DATA MINING TECHNIQUES AND GEOBIA APPLIED TO LAND COVER MAPPING

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ABSTRACT:

This article is committed to evaluate the performance of a semantic network generated by data mining for the classification of land cover using GEographic Object-Based Image Analysis (GEOBIA) in a tropical mountainous area. The study area corresponds to the Nova Friburgo County, with an extension of 933 km², located in the region of the Fluminense Ridge, presenting thus a steep mountainous relief. Based on a visual interpretation of the images, eight land cover classes were defined: rockies, forest, grasslands, sparse grasslands, burn scars, reforestation, shadow, and urban areas. The dataset used for data mining was composed by 130 attributes and by 225 training samples accounting for all land cover classes. The algorithm C4.5, implemented in the software Weka 3.6.4, was employed for the data mining procedure. The following attributes were selected by C4.5: NDVI, fourth principal component, second angular moment, homogeneity, entropy, and slope. The obtained global accuracy was 88%, and the Kappa index reached 0.81. Only the class 'urban areas' presented omission errors greater than 50%, being confused in some cases with sparse grasslands, forest, and burn scars. In view of the obtained value for the Kappa index, we can state that the classification presented an excellent accuracy according to a rating scale specially elaborated for such index.

1. INTRODUCTION

The traditional techniques for the classification of remotely sensed images consist either of pixel-per-pixel or region-based approaches, focussing on the targets spectral peculiarities in order to extract thematic information. In the GEOBIA domain, pixels are grouped in segments acknowledged as objects, according to their spectral properties and taking into account geometrical characteristics of the generated segments, so that such objects become the primitive entities for classification (Navulur, 2006). In a diverse way from the traditional classifiers, which solely use spectral information to identify the probable class to be assigned to each element of analysis, GEOBIA takes into account a wide range of information extracted from objects. In this way, besides spectral properties, objects own manifold attributes (descriptors), associated with their shape and geometric characteristics, texture, contextual and semantic relationships between classes belonging to the same or any other level of segmentation, which can be used for image analysis in a way to resemble human cognitive processes for image interpretation (Navulur, 2006; Marpu, 2009; Camargo et al., 2009a).

GEOBIA basically consists of two methodological stages: (1) segmentation, a technique used to regionalize the scene into multiple disjunct objects; and (2) classification based on decision rules, which reveal the objects properties expressed by their attributes (Navulur, 2006; Lang, 2008). The segmentation algorithms subdivide an image into regions or segments, reducing its level of detailing and complexity, since it is now formed by objects (Lang, 2008). The object corresponds to a discrete region of an image that is internally coherent and at the same time different from its surroundings (Castilla and Hay, 2008).

Segmentation is followed by the creation of an object-based knowledge model, which is represented as a hierarchical semantic network, responsible for storing the interpreter´s knowledge on the study area and guiding the objects classification. During the knowledge model construction, the following issues must be observed: (a) appropriate definition of classes and subclasses according to the segmentation level; (b) selection of adequate attributes for the objects classification (spectral, texture, morphological, topological), which are inherited by the corresponding subclasses; and (c) determination of the fuzzy membership functions (curve design and thresholds) (Mavrantza and Argialas, 2008). Blaschke et al. (2008) suggest that the focus of GEOBIA must lie on the development of intelligent geographical databases, which gather applicable information for a given geographical context.

The construction of a semantic network is one of the most important stages in an object-based classification. Nevertheless, it is also an effort consuming task due to the difficulty in selecting the best set of attributes, among an enormous amount of attributes that can be extracted from the objects and that appropriately describes the classes to which such objects belong. The semantic network can be elaborated heuristically by the human interpreter, who interactively and iteratively tests the attributes, functions and thresholds for a proper discrimination of classes, or in an automated form, through the application of data mining techniques. These techniques consist in the extraction of knowledge from a huge database by means of intelligent methods. One of the models available in the realm of data mining is the decision tree, represented as a flowchart resembling the structure of a tree and which can be easily converted in classification rules (Han and Kamber, 2006).

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The strength of GEOBIA lies on the fact that objects provide a massive database for classification (Marpu, 2009). Since objects correspond to a grouping of neighboring pixels, it is possible to extract for each them statistical parameters and other attributes related to their properties. Thus, a set of attributes is associated to each object, which, in the case of spectral properties, correspond to the statistical treatment of the pixels digital numbers, and in the case of texture properties, to the mathematical manipulation of the digital numbers spatial distribution in each object.
In the case of images generated by mathematical transforms of spectral bands, like principal components or vegetation indices, or of any other raster data, like discrete numerical grids (thematic maps) or continuous ones (e.g. digital elevation models - DEM, slope, temperature, etc.), the pixel digital number does not correspond to spectral properties, but rather to the value derived from a mathematical operation, or the value associated with a thematic class, or the value corresponding to the magnitude of the event being represented. In this way, the original attributes resulting from the statistical treatment of the digital numbers are denominated as statistical properly speaking, and may correspond to the mean, standard-deviation or variance of spectral values, indices and magnitudes, depending on the input data subject to the statistical manipulation.
The texture of targets found on the Earth surface, which corresponds to the spatial distribution of the digital numbers of an image, is one of the most important characteristics used for interpretation. However, it is not easy to be described (Haralick et al., 1973; Marpu, 2009). The advantages of applying texture information on targets of medium spatial resolution has been demonstrated in several studies (Dekker, 2003; Dell´Acqua and Gamba, 2003; Riedel et al., 2008). Haralick et al. (1973) proposed the calculation of texture metrics through the Gray Level Co-occurrence Matrix - GLCM and created 14 parameters characterizing texture. This method extracts texture by means of the spatial relationship existent among the digital numbers in several directions. According to Ito et al. (2011), due to its simplicity and effectiveness, it is regarded as a reference method by many authors worldwide.
This article aims at evaluating the performance of a semantic network meant for an object-based land cover classification generated by data mining. For this purpose, this network consists of statistical attributes, resulting from the statistical treatment (mean and standard-deviation, in the particular case of this work) of the digital numbers belonging to each object, as well as of texture attributes, calculated by the GLCMs according to the method of Haralick et al. (1973).

2. MATERIAL AND METHODS

The study area is the Nova Friburgo county, which extends over a surface of 933 km², sheltering a population of 182 thousand inhabitants (IBGE, 2011a). It belongs to the Rio de Janeiro State, southeast of Brazil, between the geographic coordinates 22º08’ and 22º28’ S; 42º44’ and 42º11’ W. The county is located on a geomorphological unit named as Reverse Plateau of the Fluminense Ridge Region, and presents steep mountainous relief, with altitudes ranging from 400 to 2,300 m, and hence, it is highly prone to landslides and erosive events in face of the high steepness of its slopes associated with the expansion of economic activities in this region (Dantas, 2001). The highest and steepest areas, due to their constrained accessibility, maintain the Atlantic Forest in good preservation conditions.
The land cover mapping in Nova Friburgo was based on the application of GEOBIA in the Definiens Developer 7.04. This platform contains different segmentation algorithms, like the multiresolution or FNEA algorithm, and classifiers, including the nearest neighbor and fuzzy logic.
The multiresolution segmentation algorithm generates objects according to homogeneity criteria in different levels of scale, which can then be grouped or subdivided into further objects in new levels (Definiens, 2007). When it is applied to a database with a pre-existing segmentation level, it will merge objects at higher levels into coarser superobjects, or subdivide them into finer scale subobjects at lower levels, what enables the creation of a hierarchical network connecting all segmentation levels.
The homogeneity criteria used in the multiresolution segmentation are set based on the combination of the pixels spectral properties (color) and the shape of the generated objects. The shape and color parameters sum to one and respectively determine the extent to which color and shape information is used in the segmentation process. The shape parameter is additionally subdivided into compactness and smoothness. A high value of compactness leads to smaller and very compact segments, and hence, is more suitable for man-made objects, while a high value of smoothness leads to segments optimized to have smooth borders, which are on their turn more suitable for natural objects (Kressler and Steinnocher, 2006).
The scale factor is an important parameter employed by the multiresolution segmentation algorithm and it estimates the average size of objects to be created (Definiens, 2007). The higher the value assigned to this parameter, the bigger the size of the generated objects, and hence, the fewer the objects to be created.
A weight must be as well assigned to the input images, according to their degree of importance in the segmentation process. This weight ranges from 0 to 1, and the greater its value, the bigger the importance granted to the respective input image is (Definiens, 2007).
The platform WEKA 3.6.4, developed by the University of Waikato, New Zealand, was used for data mining. This open source software presents a collection of learning algorithms, consisting of pre-processing, classification and regression tools, besides grouping and association rules, which can also be directly applied to the input dataset (Hall et al., 2009).
The database comprised orbital images and relief data. The images were acquired in August 2009 by the ALOS/AVNIR-2 sensor, with a spatial resolution of 10 m, corresponding to three bands in the visible range and one in the near infrared range, pansharpened with the panchromatic image of the ALOS/PRISM sensor, with a spatial resolution of 2.5 m. The relief data were obtained from the geomorphometric database TOPODATA, resulting from the processing of SRTM (Shuttle Radar Topography Mission) data provided by USGS (United States Geological Survey). This processing aimed at filling sinks and refining the original data, yielding digital elevation models (DEM) with 30 m of spatial resolution (Valeriano, 2005).
The basic stages of the experiment reported in this paper are described in the following subsections, comprising the database preparation, images segmentation, generation of the hierarchical semantic network, land cover classification and validation.

2.1 Database Preparation

The database preparation consisted in the ALOS images and DEM processing. The multispectral bands were pansharpened with the panchromatic band, and the four resulting bands were subject to mathematical transforms.
Since the rational polynomial coefficients (RPC) of ALOS

images are exclusively provided for data obtained in the Asian continent, 40 ground control points (GCPs) were collected on orthophotos with 1 m of spatial resolution covering the study area at a 1:25,000 scale (IBGE, 2011b) in order to orthorectify the AVNIR (70 x 70 km) scenes. The elevation was extracted from the SRTM data (Jacobsen, 2005; Richter and Teichert, 2008). For the PRISM image (70 x 35 km), 20 GCPs were employed. The orthorectification was executed in ENVI 4.7, also using sensor attitude and ephemeris data obtained from the ALOS technical support team.

The next step was the pansharpening of AVNIR-2 and PRISM images using the Gram-Schmidt method, available in ENVI 4.7. This method consists in the simulation of a panchromatic band from the multispectral bands, and the application of the Gram-Schmidt transform to the set of multispectral bands and the simulated panchromatic band. After that, an inverse transform is accomplished, replacing the first band by the simulated panchromatic image. The Gram-Schmidt method presents greater accuracy than the Principal Components Analysis - PCA, for the former one uses the sensor spectral response to simulate the panchromatic band (ENVI, 2009). In the work of Pinho et al. (2005), the authors evaluated pansharpening methods applied to QuickBird images. They concluded that the Principal Components and the Gram-Schmidt methods, when applied to the four multispectral bands, presented the best results, although the latter one showed a comparative superiority. In the work reported in this paper, the authors as well acknowledged the spectral fidelity of the Gram-Schmidt method in a true color composition of the pansharpened bands when compared to the same composition of the original multispectral images.

These pansharpened bands yielded new images resulting from the application of PCA and the conversion of the RGB into the HLS (Hue - H, Lightness - L, Saturation – S) system. The Normalized Difference Vegetation Index – NDVI was also extracted from such bands. All derived images were delimited by the study area boundaries and resampled so that all of them presented the same spatial resolution of 2.5 m. All these procedures were executed in ENVI 4.7.

Following these procedures, the slope grid was generated using the TOPODATA DEM and the *3D Analyst* module of ArcGIS 9.0. Both the DEM and the slope grids were delimited by the study area boundaries and resampled to 2.5 m. The database was then composed by 14 layers: four pansharpened multispectral bands of ALOS, four principal components - PC, three components HLS, NDVI, DEM and slope grid.

2.2 Images Segmentation

Three consecutive levels of segmentation were generated with the progressive reduction of the scale factor at each new level, containing an ever increasing number of objects of smaller sizes. Due to the spatial resolution and the morphometric configuration of the targets of interest in the images used for land cover classification in this work, the spectral parameter or color tended to be more important for segmentation than the shape parameter. For this reason, in all of the three segmentation levels, 0.1 has been assigned to the shape parameter, and consequently, the color parameter was set to 0.9, for they are complementary. The compactness and smoothness parameters were established heuristically, according to the diversity of classes found in the scene. Since targets of more regular geometry were present in the study area, like urban areas, burn scars, agricultural plots and reforestation areas, as well as targets with irregular boundaries, like forest, grasslands and sparse grasslands, and rockies, the value 0.5 was ascribed to the compactness parameter, and hence, smoothness was set to the same value, since they are complementary.

For the second and third levels of segmentation, the weight value of 1.0 was assigned to the unique input image - NDVI, as a means to separate objects with vegetation from those with no vegetation at all. In the first segmentation level, the four pansharpened multispectral bands were used, aiming at discriminating the diverse types of targets existent in the scene and selected for classification.

2.3 Generation of the Hierarchical Semantic Network

The land cover classes were initially established based on a visual analysis of the pansharpened images, and were later adjusted in an iterative way as a function of the preliminary classification results. Eight land cover classes were defined: rockies, forest, grasslands, sparse grasslands, burn scars, reforestation, shadow, and urban areas.

In total, 225 samples were collected for training the decision tree algorithm, accounting for the eight land cover classes, what approximately corresponds to 30 samples per class, excluding the class burn scars, since it presents a reduced area, and hence, a limited number of objects.

The initial dataset for data mining, comprising statistical and texture attributes extracted from the first and finest level of segmentation, was generated in Definiens Developer 7.04. After the importing procedures, the input dataset was subject to a preliminary filtering (for removing noise and inconsistencies) executed in Weka 3.6.4, presenting 130 attributes (Table 1).

Attribute (or Descriptor)	Type	Total
Mean	Statistical	16
Standard-deviation		12
GLCM 2nd Angular Moment	Texture	27
GLCM Contrast		28
GLCM Entropy		30
GLCM Homogeneity		17

Table 1. Attributes used for data mining

For the calculation of the texture attributes, executed in the Definiens Developer 7.04, the GLCMs proposed by Haralick et al. (1973) were used. As previously explained, this approach extracts texture by means of the spatial relationship existent among the digital numbers in several directions. Among the available 14 texture parameters, four of greater relevance were used (Baraldi and Parmiggiani, 1995; Ito et al., 2011):

- Second Angular Moment or Energy – measures the uniformity of texture, i.e. the amount of repeated pairs of pixels. High values indicate that the distribution of grey levels is constant, occurring a great repetition in the variation of the digital numbers. For a normalized matrix, the values are either positive or smaller or equal to 1.
- Entropy – assesses the disorder in an image, corresponding to an inversely proportional measure to the second angular moment. High values indicate that the image does not own a uniform texture.
- Contrast – corresponds to the difference between the highest and lowest values of a set of neighboring pixels. High values of contrast are associated with images composed by digital numbers of great amplitude, i.e. with a rough texture.
- Homogeneity – measures the homogeneity of an image. High values correspond to small tonal differences between

adjacent pixels. This parameter is inversely proportional to the contrast and energy.

The classification rules derived from data mining were set by the C4.5 algorithm, created by Quinlan (1993) and implemented as the tree.J48 classifier in the Weka 3.6.4 platform. This algorithm builds decision trees based on training samples and through a recursive procedure of data partitioning. The trees are expressed as a flowchart, where each internal node executes a test with a given attribute, the branch (or arc) represents the test result, and the external node (or leaf) accounts for the expected class. For each node, the algorithm chooses the best attribute to separate the data in individual classes. The attributes that are not included in the tree are regarded as irrelevant (Han and Kamber, 2006). If the number of samples and/or their class descriptive ability are not appropriate, the decision tree will incorrectly classify many objects. Big trees tend to data overfitting, while very small trees end up by missing important attributes of the data. The algorithm always strives to produce less complex and smaller trees, for they are more easily understandable and show a better performance. For this end, it uses entropy in order to assess to what extent the node is informative. Small entropy values mean that less information will be used to describe the data (Silva, 2006).

2.4 Land Cover Classification

The decision trees for land cover classification generated in Weka 3.6.4 were implemented in the Definiens Developer 7.04 platform, through the conversion of the decision rules provided by the trees into crisp thresholds of hierarchical semantic networks. Several classifications were generated based on decision trees taking into account statistical and texture attributes. The selected decision tree was the one that presented at the same time a logical structure and a good classification result, which was then subject to statistical validation.

2.5 Assessing the Land Cover Classification Accuracy

In order to assess the land cover classification accuracy, 1,400 random points were collected through stratified sampling based on the share of the expected areas of each class. A minimum number of 50 samples per class was observed, as defined by Congalton and Green (2009), for maps covering surfaces smaller than one million acres and containing less than 12 classes. Such samples referred to pixels so as to precisely avoid the bias that would occur in case the objects were selected as samples, given their great variation in their size. However, due to the reduced area of some classes, it was not possible to observe the minimum number of samples for all of them.

Having the information of reference and assigned class to all samples, it was then possible to elaborate an error matrix, which is composed by reference samples in its columns, according to the information extracted from the orthophotos of Project RJ-25 (IBGE, 2011b), and by classified samples in its rows according to the classification result. The orthophotos were produced by an aerophotogrammetric survey accomplished in 2005, with a spatial resolution of 0.7 m and at an approximate scale of 1:30,000, and they were used to solve eventual interpretation conflicts. The authors did not discard the information that could be visually extracted from ALOS images, which effectively guided the identification of the reference samples classes.

The error matrix indicates the omission errors, which correspond to samples that were not classified according to the reference samples, and commission errors, related to samples erroneously classified as belonging to other classes. Based on the errors and agreements of this matrix, the following indices were calculated: (a) global accuracy - relation between the number of correctly classified samples and the total number of reference samples; (b) producer´s accuracy – related to the omission errors, corresponding to the relation between the number of correctly classified samples of class *k* and the total number of reference samples of class *k*; (c) user´s accuracy - associated with commission errors, which refers to the relation between the number of correctly classified samples of class *k* and the total number of classified samples of class *k*; (d) Kappa index (K); e (e) conditional Kappa index (Congalton and Green, 2009).

3. RESULTS

3.1 Land Cover of Nova Friburgo

Figure 1 presents the decision tree that was trained based on the set of statistical and texture attributes and used for the land cover classification in Nova Friburgo (Figure 2). Ouf of the initial 130 attributes belonging to the input dataset, the data mining algorithm selected the following ones: NDVI, fourth principal component (PC 4), second angular moment, homogeneity, entropy, and slope. The decision tree structure is as follows:

• Initially, the tree is divided into two major branches using the NDVI information.

• In the left branch, classes with the lowest values of NDVI were discriminated, like those ones with no or very sparse vegetation: sparse grasslands, shadowed areas, burn scars, rockies, and urban areas.

• The right branch, with greater NDVI values, comprised forest, reforestation, and grasslands.

• In the left branch, the second angular moment was used to classify urban areas. This attribute measures the uniformity of texture, and values closer to 1 indicate homogeneous targets, i.e. those with uniform texture (Baraldi and Parmiggiani, 1995). This explains the low threshold value established to extract urban areas.

• In the third level of this branch, shadow was classified based on entropy, which values correspond to uniform texture when low.

• In the following level, the NDVI was used to classify burn scars, differentiating them from sparse grasslands and rockies, for the former class presents the lowest NDVI values, since there is no trace of vegetation on a recently burnt terrain. In the case of rockies, the presence of rock vegetation is common, what explains the fact that their NDVI values are bigger than the ones presented by burn scars.

• In total, 19 samples of sparse grasslands were classified by the highest values of the NDVI homogeneity, while the remaining samples were separated from rockies for presenting the lowest values of slope, what indicates that rockies are found on the steepest slopes.

• In the right branch, the greatest values of the NDVI homogeneity classified sparse grasslands.

• In the immediate lower level, reforestation was discriminated from forest by the fourth principal component. According to Mather and Koch (2011), the last principal component highlights the contrast between the visible and the infrared bands. This is precisely the case of the reforestation class, which shows a high correlation among all visible bands, which own a low response on average, and a high response in the near infrared band, even higher than the one presented by forest.

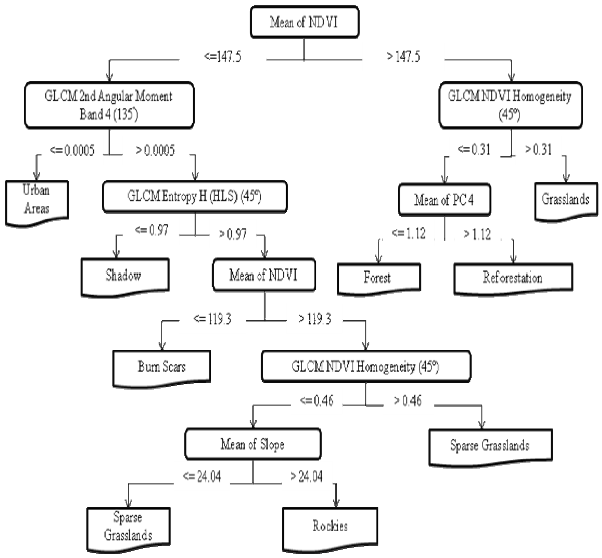

Figure 1. Decision tree generated by the C4.5 algorithm

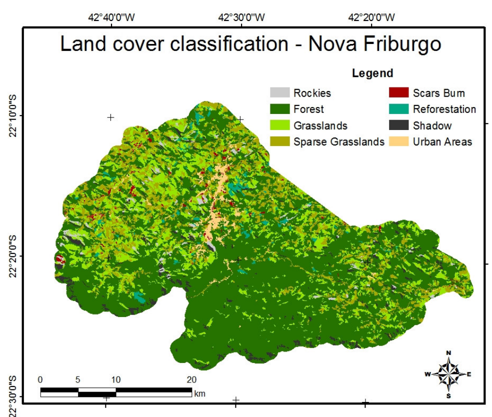

Figure 2. Land cover classification – Nova Friburgo, RJ, Brazil

3.2 Land Cover Classification Accuracy

The obtained global accuracy was 88% and the Kappa index attained 0.81 (Table 2), regarded as of excellent quality according to a qualitative rating of Landis and Koch (1977). Only the class 'urban areas' presented omission errors greater than 50%, being confused in some cases with sparse grasslands, forest, and burn scars. On the other hand, this class did not present commision errors, i.e. the user´s accuracy reached 100%. The classes grasslands and burn scars, on their turn, presented low user´s accuracies, due to the reported confusion with urban areas.

The values for the user´s conditional Kappa index lay between 0.38 and 1.00, while for the producer´s conditional Kappa, these values ranged from 0.45 to 0.96. The worst performance was observed for the classes burn scars and sparse grasslands, which respectively obtained 0.38 and 0.50 for the user´s conditional Kappa index. Regarding the producer´s conditional Kappa index, the worst performance was attained by the urban class, with a value of 0.45.

4. CONCLUSIONS

Considering the global Kappa index, it is possible to state that the generated classification presented an excellent accuracy according to a special ranking established by Landis and Koch (1977). The land cover classes, when individually evaluated by the conditional Kappa index, showed an accuracy varying from very good to excellent, since the great majority of the obtained indices lay over 0.60.

This work demonstrated the importance of including additional information other than purely spectral for the discrimination of land cover classes. In this particular case, slope was able to differentiate two classes which presented similar spectral and texture response, as it was the case of rockies and sparse grasslands, discriminated in the last branch of the decision tree with the aid of such geomorphometric attribute. In operational terms, the elaboration of the semantic network by means of data mining proved to be advantageous, for allowing the automation of both the attributes selection and the decision rules definition, demonstrating hence to be less vulnerable to the interpreter´s subjectivity. Moreover, this classification approach allows the reapplication of the hierarchical semantic network in further areas with similar characteristics as to the existing types of land cover classes and their spatial configuration (Camargo et al., 2009b).

Table 2. Error matrix of the land cover classification

Class		Reference Samples								
		Ro-ckies	Forest	Grass-lands	Sparse Grass-lands	Burn Scars	Refo-resta-tion	Sha-dow	Urban Areas	Total Classi-fied
Classification	Rockies	20			1	1		3		25
	Forest		418	12			2		7	439
	Grasslands	4	4	78	3		4			93
	Sparse Grasslands	4		7	30				16	57
	Burn Scars	1				7		1	9	18
	Reforesta-tion		1				15			16
	Shadow	1	2					41		44
	Urban Areas								28	28
Total Collected		30	425	97	34	8	21	45	60	720
Producer´s Cond. Kappa		0.66	0.96	0.78	0.88	0.87	0.71	0.91	0.45	Kappa Index
User´s Cond. Kappa		0.79	0.88	0.81	0.50	0.38	0.94	0.93	1.00	0.81

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