Interactive and Automated Segmentation and Generalisation of Raster Data

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Abstract
This paper review past and current research activity in the area of generalisation of spatial data and presents a new methodological framework for segmentation and generalisation of raster data. In order to overcome drawbacks associated with supervised classification and generalisation of raster data, an Interactive Automated Segmentation and Raster Generalisation Framework (IASRGF) was developed and tested. Test results of the IASGRF shows that all objects derived from the generalisation of landuse data over Canberra, Australia, were well classified and mapped. The error assessment indicates that the percentile classification accuracy is 85.5%, whereas the commission error is relatively high (38.5%). More importantly, the maximum likelihood classifier using training sites and associated ground truth data suggests that the Kappa index is 0.798, which can be interpreted as a reliable and satisfactory classification result. In order to further enhance supervised classification, a post-classification was carried out. As a result, this extra process improved the overall classification accuracy slightly, however its commission error also increased by 6%.

1. Introduction

The motivation of this study was to develop a workflow to detect landuse features from satellite imagery and apply the concept of raster generalisation to a generalisation framework for both vector and raster data. Generalisation of Geographical Information System (GIS) data is one of the challenging tasks for cartographers. It is particularly difficult to automatically generalise thematic raster maps derived from remotely sensed data. Over the past two decades many generalisation techniques have been developed. Generalisation of vector data and a generalisation framework for road networks was discussed previously by the authors (Kazemi and Lim 2007 and Kazemi and Lim, 2005c). On the other hand, generalisation of raster data such as satellite imagery has been studied by, for example, Petit and Lambin (2001), Daley et al., (1997), He et al., (2002). Kazemi et al., (2005a) also applied three generalisation techniques (supervised classification, thematic generalisation and spatial aggregation) in order to build a raster generalisation framework known as Interactive Automated Segmentation and Raster Generalisation Framework (IASRGF) for segmentation and generalisation of satellite imagery. This paper further discusses the IASRGF, which was developed to overcome drawbacks associated with supervised classification and raster generalisation. Test results of the IASRGF shows that all objects derived by generalising landuse data from Landsat-7 imagery over Canberra, Australia, were satisfactorily classified and mapped. Raster generalisation algorithms (e.g. aggregate, boundary clean, expand, majority filter, region group, shrink, thin) embedded in a typical GIS software package can be applied to either clean up small erroneous cells/pixels such as unclassified data derived from remotely sensed imagery, or for the generalisation of raster data obtained from a scanned paper map in order to remove/smooth out unnecessary details including lines and texts or data imported from some other raster format (ESRI, 1992). The majority of existing software packages lack workflow, procedures or straightforward practical guidelines (protocols). If a cartographer's expertise and knowledge are applied to the software, many raster generalisation problems could be solved. Daley et al., (1997) compared a raster method (MapGen) and an object-oriented method (ObjectGen) to automatically generalise forests from multiple image datasets ranging from 1m to 1km spatial resolutions by segmentation of remotely sensed images (MEIS 1m, AVIRIS 20m, TM 30m, and AVHRR 1km), at corresponding resolutions to the GIS files to constrain the generalisations. MapGen is an automated raster generalisation system that is based on a set of polygon and vector generalisation rules. Each polygon rule specifies how to merge neighbouring polygons if their size is smaller than a specified minimum tolerance. In this system, feature attributes are stored in a database for fast sorting and selection. The GIS dataset used was composed of topographic data and forest cover maps, both at the 1:20,000 scale. Generalisation was carried out on

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three forest cover maps to create broad classes for deriving data with a map scale ranging from 1:20,000 to 1:250,000. It was concluded that there were no significant differences in class areas between the two generalisation methods and the original areas. Approximately a 72 percent reduction of the original input data was achieved without significant errors in class areas. However, the authors used ObjectGen and MapGen for purely research purposes and did not demonstrate the operational use of their methodology. Similarly, Cihlar et al., (1998) developed a Classification by Progressive Generalisation (CPG) procedure using fused AVHRR and Landsat-5 (30m resolution) data. It was demonstrated that CPG gave superior accuracy to other existing classification methods. They also demonstrated that CPG is user-friendly and has potential applications for other merged imagery datasets. Jaakkola (1998) also presented a rule-based generalisation methodology for generating land cover maps from raster data. It was shown that it is feasible to automatically derive small scale land cover maps from large scale data using raster generalisation techniques and map algebra. Forghani et al., (1997) applied various combinations of morphological operations (e.g. dilation, erosion, skeletonisation) to extract and generalise roads from aerial photography. However, one shortcoming of this approach was that it is computationally expensive. Also, significant testing is required to determine an optimal threshold when applying different morphological operations. Furthermore, Gjertsen (1999; cited in AGENT, 1999) at the Norwegian Institute of Land Inventory developed a workflow for the generalisation of a Norwegian national land type database that relies on the use of two generalisation processes: attribute-based generalisation (e.g. reclassification) and geometry-based generalisation (e.g. line elimination, class integration, area aggregation and area elimination). A total of 13 classes were used in the generalised classification system, and all area features were reclassified based on their attributes. It seems that this approach has the potential for operational use. In addition, Walter (2004) applied an object-oriented classification of multispectral remote sensing data using a supervised maximum likelihood classification. A GIS database was used to derive training areas to update topographic maps at 1:25,000 scale. However, it was not clearly explained how generalisation was used to update the topographic database. In another study, Wenxiu et al., (2004) developed a knowledge-based generalisation of landuse maps for scales 1:10,000 to 1:50,000 using Arc/Info's generalisation tools. Two generalisation knowledge sources were used, including general knowledge (e.g. geometric and topological, GIS analyst's knowledge and experience on generalisation operations and GIS data management), and thematic knowledge (e.g. terrain knowledge, application-based knowledge). A series of rules, including rules of feature selection, attribute transformation, and rules for merging features, were employed. Although this research focused on vector generalisation it provides some constructive ideas on the integration of expert human knowledge. He et al., (2002) investigated effects of rule-based spatial aggregation index and factual dimension techniques on classified Landsat-5 imagery in an attempt to compare the effects of majority and random rule-based aggregations when examining the distortions introduced by data aggregation with regard to cover type quantities and landscape patterns. The findings indicate that these spatial aggregation methods over a broad range of spatial scales (30-990m) lead to different outcomes in terms of cover type proportions and spatial patterns. The rule-based aggregations resulted in distortions of cover type percentage areas reported in other studies (e.g. Moody and Woodcock, 1995). In contrast, using random rule-based aggregations did not distort the results significantly. This is superior to the majority rule-based aggregations; hence this technique is a promising tool for scaling data of fine resolution to coarse resolution while retaining cover type proportions. Notwithstanding the extensive research that has been undertaken, there are still intractable problems regarding these approaches which often make them impractical in an operational environment. Fully automated generalisation of raster and vector data has still a long way to go. Meanwhile, to meet current map production requirements for generalisation of raster data, a common approach is to classify imagery with the application of a trained image analyst / cartographer's knowledge, to reclassify and recode that classified data, and to then apply statistical and spatial filtering methods.

2. Study Strategy

A schematic representation of the research methodology is presented in Figure 1. This research complements a previous study (see Kazemi and Lim, 2005b) in which ArcGIS generalisation capabilities were tested. The framework is based upon parameters presented in Daley et al., (1997) and Petit and Lambin (2001). However, all the processes in the flowchart are considered specifically for raster generalisation using both Leica Geospatial ERDAS IMAGINE and ESRI ArcGIS systems.

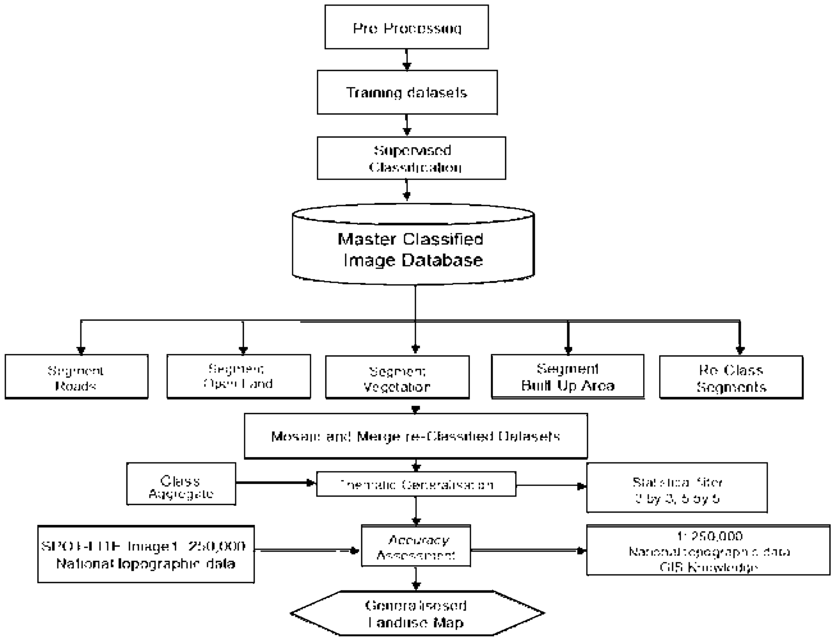

Figure 1: A flow diagram showing the strategy used to segment and generalise raster data

Figure 2: Study area, Canberra, Australian Capital Territory (ACT) Australia.
(Data courtesy Geoscience Australia © 2001)

These provide generalisation functions through a variety of algorithms and operations on raster data. Various functions, such as the maximum likelihood classification, filtering, aggregate, merge algorithm, with a variety of parameters, have been tested. Image segmentation applies both spectral information (feature vector of the pixels) and spatial information (size, shape, texture, contextual information and adjacency to other pixels) to detect appropriate segments / classes within a given image. In this study Landsat-7 imagery acquired over Canberra (Figure 2) was pre-processed and segmented into 19 landscape themes, each containing several sub-classes, forming a total of 10 classes in the master image database. The road class was firstly derived from the pixel-based classification because, at a resolution of 30m, and the geometric linear characteristic of the object, the road consists of many pixels and needs to be verified with existing ancillary GIS data (e.g. 1:250,000 national topographic data, Landsat-7 imagery). Similar themes based on the landuse category were collapsed and, thereby, generalised. Problematic features (e.g. residential buildings and industrial buildings, roads and building roofs) which exhibit similar spectral characteristics were then reclassified. This was done through on-screen digitising of the problematic features based on the GIS analyst's knowledge and the ancillary information (e.g. existing topographic maps, street directory road maps). These features were then subtracted from the master classified database followed by reclassification of each of the subset datasets. Also, existing roads were buffered and rasterised. In a later step, the reclassified subset databases were mosaiced with the master database to form the final segmentation thematic map. Finally, thematic generalisation was applied.

2.1 Data Pre-Processing

Because data could come from disparate sources and often the user has limited knowledge of the source, it is essential to perform some validation and testing of data prior to starting generalisation. Topology validation, geometric feature validation and feature attribute quality checks were performed on the 1:250,000 national topographic roads data which was used in this study.

2.2 Generalisation Methods

Three techniques were used to control the properties of the generalised data which should be distinguished:

2.2.1 Supervised classification: was used to group objects, using an object-oriented segmentation method, into several landscape themes, each containing several sub-classes, forming a total of 19 classes. Similar classes were combined to form a total of 10 land cover categories.

2.2.2 Thematic generalization: was used to merge the derived classes, on the basis of similarities in their landscape characteristics. It is difficult to automate this process due to its complex, diverse and non-deterministic nature, particularly when attempting to effect a subjective and intuitive procedure (i.e. when, where and how to generalise).

2.2.3 Spatial aggregation: was applied to raster data to aggregate cells on the basis of their spatial neighbourhood. Experience shows that this method is particularly applicable to the treatment of land cover (Moody, 1998 and Petit and Lambin, 2001). The buffered road data was rasterised at the closest resolution (30m) to the ETM+ resolution, and was gradually aggregated with a majority filter. In this way, generalisation of cluttered features becomes an easy task.

2.3 Supervised Classification

The objective of multispectral image segmentation is to segment the image into spectrally homogeneous regions. Multispectral image classification is categorised into two main approaches: whether supervision from an operator is required or not. The GIS or image analyst closely controls a supervised classification process by selecting pixels that represent known landscapes. Obviously, the analyst uses GIS data and ancillary information (e.g. ground truth data, existing landuse data, SPOT-4 data, etc) to facilitate the classification. In this process the analyst trains the machine to recognise the similar patterns (pixels) or homogeneous regions that represent each class. Defining a set of desired classes is an integral part of the process and it is possible to define as many classes as required. Then an appropriate strategy is selected for assessing the information in the available data, and to make decisions for labelling classes. The spectral signatures of landscape types might be confirmed by reference to ground data (e.g. Foody, 2002 and Wang et al., 2004) or by the analyst defining the classes by interactive extraction of training areas (Leica, 2004). These spectral signatures are then used to classify all pixels comprising the image. The supervised technique is well documented in the literature and is the most popular multispectral classification method (Richards, 1986, Johnson, 1994 and Petit and Lambin, 2001). Among the most popular supervised classifiers are minimum distance, parallelepiped, and maximum likelihood. A maximum likelihood algorithm estimates the likelihood of a particular pattern belonging to a category. One of the advantages of the maximum likelihood classifier (MLC) is that it is easy to use and theoretically guarantees minimisation of the classification error. This is the most widely employed classification algorithm for digital classification of imagery (Bolstad and Lillesand, 1991, Trietz et al., 1992, Johnson, 1994 and Forghani et al., 2007). The MLC technique was used in this study for image classification as it takes into account spectral descriptions for classes modelled using multivariate Gaussian densities (Yang, 2007). In this work the training areas were selected with the use of area-of-interest tools and stored in a Signature Editor file. The result of this supervised classification of the ETM+ imagery is presented in Figure 3. In built-up areas, problematic features such as roofs, streets, and pavements, exhibit similar spectral reflectance and this increases misclassification errors. To overcome this problem and to improve the classification success rates, several classes were initially selected and assessed by available GIS datasets. Maximising the number of training areas helps to minimise confusion between similar features and decreases the misclassification rate.

2.4 Image Reclassification

The main concern in this research is to map out the landuse classes.

The buffered road map in raster format was used as control data. The segmented data was then compared to the existing roads map and landuse data to assess the classification accuracy. Later, spectral classes with similar cover types were merged to form 19 classes. The resulting modified signature file was applied to perform the MLC using a standard deviation of 2. Then finally, a map was produced showing 10 classes (see Table 1).

2.5 Thematic and Spatial Generalisation

Raster-based generalisation of Landsat ETM+ imagery land cover data using statistical filtering available in ERDAS IMAGINE and the aggregation operation tool of ArcGIS is shown in Figure 3. These tools provide raster map algebra methods that resample raster map layers using various aggregation techniques such as averaging and interpolation of raster map layers. The input raster layer was generalised so that each raster cell covers an area of 30 x 30 meters on the Landsat imagery. Aggregate is a generalization function applied for raster data. A similar function called 'dissolve' that is used for polygon themes stored as vector data. The 'dissolve' function removes borders between polygons having the same value for a given attribute.

Table 1: Descriptions of landscape classes from ETM+ data supported by a GIS database

[redacted]		
	1, 2	Water
	3, 4, 5	Bare land
	6, 7	Agriculture
	8, 9	Grasslands
	10	Shrublands
	11,12	Forests
	13,14	Commercial and industrial areas
	15	Residential areas
	16, 17, 18	Roads
	19	Other

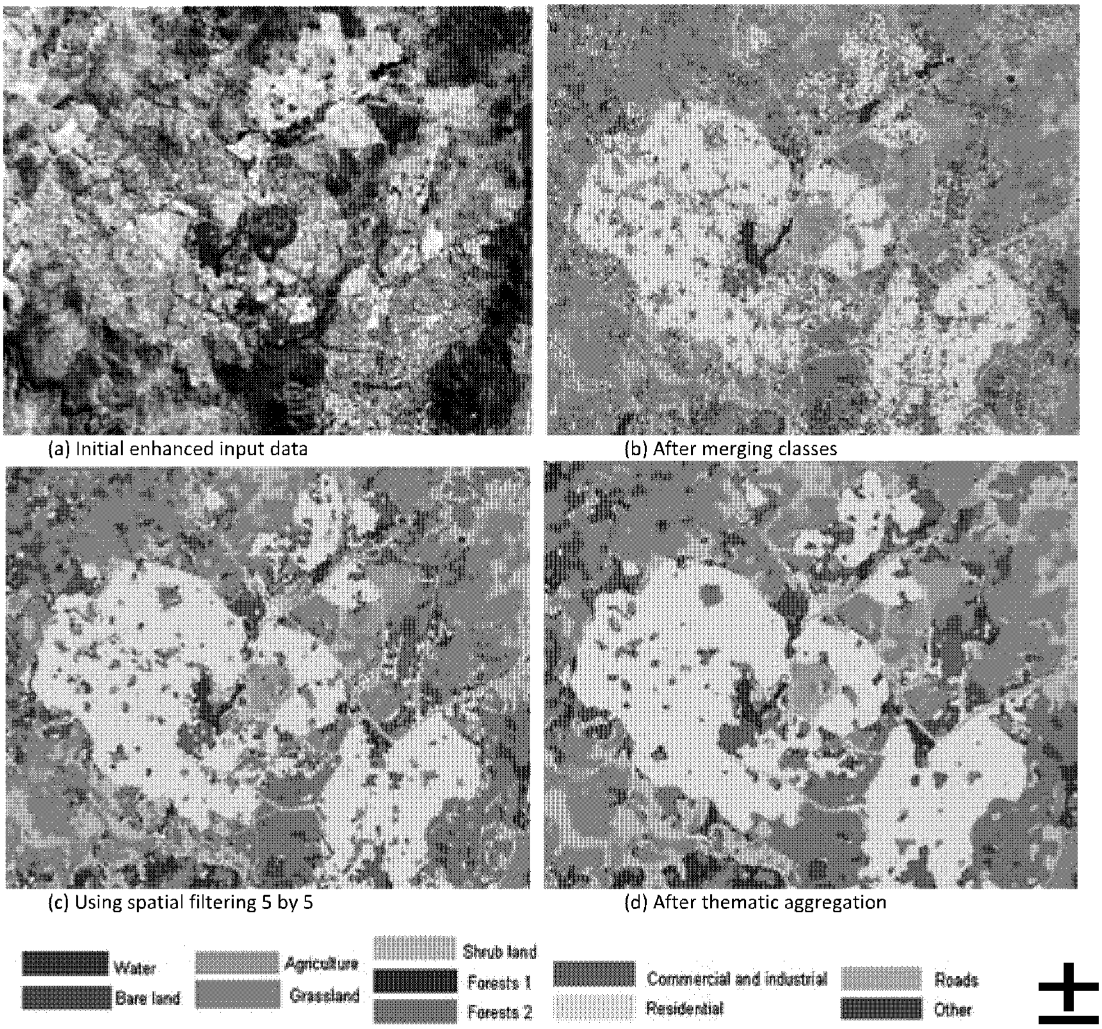

Figure 3: Comparison of classification and generalisation outputs.
(Data courtesy Geoscience Australia © 2001)

3. Discussion

It is important to gauge the accuracy of the segmentation method. To evaluate output of the proposed raster classification and generalisation framework, the accuracy of the final segmentation and generalised map was visually evaluated by superimposing the road buffer layer and other landuse data over the classified image. Also, the segmented image was numerically compared to the existing landuse map using coincidence matrices and accuracy measures. Mapping man-made features in a heterogeneous environment such as a built-up area is problematic since the roads and other man-made structures (e.g. buildings) exhibit similar spectral characteristics. Bare soils, dirt roads, tracks, and roofs have very similar spectral signatures. The confusion of these features with roads is clearly demonstrated. Overall classification accuracy was 85.5 percent. In Table 2, the accuracy measures (Kappa coefficient, overall classification accuracy, producer and user's accuracy, commission and omission errors) corresponding to the various classes are presented along with the error matrices for supervised classification of Landsat ETM+ data. Gurney (1981) indicated that when an automated classifier is used over an urban area, errors increase considerably. The results demonstrate that approximately 85.5 percent of all objects were correctly classified. The results were validated by calculation of the pixel-by-pixel accuracy. The certainty and uncertainty of the classified pixels were validated for the study area. The accuracy for classification and generalisation of man-made structures increased over rural areas, as the image exhibited a greater contrast between the roads and other elements. The estimated overall accuracy based on the reference map agreed with the overall visual interpretation of the output. To demonstrate the quantitative assessment of image segmentation, the classification accuracy, omission errors and commission errors for each class were computed and presented in a confusion matrix (Table 3). This approach to image segmentation accuracy evaluation is widely documented in the literature (e.g. Harris and Ventura, 1995 and Wang et al., 2004). Ton et al., (1991) described the omission errors as the omitted pixels in the classification process divided by the total number of pixels in the land cover type, whereas the commission error represent pixels labelled as the land cover type by the algorithm but not by the ground truth data. The classification accuracy of a land cover type is defined as the number of correctly classified pixels divided by the total number of pixels in the land cover type. It is clear that classification accuracy plus the omission error should sum to 100 percent. The commission error is considered as a separate statistic.The accuracy assessment presents the overall accuracy, Kappa, commission (% of extra pixels in class) and omission (% of pixels left out of class) errors, producer accuracy and user accuracy for classified image. The confusion matrix results demonstrate how each of the accuracy assessment is derived. The maximum likelihood classifier using training sites and associated ground truth data produced an overall accuracy of 85.5% and a Kappa coefficient of 0.798. Cohen's Kappa coefficient statistical measure (κ) is considered to be a robust measure for the uncertainty associated with spatial information (Hope & Hunter, 2007). While there are no absolute cut-offs for the Kappa coefficient, 0.7 or higher is widely accepted as a satisfactory value. In this study, the Kappa value for the classified image was 0.798 indicating that an observed classification is in agreement to the order of 79.8 percent. This value indicates a substantial agreement based on the Kappa categories by Landis and Koch (1977). The overall accuracy is defined as a percentage of the test-pixels successfully assigned to the correct classes. The overall classification accuracy decreased in areas where the roofs of buildings, bare soils, concrete, and tracks roads have very similar spectral characteristics. This problem can be related to increasing noise due to the heterogeneous nature of the spectral response of urban areas (Gerke and Heipke, 2008) and cleared agricultural lands. Similar classification accuracy has been reported using maximum likelihood classifier with identification of six broad cover types over a rural/urban area from SPOT and TM data (Welch, 1985, Moller-Jensen, 1990 and Barr, 1992).

Table 2: Image segmentation accuracy summary statistics

[redacted]						
	4	1	99	96	100	
0.798	18	12	88	84	82	
	17	9	91	80	87	
	21	7	93	83	79	
	32	13	87	87	85	
	24	5	95	95	87	
	60	25	75	79	78	
	63	19	81	82	75	
	74	33	67	79	74	
	65	20	79	83	86	

Table 3: The confusion matrix results generated from classified data and reference ground data

[redacted]											
	95	0	1	2	0	2	0	0	0	0	100
	0	86	2	0	0	0	3	4	0	5	100
	0	4	85	1	3	5	0	0	0	1	99
	0	0	6	76	5	3	0	0	0	2	92
	0	0	0	1	90	1	0	0	0	3	95
	0	0	3	2	4	85	0	0	0	1	95
	0	0	0	0	0	0	74	13	8	4	99
	0	0	0	0	0	0	8	78	4	2	92
	0	0	0	0	0	0	0	3	84	2	89
	0	5	3	1	0	0	3	10	4	69	95

Note: Wa = Water, Ba = Bare lands, Ag = Agriculture, Gr = Grasslands, Sh = Shrublands, Fo = Forests (1 & 2), Co = Commercial / industrial, Re = Residential, Ro = Roads, Ot = Other

Accuracies in the range of 55-81% have been reported. To enhance the supervised classification results, post-classification was carried out. It was found that this improved the overall classification accuracy slightly, but commission errors also increased (by 6%).

4. Conclusions

The aim of this study was to develop a new methodological framework for segmentation and generalisation of raster data. The Interactive Automated Segmentation and Raster Generalisation Framework (IASRGF) can be used to map out features from satellite imagery using an object segmentation and database generalisation approach. Three methods – supervised classification, thematic generalisation and spatial aggregation – were used to test the raster generalisation framework by applying the methodology to the integration of GIS data and remotely sensed data to segment landuse classes. The study demonstrated the usefulness of an image segmentation technique for deriving landuse categories. This framework can serve as a practical methodology to segment Landsat-7 or similar datasets over urban and rural areas where traditional image classification methods fail to deliver satisfactory results. It is suggested that the methodology can be tested further for multiple scale generalisation through the integration of different satellite images from fine resolution to coarse resolution.

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