individual entity or the broader structure constituted by the entity. We do not know how the interplay between the background context and particular thematic entities impacts the efficiency with which the map is interpreted. In Figure 5, extracted from an eye-tracking exercise, there are fixation points over the Montparnasse train station in Paris, but it is not clear whether the user looked at the station as a single entity or at its component parts. Consideration of Gestalt theory is perhaps one way of gaining answers to these and other perceptual questions.

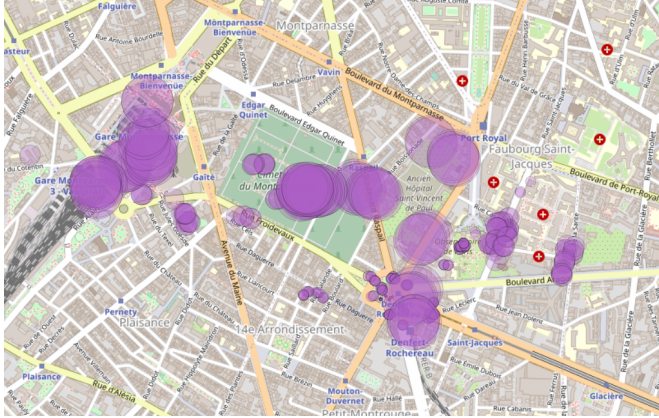


Figure 5: Fixation points of someone asked to look at the map and to pan and zoom until they know where they are. Only one scale is used here to visualise the fixations, but the user did look at several scales during their exploration. The radius of the displayed fixation points conveys the imprecision of the eye-tracker device, depending on the scale (small circles correspond to fixations when the user was looking at a map at larger scales, and conversely) (©OSM contributors for the map background).

## 2.3 Meaning and Gestalt Theory

It is acknowledged that the power of the map lies in its abstraction, designed (hopefully) in a manner that readily enables pattern identification and thence insight. McEachren and Ganter argue that the map reading process is one of identifying recognizable patterns which, based on our knowledge and experiences, leads to insight and discovery [41]. But what is meant by a ‘recognizable pattern’? More generally, we might wonder what it is we do see. We might see either the tree or the forest, the house in the street or a small part of the city, or perhaps both. Such questions lead us to reflect on 1) the so-called ‘part whole’ compositions of a map, and 2) the functional ‘part of’ relations that exists between entities and that underpin our conceptualisations of various geographies. The first we can answer through examination of Gestalt theory, the second we can explore through ideas of Structuralism, and its connections with ontological modelling [42].

### 2.3.1 Gestalt Theory

Gestalt theory explores the way in which the shape, regularity and proximity of symbols lead us to group and connect things together. Gestalt theory holds that the perceptual field does not appear to us as a collection of disjointed sensations, but rather possesses a particular organization of spontaneously combined and segregated objects [43, 44]. These organisations become apparent through a process of emergence. According to Wertheimer (one of the three founders of Gestalt Psychology), there are specific principles that govern the process of emergence according to various visual properties of an object. These include: proximity, similarity, uniform density, common fate, direction, good continuation, closure, equilibrium, and symmetry. Some of these so-called laws are illustrated in Figure 6. The theory explicitly acknowledges that the whole is different from the sum of its parts; i.e. that the whole is not determined by the behaviour of its individual elements. Gestalt theory argues that these ‘structured wholes’ (or Gestalten) form the foundation blocks of meaning. In a cartographic context this regularity and juxtaposition of form, of various group patterns and enclosing shapes is what conveys various geographies.

Interest in perceptual principles (such as those articulated through Gestalt theory) has felt highly relevant in exploring the visual hierarchies of a map and as a way of understanding how context affects the interpretive process. When viewing the map, the human mind makes meaning from these whole-part spatial arrangements and it is, therefore, the role of the cartographer (whether human or computer-driven) to control the design process so as to give emphasis to certain Gestalten whilst suppressing others, depending on the task. [43] highlight how cartographers use such grouping principles to great effect, knowing that all else being equal, the most similar elements (in terms of colour, size, orientation, symmetry, parallelism, continuity and closure) will perceptually group things together. Changes in map scale (or level of detail) are critical in controlling the emergence of various Gestalten. Thus at one level of detail, it is possible to see the commonly shared orientation of buildings and roads that define a street. At another, we can see the variation in the density of housing that usually delineates the ‘old town’ from the rest of the city, and at another, we can see the city’s connection among a collection of other cities. As we travel between these conceptualisations, the cartographer endeavours to prevent us from ‘losing our place’ in the map by retaining characteristics of those entities that persist over a range of scales. Thus as we transition between scales, the city remains regimented and angular in its

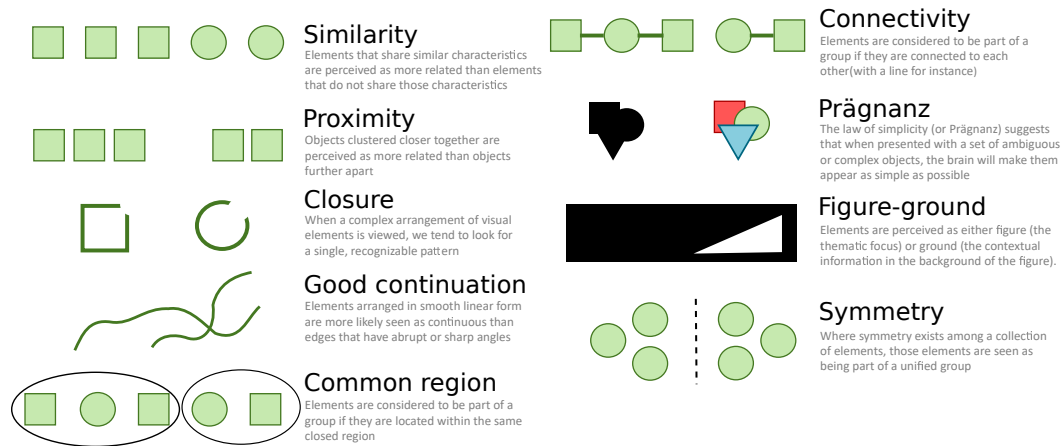


Figure 6: Illustration of the Gestalt so-called laws that apply most to cartography.

anthropogenic form, the key defining properties of the landscape's morphology are preserved; that the rivers continue to smoothly flow in the eye of the beholder, even when their representative form is made much simpler.

It is interesting to observe how cartographic outputs take account of Gestalt principles (such as good continuation, uniform density, closure, and symmetry) in the rendering of geographical entities. For example the good continuity principle allows 'breaks' in linear features, safe in the knowledge that the human eye will see the line as being joined up and continuous. The continuity principle has underpinned work in the generalization of river [45] and road networks [46]. It also has relevance in text placement where toponyms lie over linear features. A range of Gestalt principles were considered in the optimal design of map legends in the work by [47]. This process of 'visual completion' also allows for the partial occlusion of features, again, without their loss. This is a design aspect that is readily undertaken by the human, but has proved difficult to automate. In summary, we can see how Gestalt theory helps to articulate a number of map design issues as they pertain to scale. From an automated mapping perspective, the challenges are in 1) identifying various Gestalten (through pattern recognition techniques) and 2) measuring the strength of these groupings, 3) ordering Gestalten according to their relevance to a given map task, and 4) preserving certain geographies across scales whilst letting go and replacing others.

## 2.4 Structuralism – Understanding the Geography of the Symbolised Entity

Gestalt theory is, by definition, focused on the visual form. What is also important in giving meaning to the map, is the role of geographic knowledge in interpreting the map. For example we do not need to look at a map to know how landscape morphology affects the course of a river or to understand that a station is the means by which we gain access to a railway network. We draw on such understandings of the world when we come to interpret the map. The interpretation of the perceived associations that we see in the map are informed by the user's geographical experiences and their knowledge of an entity's behaviour or function [48]. Cartographic design can take advantage of such knowledge. For example in the design of a road atlas, the cartographer can omit rural detail, safe in the knowledge that the map reader will infer the presence of buildings in the landscape rather than seeing the countryside as 'empty' of habitation. Where the road crosses the river, they can omit the bridge without the driver thinking they will get wet feet. We therefore argue that it is necessary to formally model these geographical behaviours and dependencies so that the same design capacity can be incorporated within automated cartographic systems.

Such an idea has interesting parallels with Structuralism. The origin of Structuralism lies in linguistics and Gestalt psychology [49] and has seen diverse application among many disciplines, including mathematics [50]. From a sociological perspective, [51] defines Structuralism as 'the belief that phenomena of human life are not intelligible except through their interrelations.' Structuralism, in the context of map design, can be viewed as a method that analyses geographic meaning in terms of an entities' underlying structural forms, interactions and behaviours. In particular, structuralism directs us to explicitly describe the inter relationships between entities. This is necessary if we wish to generate meaningful and coherent geographies at multiple scales. When considering the behaviour of an entity, it is to highlight its interactions and functional role (for example the interaction between a river, a road and a bridge). The form and meaning of those relationships depend upon 1) the spatial and topological arrangement of those entities, and 2) their behaviours and interdependencies. Structuralists would argue that it is these geographical interactions (natural and anthropogenic) that give rise to the various patterns, shapes and associations that we see in the map, whether it is the



natural form of a river that is governed by the shape of the valley floor, or the engineered walls of a harbour that provide safe anchorage for ships. Indeed it is our knowledge of these interactions and processes that enables us to interpret the map.

A structuralist view argues that a map should be seen as a system of signs (a semiotic system) made up of the signifier (the icon) and the thing signified (eg the bridge). Structuralism requires us to consider what is signified when deciding what to do with the signifier. This is different from typical approaches to map generalization where what is signified is often ignored and the task is reduced to a set of Cartesian and vector-based operations.

Structuralism argues that the meaning of a signifier can only arise from the simultaneous presence of other signifiers – in other words, it is what surrounds a signifier that provides context and meaning. This again is very different from typical approaches where the signifier is generalised in the absence of consideration of other signifiers. The immediate challenge that arises from these two observations is in deciding 1) which behaviours to model, and 2) which other signifiers we should take account of given a particular design task. We might consider signifiers that are close by as being more important than those further away, or signifiers that are thematically associated (e.g. buildings and their association with roads) but this remains a challenging area of research.

A Structuralist perspective can help us rank the importance of various map content for a given map task (in deciding whether it warrants inclusion in the map or not). Importance can be determined if we understand the role played by the entity for a given map task. For example, the activity of trade by way of the oceans accounts for the shape and size of ports – ports that connect land-based infrastructures with the sea. It is through a Structuralist perspective that we can understand the significance and relevance of ports in the production of say, a global trade map. In this instance, it is the cartographer's structuralist perspective that determines what visual emphasis is given to the symbolisation of ports. It is Structuralist thinking that explains why minor roads servicing remote mountain villages are retained even at relatively small scales or why tourist sites and viewpoints typically form part of a car road atlas. It is also what enables us to replace the dense clustering of thousands of discrete building entities with a single dot with the word 'London' next to it. The 'dot' takes advantage of our conceptualisation and experience of 'city-ness', and enables us to transition between these scale-dependent conceptual cusps [52].

Adopting a structuralist perspective allows us to view map generalisation as the effective portrayal of the relationships between and among symbolised entities (rather than the manipulation and simplification of an entity in vector space). In this way, we can imagine the task of map generalization as being the identification and communication of the essential qualities and characteristics of specific relationships given a specific task and a context of use. In not adopting a structuralist approach, we would argue that the map is invariably viewed as a collection of independent geometries to which a sequential set of map generalization algorithms are applied. We argue that algorithms that fail to be structuralist in nature will inevitably have limited application, and will only operate over small changes in scale.

## 2.5 Incorporating Structuralism Through Ontological Modelling

So how might we incorporate a Structuralist perspective in an automated context? The idea of making explicit the relationships and dependencies among each geographical entity is what has driven the interest in ontological modelling – within the geographic discipline, GIS [53] and specifically within the realm of map generalization [54, 55, 56, 57, 58]. We define an ontology as "an explicit specification of a shared conceptualization" [59] and this allow us to formally represent the semantics and relationships between entities. Ontologies, as well as other semantic web techniques help us to deal with the semantic interoperability of datasets and processes [60]. They help in the sharing of disparate modelling techniques among different people and organisations [61].

To illustrate their utility, let us consider the example of the highway interchange structure, (often a significant anchor in multi-scale maps because of their visual saliency and their role in car navigation). To ontologically model it, we have to find the defining characteristics of a road interchange. From Figure 7, we might argue that it is the complex interconnection of at least one dual carriageway with another road, via the use of slip roads but a precise definition is illusive and not all researchers will agree upon the same defining terms and definitions in their algorithms. However an ontological model of the structure, (such as Figure 8) can help align such disparate definitions and create more inter-operable solutions.

Since the publication of some seminal papers on ontologies, several ontologies of spatial/geographic/cartographic information have been proposed. GEONTO-MET is a generic ontology of spatial information aimed at geographic information services [62]. Ontologies have been proposed to model landscape [63], and surface water features [64]. Of more specific relevance to cartography is the work of [65] who developed an ontology of topographic features based on the written specifications of a national mapping agency. Townontology is another interesting project that proposed an ontology of urban concepts for urban planning, with a capacity for multiple representations of various geographic concepts [66]. Ontologies consisting of very general terms common across all domains (so called 'Upper or Foundation



Figure 7: Two examples of a highway interchange structure, a simple one on the left, and a more complex one on the right, illustrating the difficulty to clearly define what this structure is.

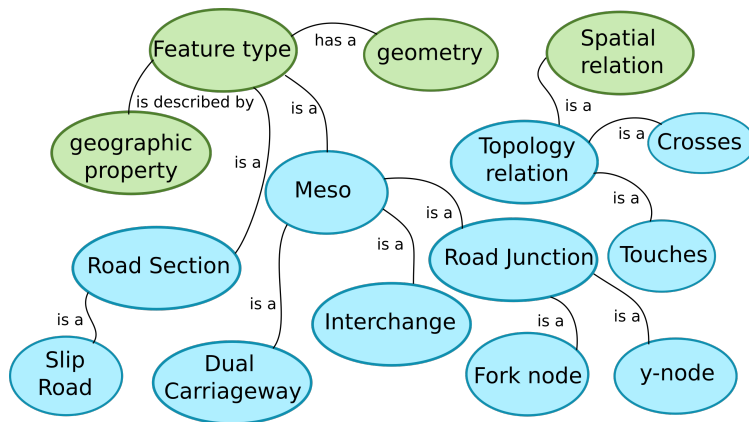


Figure 8: Some concepts and relations for the ontological modelling of the highway interchange structure.

Ontologies') have been proposed as a way of modelling spatial and cartographic concepts. Key examples of this include BFO [67, 68], and DOLCE [69].

[70] proposed a geographical ontology made up of "composite geographic information constructs", created from "simple geographic information constructs" but it remains unclear if such a conceptualisation is sufficient from a cartographic perspective or whether a more domain specific ontology is required. Experiments by [71] revealed the challenges of creating geographical ontologies sensitive to ideas of scale. In response [72] proposed a model able to represent different abstract concepts at different map scales.

Using ontological modelling to better describe the complex structures and patterns in a map is not a new idea. For instance, an ontology-based approach to the enrichment of spatial databases with complex structures was proposed by [73]. In their research, the ontological modelling of many properties and relations of complex structures was first undertaken. A congruence principle was used to count how many of these properties were met by a group of spatial objects, and this was used to decide if the group was an instance of a given structure. An idea that was later applied to house patterns [56]. An ontological model of spatial relations in maps was also proposed to help in the development of interoperable automated mapping processes [74]. The ontological modelling of the entities in a map was also used to guide the generalisation process. It was used, for instance, to adapt the parameters of line simplification to the type of input lines (since a river is not generalised in the same way as a road) [75]. Ontological modelling therefore helps us to understand how cartographic features are related, and how they can be abstracted at smaller scales. In a coastal area, knowing that a cove and an harbour are two types of bays, ensures they can be generalised in a similar way. Making explicit the relation between a bay and a point or cape can help in the preservation of this relation during the generalisation process [54]. Modelling the spatial relations between map features has also been used to guide the aggregation (or collapsing) of those features during generalisation [76]. The same approach has been applied to bathymetric generalisation where bathymetric landforms are composed of several simple cartographic constructs such as contour lines or sounds [77]. The model proposed by [77] uses ontological modelling to describe how algorithms can resolve specific constraints and to guide the automated process. Ontologies have been used several times to describe

the procedural knowledge of automated cartography and on-demand mapping, as proposed by the seminal paper by [55]. Ontological models of user requirements and map specification have been proposed [78], as well as ontologies of cartographic symbols [79], and of cartographic generalisation operators to infer the best choice of operator in a given on-demand mapping use case [80, 81]. Also worthy of mention is MapGenOnto since it is an attempt to merge and synthesize past propositions into an ontology of map generalisation. It contains parts describing the complex structures and patterns of map entities [58] and was collectively created during meetings organised by the International Cartographic Association Commission on map generalisation [57, 82].

### 3 Pattern Recognition techniques

Pattern recognition in maps is a branch of spatial data mining, which takes its roots both in spatial analysis and in various data mining fields in statistics and computer science [83]. One common definition of pattern (or structure) is a property within an object, or between objects that is repeated with sufficient regularity [84]. From a cartographic perspective, we might ask how pattern recognition techniques can be used to detect the structures that humans so readily see in maps. In effect this amounts to the automatic detection of meaning within a cartographic database. This was something that Laurini was exploring in his ideas on automatically deriving visual summaries from geographic databases [85].

We have seen in the previous sections that recognizing patterns in existing vector databases is an important step in achieving higher levels of automation in map design. In this section, we report on recent map pattern recognition algorithms while reviewing various cartographic spatial analysis techniques. We then discuss some machine learning techniques and their contribution to this field.

#### 3.1 Detecting patterns via cartographic spatial analysis

Cartographic spatial analysis draws from many disciplines. It includes all the techniques used to query geographic databases, based upon their topological, geometric, or geographic properties. The goal of spatial analysis is usually to make explicit information that is implicit in the database and to enrich the database for future use.

The ambition of cartographic pattern recognition is to build algorithms that can detect specific map structures. Irrespective of algorithm choice, the goal of pattern recognition is to gain such information whilst minimizing computational effort. Pattern detection plays an important role in the map generalisation process (for example [86]). Efforts in automated cartography have sought to identify lots of geographic properties and structures contained within the map. Map structures belong to one or many of the following categories:

- Objects with specific shapes (e.g. a roundabout)
- Complex objects that are composed of multiple elements (e.g. a ring road)
- Objects relatively unique to their environment (e.g. a building in an otherwise empty rural region)
- Specific structures in a network (e.g. a "Y" intersection)
- Specific arrangements of multiple objects (e.g. an aligned set of buildings)

The process of building new algorithms able to detect specific structures can be divided into four (often iterative) steps (Figure 9).

Step 1: formally describe the spatial and semantic properties of the structure to identify indicators that could be used to measure those properties. Describe ontologically the function of the structure. [87] demonstrated (for railway networks) that it is possible to use UML class diagrams to formalize the relations between different map features. The challenge is ensuring the use of crisp definable geographical concepts (such as "city centre"). Where definitions are vague, questionnaires can help elicit and prioritise properties [88, 89]. Care in the formalisation process makes it easier to build the associated model and analysis. By way of example, Figure 10 lists some of the measures we might use to detect city ring roads.

Step 2: Calculate those properties that are implicit in the data (data enrichment). Geography allows us to infer things. For example, it is interesting to reflect on how information about a city can be inferred from examining the properties of the road network alone. Heinzle was successful in defining and identifying shapes and patterns typically found within the road network (Figure 11). Her graph-based approach allowed the successful detection of circular roads, grids, stars and strokes [90, 91]. [92] worked on utilising strokes (based on the good continuation principle of Gestalt theory) to make road networks that were topologically complete. [93] demonstrated how prominent areas of the city can be inferred from the analysis of the database. [94] used analysis to preserve distinct hydrographic patterns by taking

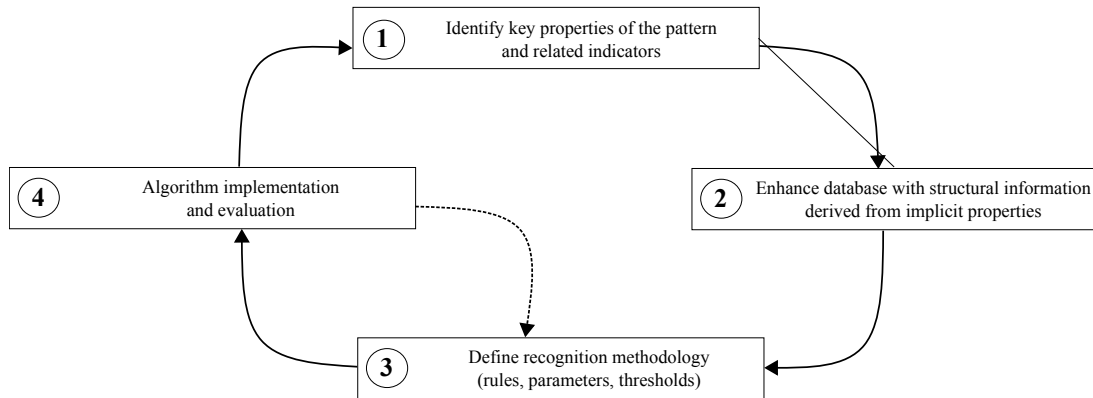


Figure 9: A four-step approach to implementing a pattern recognition algorithm

Ring Road Properties	Related indicator(s)
Large enough	Length, radius, area
Approximates a circle	Compactness, convexity
Connects most parts of the city	Closeness centrality
Contains the gravitational centre of the city	Centroid of city polygon
Forms a closed cycle	Cycle detection
Road name may include "ring" or equivalent	Explicit attribute
Connects with a number of major arterial roads	Strokes graph analysis
Internal road density higher than external density	Graph density
Alleviates congestion	Betweenness centrality
Minimises the number of changes in direction	Angular centrality

Figure 10: Some typical properties of a ring road and their associated indicators.

into account variations in morphology. Road data can also be enhanced with information regarding its continuity and hierarchy [95]. Space syntax (building on the work of [22]) is a means by which we can describe the properties of entities. For example, it has been used to measure the properties of road networks [96, 97]. In the context of building patterns, [98] proposed a comprehensive typology of building patterns and their characteristics.



Figure 11: Grid, circle and star patterns found in the French road network.

Sometimes the properties of the structure we are searching for build on other structures that do not yet appear in our database. In such instances, it is necessary to detect the base structures prior to identifying higher-order structures. However, this does not apply if the detection of structure A is based on structure B but B is defined in terms of structure A. [99] calls this 'recursion in pattern recognition' and explores its resolution in the context of river network generalization.

Step 3 is the implementation stage, increasingly undertaken using open-source languages to facilitate the sharing of code. Many approaches have used graphs to model and analyse geographical networks and identify various patterns. For example, [100] retrieved all the cycles in a road network graph, and then filtered out the cycles that didn't correspond to ring roads (defined as large circular roads around the city). The method has its limits since it is not able to detect more complex forms such as rings that only partially enclose the city. The search for cycles is made faster through a process of block aggregation which simplifies the network. Building polygons from road networks and calculating various parameters is another common technique and was used to detect grid shapes [101]. Buildings can also be modelled as graphs, either to study their individual shape or their arrangement relative to others [102, 103]. Minimum spanning trees (MST) have been used to detect clusters, as well as collinear and curvilinear building alignments [104].

With both topological and metric models, we can formalise rules that describe geographical properties (for example "two roads are deemed continuous if the angle between them is less than 30°"). Though simple to implement, it is rare that it works in all contexts and "fuzzy logic" has been used to increase the robustness of such results. For example [105] classified river networks into five types of drainage patterns. This method is especially useful when the rules defining the patterns are vague. This idea of modelling membership values and non-binary congruence (rather than strict thresholds) is discussed by [56] who applied the idea in the generalization of terraced houses. In deciding which characteristic best conveys the semantics of an entity we often need to rank the significance of these patterns. Examples of efforts to do this include the classification of rivers [106] and the ranking of the building alignments using a straight line-based technique that takes into account the positions and the similarities of a cluster of objects [107].

Step 4: A final step in the development of pattern recognition techniques is in their evaluation. There have been various debates over how outputs are evaluated. A user-centred perspective argues for perceptual studies. Geometric and topological measures have proved popular but are only meaningful over relatively small changes in scale. Machine learning techniques require large amounts of data in order to train the model. A minimum requirement is to calculate the percentage of detected patterns as well as the number of false positives. [108] proposed a railway line selection process in which they include evaluation of their results. They detected specific portions of cluttered railways, simplified them, and then measured the success of their algorithm varying the thresholds depending on the scale chosen.

For a description of the key steps in developing pattern recognition techniques for modelling building alignment see [109], and of pattern recognition techniques in combination with agent-based methodologies see [110]. Over the past decade, some have taken advantage of the considerable development of machine learning techniques to combine them with various spatial analysis techniques. For example, [111] first constructed graphs to detect building clusters and then used a machine learning random forest algorithm to recognize certain patterns in the clusters. Another example is furnished by [112], who sought to extract salient buildings that act as landmarks at road intersections. In the following section, we look at machine learning techniques in more detail.

### 3.2 Pattern recognition using machine learning techniques

Despite the many and varied cartometric algorithms that exist, it is often difficult to precisely describe the specific spatial and semantic properties of the geographic entities contained within the map. In such instances, it may be easier to search for examples of particular instances rather than to identify their underlying properties. Map users can readily decide for themselves if a circular road is an instance of a city ring road just by looking at the map, but it is very difficult to derive the defining spatial properties through this visual recognition process [89]. Supervised machine learning seems to be the best approach in such cases, and this subsection discusses how machine learning models can help us to recognise the patterns and complex map features that are so readily seen by the human eye.

Machine learning is often seen as being synonymous with deep learning, but there are other approaches to supervised learning; we review these first. In machine learning methods that are not based on neural networks, the input of the model is not the map (or an image of the map), but a vector of descriptors that characterise a particular feature. In the example of the ring road, the various qualities (or characteristics) that could describe a circular road might be its length, inner area, compactness, the road density ratio between the inside and outside of the ring road, its classification, and the number of arterial roads connected to the circular road [89].

A similar approach can be used to extract landmark buildings from a spatial dataset, comparing attributes of a building with its neighbours such as the uniqueness of its shape, its area or the distance to a road intersection [112]. These

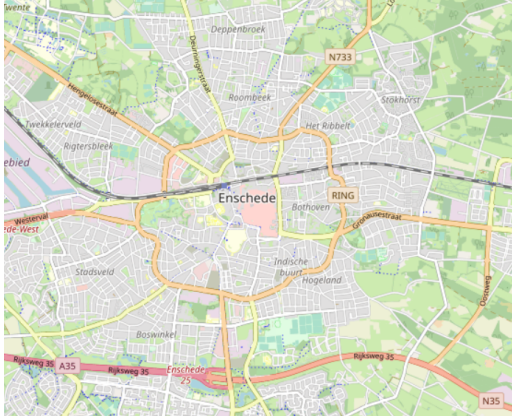


Figure 12: A ring road around Enschede, the Netherlands, that is easily recognised as an example of ring roads (©OpenStreetMap contributors).

vectors are subsequently used to train a decision tree model. [113] used this approach to identify landmarks for car navigation, and more generally to recognise buildings that stand out in a topographic map though with limited success.

By using such geometrical and topological characteristics, we can use machine learning to infer the semantics of the cartographic data. For example classify a polygon according to its entity type (a road, a parcel, or a building). In the work of [114] a decision tree method was used, and later the efficiency of this classification process was improved using Bayesian inference [115]. In modelling road networks, it has been shown that it is possible to infer the nature of the road using Markov random fields [116].

As well as being able to determine the semantics of individual objects in the map, machine learning can also be used to recognise more complex patterns. [117] demonstrated how it is possible to classify urban structures based on the geometric and spatial distribution of features, in this case using Support Vector Machine. [118] demonstrated how it is possible to recognise terraced houses (a typical British building pattern), based on features derived from ontological modelling. In this case, a Bayesian inference method was used to deal with the uncertainty among the features. The Support Vector Machine (SVM) method has also been used to recognise street grid patterns based on the edges and nodes of the road network graph [119]. The Random Forests algorithm is a recent evolution of the decision tree method and has been used to recognise building group patterns, based on features related to the geometry and the spatial distribution of the buildings [120].

In recent years, deep learning methods have overshadowed other machine learning methods as a way of detecting patterns in maps. In the interests of brevity, we refer the reader to [121] for a detailed understanding of this method. Aside from deep learning, image-based techniques have also proved popular in map analysis. This is a set of techniques in which the input of the neural network is an image of the map. In Figure 12, the Enschede ring road is salient because of its geometrical and topological properties, but also because of the way it is portrayed in the map, and then visually perceived by the map reader. The ability of deep learning models to process map images allows the integration of this perceptual dimension in the pattern recognition process.

The significant impact of deep learning on computer vision has intuitively led to their application in cartography whereby cartographic images are used to classify images of a map. From small sections of the map, such models can classify these images in terms of the dominant structures that they contain. For instance, Figure 12 could be classified as a "ring road" by a convolutional neural network model trained to recognise such structures. Such an approach has been used to classify 1) urban regions into several categories (inner city, urban, suburban dwellings) [122], 2) images of road junctions into several categories of varying complexity [123], and 3) to decide if an image containing roads is connected to one or more highway interchanges [124]. Training convolutional neural networks requires a large number of annotated images, and being able to use all the existing generalised maps to automatically generate these annotated examples is a considerable challenge [124]. Merely classifying an image is not really sufficient in order to recognise patterns and structures, because it does not explain where the structure or pattern is located within the image. To address this researchers tried segmentation models, such as U-Net [125], which classify each pixel of the image into several classes. Segmentation neural networks perform better than classification networks (for example in recognising highway interchanges [124]) because it is more practical to identify the pixels of the image that cover the interchange (Figure 13). A similar U-Net has given good results in generating relief shading from a digital elevation model (DEM) [126]. Generating relief shading from a DEM requires us to recognise the main structures of the terrain.

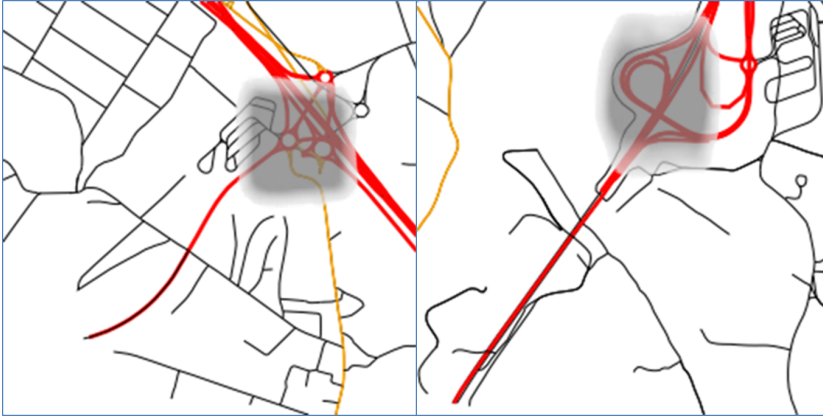


Figure 13: Two examples of the recognition of highway interchange patterns using the segmentation model from [124]. The darker the pixel, the greater the probability that it covers part of an interchange.

Though designed for analysis of remote sensing images, it has been shown that a U-Net can also be used to recognise groups of buildings [127], and we believe that a similar approach could work with maps instead of aerial images as input.

Deep learning models have also been used to search for patterns in historical maps (maps that only exist as scanned images). Reusing the models designed to recognise text in a photograph, it is possible to also recognise text in old maps [128]. It has also been suggested that deep learning segmentation of historical maps can be combined with morphological operators to recognise roads, rivers, or building blocks [129].

The models that use images as input are limited in their results because the images do not convey as much information as their vector equivalent [130]. In addition to convolutional neural networks (i.e. the networks used in image-based deep learning models), graph-based deep learning has proved to be another popular technique [131]. It is possible to compute mathematical convolutions on graphs, as well as on tensors, and so network architectures designed for image tensors can be ported to graph models, in order to classify nodes, edges, or the whole graph. A tensor is a way of representing image (or in this case map) information. Tensors can be described as a generalization of (a set of) matrices, usually represented using  $n$ -dimensional arrays. For instance, an RGB image of a map is a  $n \times n \times 3$  tensor, but the dimension becomes  $n \times n \times 4$  if we also encode the altitude of each pixel in the tensor. Tensors can be seen as more expressive extensions of the basic raster representation of geographic information, able to capture more information from the map [132].

Graphs are also a popular way of modelling structure and networks in cartographic data [24], so graph-based deep learning seems to be a promising solution to the better encoding of cartographic vector data. The most obvious way to create a graph from cartographic data is to focus on networks (roads, rivers, railways, etc.) that are natural graphs (Figure 14(a)). In river networks graph convolutional networks [133] have been used to recognise drainage patterns (e.g. dendritic, distributary, etc). They have also proved useful in detecting patterns and structures in road networks. These techniques have been used to infer the importance of a road [134], and their nature [135, 136, 137]. Graph-based models have also been used to model specific structures within the road network (such as recognising highway interchange patterns [138]), with results more promising than the image-based methods previously discussed.

Polygons can also be modelled as graphs with vertices considered as nodes and the segments between the vertices considered as edges (Figure 14(b)). This graph model can be used to encode building polygons using Fourier transform, and thus cluster groups of buildings that have a similar shape [139]. A similar approach again using Fourier transform has been used to generate generic building encodings [140], and to recognise groups of buildings [141]. TriangleConv is a deep learning model that uses graph structures with vertices as nodes, but where convolutions are not based on Fourier transform (as in the methods of [142]). Instead, TriangleConv is trained to classify the shape of buildings into several templates (U-shaped, L-shaped, T-shaped, etc.). TriangleConv has also been upgraded into a few-shot classifier [143], i.e. a model that is first trained with many examples on a simpler problem, and then fine-tuned on the specific building classification using fewer examples.

A third way to compile a graph from the cartographic data is to create a neighbourhood graph that connects close objects in the map, for instance using a Delaunay triangulation (Figure 14(c)). When the neighbourhood graph is created between buildings in an urban area, graph convolutional networks can be used to learn about the nodes and edges that belong to a building alignment [134]. A similar approach showed that a graph convolutional network could learn how

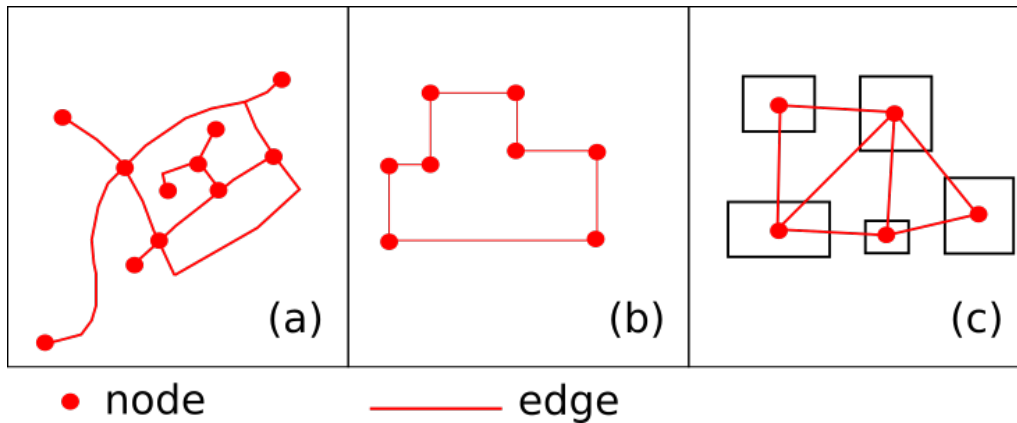


Figure 14: Three different ways to model cartographic data as graphs: (a) using a natural network structure, (b) using the vertices of a polygon, (c) using a neighbourhood graph.

to recognise different building patterns (straight and curvilinear alignments, grids, etc.) using a neighbourhood graph [144]. Graph convolutions on a neighbourhood graph between buildings can also be used to classify urban blocks into their functional category (industrial, commercial, residential, etc.) [145]. All these deep networks classify the nodes, the edges, or the complete graph, but deep learning can also solve regression tasks. [146] trained a network to compute a graph-based fractality index on urban blocks where buildings are connected in a graph.

In addition to images and graphs, there are other types of spatial encodings [147] of cartographic data, provided it can be expressed in a tensor format. For instance, in a deep learning model designed to generate land use maps from cartographic vector databases, the vector data is encoded into a tensor with measures relating to the shape of the data, and measures on the surrounding data [148]. [149] convert a polyline and its successive vertices into a tensor in order to learn how the line was simplified. It is also possible to use the fusion of several tensors, each capturing different aspects of the cartographic map [132].

#### 4 Future Perspectives for Multi-Scale Mapping

Studies in perceptual cartography have highlighted the inherent complexity of cartographic maps. We know that as the shapes and patterns between symbolised entities change with scale, so too does the meaning of the map. This idea is reflected in two recently proposed definitions:

- *A map is a perceivable, designed, enabling, interface that represents and communicates spatial entities and relations.* [1]
- *A map is a generalized representation of spatial relationships.* [150]

The relationships among and between the symbolised entities are multifarious. Gestalt theory (and its principles) helps explain the process by which we can explore the map and unearth patterns and structures. Even at a fixed scale, the map appears as a palimpsest – a layering of patterns, associations and topologies - from the localised to the regional. Efforts in automating map design (mimicking the human cartographer) have led to the implementation of a very large number of measurement techniques that now include machine learning. The problem remains, however, in knowing which structures and patterns to give emphasis to. For a particular level of detail, which characteristics (or qualities) best convey a particular geography? The desire to link design with task explains why there is so much interest in communication models. Though some argue they are deficient, they do at least place the user centre stage. In the context of individualised, web-based mapping it feels intuitively right that we hold onto the idea of a 'cartographic language' and in the context of map interaction, that of 'dialogue'. We argue that in the context of machine learning, the ambition of linking cartographic syntax and semantics is ever more important.

This paper has sought to make links between scale and structure, and structure and meaning. The paper has reviewed how pattern recognition and machine learning techniques are now being applied to make explicit the multifarious shapes and structures that give meaning to the map. The application and development of these techniques continues to highlight issues of cartographic communication which in turn, continues to drive interest in perceptual studies. More broadly we would argue that the future success of interactive multi-scale mapping will require us 1) to see the problem in terms of modelling geographic meaning through the interaction between entities (not the entity itself), 2) to explicitly



incorporate ideas of task and context of use as key drivers in the process of map design, and 3) to design a cartographic encoding process that makes sure that deep learning models really embed the complex spatial relations between vector geometries contained in a map.

## Funding

This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (grant agreement No. 101003012).

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