Scale Is Introduced in Spatial Datasets by Observation Processes

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Abstract

An ontological investigation of data quality reveals that the quality of the data must be the result of the observation processes and the imperfections of these. Real observation processes are always imperfect. The imperfections are caused by (1) random perturbations, and (2) the physical size of the sensor. Random effects are well-known and typically included in data quality descriptions. The effects of the physical size of the sensor limit the detail observable and introduce a scale to the observations. The traditional description of maps by scale took such scale effects into account, and must be carried forward to the data quality description of modern digital geographic data. If a sensor system is well-balanced, the random perturbations, size of the sensor and optical blur (if present) are of the same order of magnitude and a summary of data quality as a 'scale' of a digital data set is therefore theoretically justifiable.

1 Introduction

Digital geographic data comes in different qualities, and applications have different requirements for the quality of their inputs. A common misconception is that better quality is always preferable, forgetting that better quality means more detail and therefore more data, longer data transfer and processing time, etc. Traditionally *map scale* was used to describe the quality of geographic data comprehensively. With the reduction in scale, expressed as representative fraction, comes automatically a reduction in detail, described as cartographic generalization. Users learned which map scales were suitable for which task: orienteering uses maps in the scale range 1:10,000 to 1:25,000; for driving from city to city, maps 1:250,000 to 1:500,000 are sufficient, etc. Repeated experiences have taught us these practical guidelines and we follow them without asking for an underlying theory. The beginning of such a theory is attempted here.

In the age of digital data, the traditional definition of scales, as proportion between distances on the map and in reality, does not make sense: locations are expressed with coordinates and distances computed are in real world units. Only when preparing a graphical display is a numeric scale is used – but, in principle, digital geographic data can be shown at any desired graphical scale, even if this often does lead to nonsense. The concept of scale in a digital world has been critically commented, but no solution suggested (Lam and Quattrochi, 1992; Goodchild and Proctor, 1997; Reitsma and Bittner, 2003). The discussion of data quality of geographic data focuses on descriptions of data quality of a single dataset, sometimes differentiating different types of digital representation (e.g., Goodchild, 1994). I want to complete this dataset viewpoint with an analysis of the process by which data is produced from observations and used in discussions about actions.

In this paper I explore the process of geographic data collection and show how scale is introduced during the observation process, and should be carried forward as a quality indication. An analysis of the properties of real (physical) observation processes reveals that physical observation processes introduce a scale into the observation. This 'scale' is not an artifact of cartography, but originates in the physical observation process itself. The same 'scale' value can later be used when considering whether a dataset can be used effectively in a decision situation (Frank, 2008).

This paper begins with a short review of tiered ontology (Frank, 2001; Frank, 2003), which is necessary for the analysis. Section 3 lists the information processes that link the tiers and gives the framework used. Section 4 discusses briefly accuracy and shows how random imperfections in the observations influence the formation of objects and the values for their attributes. Section 5 looks at scale, produced by the spatial and temporal extent of the observation as a second source of imperfection in the data. Convolution gives a formal model for this effect. The influences of scale are so defined in the process from observation to object related data.

Goodchild (1994) points to the spatial extent necessarily associated with some types of geographic data; for example "land cover" (Goodchild, 1994: 616). Unfortunately, his contribution had more impact on vegetation mapping than on spatial data quality research. The present contribution extends Goodchild's observation and states that primary observations have necessarily a scale and that the scale of derived datasets can be traced through the information processing steps. In particular, the novel contribution of this paper is: (1) identifying that the scale of data is introduced during the observation process; (2) providing a formal model that can be used to predict effects of the scale of observations on other data.

2 Tiered Ontology

An ontology describes the conceptualization of the world used in a particular context (Guarino, 1995; Gruber, 2005): two different applications use generally different conceptualizations. The ontology clarifies these concepts and communicates the semantics intended by data collectors and data managers to persons making decisions with the data. An ontology for an information system that separates different aspects of reality must not only conceptualize the objects and processes in reality, but must also describe the information processes that link the different conceptualizations and transform between them. This is of particular importance for an ontology that divides conceptualization of reality in tiers (Frank, 2001) or in object and process ontologies (Bittner and Smith, 2003; Smith and Grenon, 2004). The processes transform the data and the quality of the data; understanding and formalizing the information processes allows one to describe how the quality of the observation determines the quality of derived data.

The tiered ontology used here (Frank, 2001; Frank, 2003) starts with tier O, which is the physical reality, the real world, that "what is?", independent of human interaction with it. Tier O is the Ontology proper in the philosophical sense; sometimes Ontology in this sense is capitalized and it is never used in a plural form. In contrast, the ontologies for information systems, which are the focus of this paper, are written with a lower case o.

2.1 Tier 1: Point Observations

Reality is observable by humans and other cognitive agents (e.g., robots, animals). Physical observation mechanisms produce data values from the properties found at *a point in space and time*; $v=p(x, t)$. The value v is the result of an observation process p of physical reality found at point x and time t.

Tier 1 consists of the data resulting from observations at specific locations and times (termed *point observation*). Examples would be the temperature, type of material, or forces at a point; philosophers sometimes speak of "sense data". In GIS such observations are often realized as raster data resulting from remote sensing (Tomlin, 1983), similar to the observations collected by our retina, which performs many observations of light emanating from a point in parallel. Sensors, and sensor networks in general, also produce point observations. Many, if not most measurements performed in the world are more complex, and report attributes of objects (e.g., length, weight) and are part of tier 2. Point observations are so simple that they are assumed as functions, unlike complex measurements of object properties influenced by culture and conventions (e.g., published standards or regulations).

2.2 Tier 2: Objects

The second tier is a mental description of the world in terms of mentally constructed physical objects. Objects are regions of space that have some uniformity in property. An object representation reduces the amount of data, if the subdivision of the world into objects is such that most properties of the objects remain invariant in time (McCarthy and Hayes, 1969). For example, most properties of a taxi cab remain the same for hours, and days, and need not be observed and processed repeatedly; only location and occupancy of the taxi cab change often. The critical question is how mental objects are constructed, subjectively and in response to concrete situations.

2.3 Tier 3: Social Constructions

Tier 3 consists of constructs combining and relating physical objects to abstract constructs. These are first conventions to allow communication, which link mental objects (thoughts) with symbols [Kuhn in Navratil Semantic Engineering… ?], and second constructions like money, marriage and land ownership. Constructed reality links a physical object X to mean the constructed object Y in the context Z. The formula is: "*X counts as Y in context Z*" (Searle, 1995: 28).

Social constructions relate physical objects or processes to abstract constructs of objects or process type connected by human perception and mental object formation shaped by cultural conventions. Constructed objects can alternatively be constructed from other constructed objects, but all constructed objects are eventually grounded in physical objects.

3 Information Processes

Information processes transform information obtained at a lower tier to a higher tier (Figure 1).

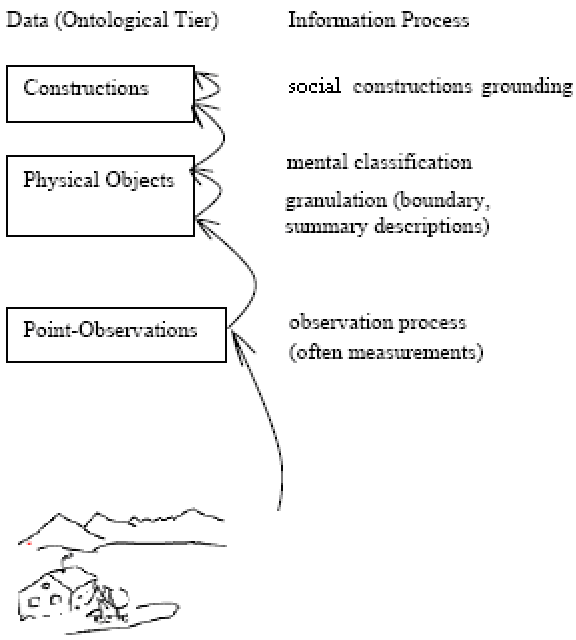

Figure 1. Tiers of ontology and information processes transforming data between them

All human knowledge is directly or indirectly the result of point observations, transformed in a chain of information processes to complex knowledge about mentally constructed objects. *All imperfections in data must be the result of some aspect of an information process.* As a consequence, all theory of data quality and error modeling has to be related to empirically justified properties of the information processes.

3.1 Observations of Physical Properties at Point

The observations of physical properties at a specific point are the *physical process* that links tier O to tier 1; the realization of observations is unavoidably imperfect in two ways:

1. unpredictable random disturbance in the value produced, and
2. observations focus not at a point but over an extended area.

A systematic bias, if present, can be included in the model of the sensor and be corrected by a function and is not considered further.

3.2 Object Formation (Granulation)

The formation of objects – what Zadeh calls *granulation* (Zadeh 2002) – is a complex process of determining, first, the boundaries of objects and, second, summarizing properties for the delimited regions. Gibson (1986) posits that humans create a *meaningful environment* mentally consisting of *meaningful things*, which I call (mental) objects. For objects on a table top (Figure 2), e.g., a coffee cup, a single process of object formation dominates: we form spatially cohesive solids, which move as a single piece: a cup, a saucer, and a spoon.

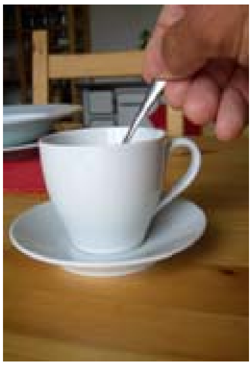

Figure 2. Objects on a tabletop

Geographic space does not lend itself to such a single, dominant, subdivision as objects typically do not move. Various aspects can be used to form regions of uniform properties, leading to different objects overlapping in the same space. Watersheds, areas above a particular height, regions of uniform soil, uniform land management (Figure 3), and so on, can all be meaningful objects in a situation (Couclelis and Gottsegen, 1997). Object classification forms groups of objects suitable for certain operations (hunting, planting crops, grazing cattle, etc.). Processes can be granulated by similar approaches in 3D plus time (Reitsma and Bittner, 2003), an important future research topic.

Figure 3. Fields in a valley

We are not aware that our eyes (but also other sensors in and at the surface of our body) report point observations. The individual sensors in the eye's retina give a pixel-like observation, but the eye seems to report size, color, and location of objects around us. The observations are, immediately and without the person being conscious about the processes involved, converted to object data, and mental processes of object formation connect tier 1 to tier 2. Most of the technical systems we use to measure object attributes hide in a similar way the intricacies of the object formation: a balance reports the total weight of the 'object', i.e., all that is placed in the weighing pane. Length measure report about comparison if length between an object of interest and a yardstick. Scheider and Kuhn (2008) describe similar, but virtual (imagined) operations related to the linguist's fictive motion (Talmy, 1996).

Object formation increases the imperfection of data – instead of having detailed knowledge about each individual pixel, only a summary description is retained. This summary may average out some of the imperfections of the point observations and the result may be more useful. Reporting information with respect to objects results in a substantial reduction in size of the data (estimations for some cases suggest a factor as high as 10^6).

Object formation consists itself of two information processes, namely, (1) boundary identification, and (2) computing summary descriptions.

3.2.1 Boundary Identification

Objects are formed as regions in 2D or 3D that are uniform in some aspect. The dominant approach is to identify surfaces and define objects as “things which move in one piece”. This uniformity in marginal coherence works for objects in tabletop space (Figure 2), but fails for geographic space because there is not one dominant way to partition the real world into objects, but several, depending on the viewpoint and situation. In order to form objects, a property that is important for the current situation is selected to be uniform. A rural field is uniform in its land cover, tabletop objects are uniform in material coherence and in their movement. Note that object formation exploits the strong correlation found in the real world; human life, would not be possible in a world without strong spatial and temporal correlation. The details of how objects are identified are determined by the interactions intended with them.

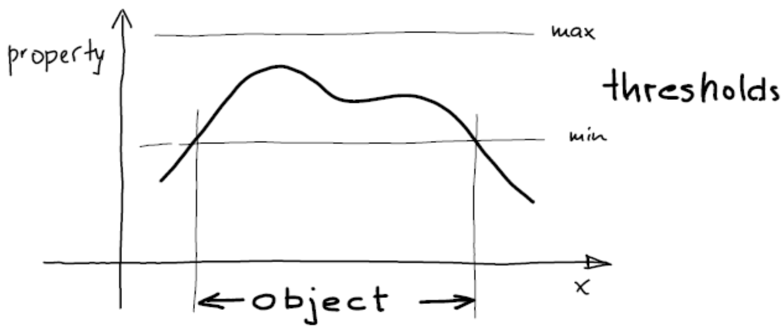

Figure 4. The property, which should be uniform within some threshold values determines the object boundaries

An object boundary is determined by first selecting a property and a property value that should be uniform across the object, similar to the well-known procedure for regionalization of 2D images. The boundary is at a threshold for this value, or at the place where the property changes most rapidly (Figure 4).

3.2.2 Determination of Descriptive Summary Data (Attributes of Objects)

Descriptive values summarize the properties of space within the object limited by a boundary. The computation is typically a function that determines the sum, maximum, minimum, or average over the region, for example, total weight of a movable object, amount of rainfall on a watershed, maximum elevation in a country (Tomlin, 1983; Egenhofer and Frank, 1986).

3.3 Classification

Objects, once identified, are classified. On the tabletop we see cups, spoon, and saucers; in a landscape, forest, fields, and lakes are identified. Mental classification relates the objects identified by granulation processes to operations, i.e., interactions of the cognitive agent with the world. Such actions are comparable to Gibson's affordances (Gibson, 1986; Raubal, 2002) when performing an action. To illustrate, to pour water from a pitcher into a glass requires a number of properties of the objects involved: the pitcher and the glass must be containers, i.e., having the affordance to contain a liquid, the object poured must be a liquid, and so on.

Potential interactions between the agent and objects, or interactions of interest between objects, assert conditions these objects must fulfill, expressed as an attribute and a range for the value of the attribute. I have used the term *distinction* for the differentiation between objects that fulfill a condition and those that do not. Distinctions are partially ordered: a distinction can be finer than another one (e.g., 'drinkable' is a subtaxon of 'liquid'), and distinctions form a taxonomic lattice (Frank, 2006).

3.4 Constructions

Tier 3 contains constructions, which are linked through granulation and mental classification to the physical objects and operations. They are directly dependent on the information processes described above, but details are not consequential for present purposes.

4. Random Effects in the Observations

A physical sensor cannot realize a perfect observation at a point in space and time. Physical sensors are influenced by random processes that produce perturbations of the observations. The unpredictable disturbance is typically modeled by a probability distribution. For most sensors a normal (Gaussian) probability distribution function (PDF) is an appropriate choice. This model is, after correction for systematic influences and bias, applicable to a very wide variety of point observations.

4.1 Influence on Object Formation

Errors in observation influence the determination of the object boundary. The statistical error of the boundary for simple cases follows from Gauss' Law of error propagation (Figure 5 does not include an uncertainty in the thresholds for graphical clarity; though the influence would be similar). The summary values are similarly influenced by random perturbations in the observations (it is likely that random effects are reduced by averaging).

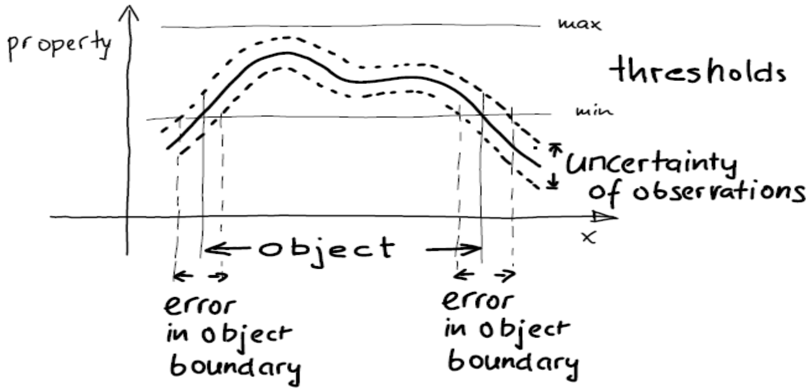

Figure 5. The influence of uncertainty in the observations creates an uncertainty in the object boundary

If the observation information processes allow a probabilistic description of the imperfections of the values, then the imperfections in the object boundary and summary value are equally describable by a probability distribution. Assuming a PDF for the property used for the determination of the boundary, one can describe the PDF for the boundary line. It is an interesting question whether the PDF transformation functions associated with boundary derivation and derivation of summary values preserve a normal distribution, i.e., if the observation processes described by imperfections with a normal distribution produce imperfections in boundary location and summary values, which are again describable by a normal distribution. Further studies may show that the effects are multiplicative and produce a Rayleigh-like distribution, or that imperfections of the processes are correlated, posing the difficult problem of estimating the correlations.

4.2 Classifications

Distinctions reflect the limits in the property values of an object, where the object can or cannot be used for a specific interaction. The decision whether or not the values for an object are inside the limits is more or less sharp, and the cutoff usually gradual. Class membership is therefore fuzzy, membership functions as originally defined by Zadeh (1974).

5 Scale in Observations

In this section the effects of the finiteness of physical observation instruments are discussed. Physical observation instruments may be very small, but not infinitely small. A sensor cannot realize a perfect observation at a perfect point in space or time. Any physical observation integrates a physical process over a region during a time. The time and region over which the integration is performed can be very small (e.g., a pixel sensor in a camera has a size of 5/1000mm and integrates the photons arriving in this region for as little as 1/5000 sec) but it is always of finite size and duration. The size of the area and the duration influences the result.

The effects of the size of the observation device is as equally unavoidable as the random perturbations of the observations, which is more widely recognized, discussed, and given a formal model (summarized in the previous section). This section proposes a formal model for the finiteness of the observation device. The sensor can be modeled as a convolution with a Gaussian of the physical reality.

The necessary finiteness of the sensor introduces an unavoidable scale element in the observations. Scale effects are not yet well understood, despite many years of being listed as one of the most important research problems (Abler, 1987; NCGIA, 1989a; NCGIA, 1989b; Goodchild *et al.*, 1999), and it is expected that the formalization given here advances this research.

5.1 Physical Point-Like Observation

The intended point-observation $v = f(x, t)$ cannot be realized, but the observation device reports the average value for a small area and a small time interval,

$$v(x,t) = \int_{-\varepsilon}^{+\varepsilon} f((x,t) + \varepsilon)\, d\varepsilon$$

where the multidimensional space-time vector value ε ranges over the size and the time interval used by the sensor (corresponding to the values of x and t). Convolution with a kernel $k(\varepsilon)$ is a formal model for the real observation at point,

$$v(x,t) = \int f((x,t) + \varepsilon)\, k(\varepsilon)\, d\varepsilon\,.$$

The value $f(x, t)$ is multiplied by the kernel value $k(\varepsilon)$, which is non-zero for a small region only around zero and for which,

$$\int k(\varepsilon)\, d\varepsilon = 1\,.$$

For sensors in cameras, a rectangular kernel or a Gaussian Kernel is assumed; the latter is optimal to satisfy the sampling theorem. Convolution with a Gaussian kernel produces an average effect on the signal.

5.2 Sampling Theorem

The sampling theorem addresses another related limitation of real observations: it is impossible to observe infinitely many points; real observations are limited to *sampling* the phenomenon of interest at finitely many points. Sampling introduces the danger that the observations include spurious signals not present in reality (aliasing). The *sampling theorem* (a.k.a. *Nyquist law*) states that sampling must be twice as frequent as the highest frequency in the signal to avoid artifacts. If the sampling rate is fixed, the signal must be filtered and all frequencies higher than half the sampling frequency cut off (low-pass filter). In the audio world the sampling theorem is well-known, but it applies to any dimension, including sampling by remote sensing or sensor network in geographical space. The sampling theorem applies to remote sensing and sensors are appropriately designed, but it is less discussed in geography and geographical information science. It may appear strange to speak of spatial frequency, but it is effective to make the theory available to GIScience, where it applies to all dimensions observed (2 or 3 spatial dimensions, temporal, etc.).

5.3 Scale of Observations

Observations modeled as convolution with a Gaussian Kernel are effectively applying a suitable low-pass filter, and produces valid results. The size of the non-zero region of the kernel *k(ε)* affects the observation result, but is not part of the physical reality observed, instead being caused by the observation system. The observations are influenced by the size of the non-zero region of the kernel. For this situation it appears reasonable to say that the observation has the 'scale' corresponding to $2\ \sigma$ of the kernel and half the sampling frequency v. A numerical description of 'scale' could use the value for σ with dimension time^{-1} (second^{-1}) and length^{-1} (meter^{-1}) respectively. If a unit of 1mm^{-1} is selected, then the numerical value is comparable to traditional map scale denominators but not dimensionless.

It is debatable whether to call this scale, adding one more sense to the close to a dozen already existing (Wikipedia lists eleven), or to use a term like *resolution* or *granularity*. I prefer 'scale' because speaking of a dataset and stating its 'scale', for example as "30'000 mm^{-1} in space and 5 years^{-1} in time", extends the current usage reasonably and describes typical topographic maps.

5.4 Effects of Scales on Object Formation

Size of smallest objects detected: the scale of the observation limits the smallest object that can be detected; objects with one less dimension than the scale are not observed, and their extent is aggregated with the neighbors. This is comparable to the cartographic minimal mapping unit. In data of a scale m one does not expect objects smaller than $f \cdot m^2$, where f is a form descriptor indicating how different an object is from a square or circle (respective cube or sphere).

Effects on uniformity: differences in property values less than the scale (for this property) are not observable, and are therefore not available when differentiating two objects; this is essentially the effect described above that small objects escape detection; the small separating object is not being observable.

Effects on attribute values: if attribute values are desired as summary values over the area of the object, the effects of the scales of observation in the property used to derive the attribute will statistically cancel – if the scale of the observation used for object formation and the property integrated is comparable. Averages (results of integrals) tend to be less extreme the larger the scale as a result of averaging in the observation process.

Effects on object classification: the scale of observation influences directly the object formation and indirectly the classification. This is most important if the class is distinct by size, e.g., small buildings vs. larger buildings.

6 Conclusions

Physical observation systems deviate in two inevitable and non-avoidable respects from the perfect point observation of the properties of reality: *random* perturbation of results, and *finite* spatial and temporal *extent* over which the observation system integrates.

Using a tiered ontology where point observations are separated from object descriptions allows one to follow how the imperfection introduced by random error and scale propagate to objects and their attributes. It was shown that precision and scale are valid descriptors of datasets, and originate with unavoidable imperfections of physical observations. Random effects are described by a probability distribution function (PDF), and the propagation of effects of random errors follow, in simple cases, Gauss' Law of error propagation; in general a transformation for the PDF is computed.

The effects of finite support for the observation can be modeled as a convolution with a Gaussian Kernel, and the non-zero extent of the kernel determines the 'scale' of the observation. The signal must be filtered with a low-pass filter to cut off all frequencies above half the sampling frequency. Convolution with a Gaussian kernel achieves this approximately.

The description here used a prototypical remote sensing observation as sensor, which produces point observations where the low-pass filter is implied in the observation system. It is recommended to investigate how the sampling theorem applies to sensor networks and other geographic observations. Well-designed observation systems are balanced such that effects of (1) random perturbation, (2) the extent of the sensors, and (3) the blur of the optical system (if any) produce imperfections of comparable size. Datasets produced by well-designed, balanced observation systems can be characterized by scales – as was traditionally done.

Geographic Information Systems are used to combine data from different sources; the theory outlined above shows how to treat cases where not all data have the same scale. In particular, it was shown how the notion of scale applies to so-called vector (object) data sets (Goodchild, 1994) and traces it back to the known methods for raster data.

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