Social Specialization of Space: Clustering Households on the French Riviera

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ABSTRACT
The aim of this paper is to estimate the extent of social specialization of residential space within the French Riviera metropolitan area. Unlike classical approaches, where social groups are pre-defined through given characteristics of households, our approach determines clusters of households inductively. Socio-demographic characteristics of households are thus measured through 16 different indicators. Clustering is then carried out through the optimization of two distinct criteria. Simulated annealing, simple and multi-objective Genetic Algorithm were adapted for this purpose and has produced pertinent results.

Categories and Subject Descriptors
H.2.8 [Information Systems]: Database Applications—Data Mining, Spatial databases and GIS; I.5.3 [Pattern Recognition]: Clustering; J.4 [Computer Applications]: Social and Behavioral Sciences—Sociology

Keywords
NSGA-II, Simulated Annealing, Metropolitan Areas

1. INTRODUCTION
Social specialization of residential space within an urban area is the concentration of households according to some characteristics like social status, demographic characteristics, ethnicity, etc. in certain urban subspaces. Understanding the logic of social specialization is of course crucial in order to define policies like urban planning or housing.

Geographers have traditionally used two approaches in order to study social specialization of urban space. The first is to pre-select social groups defined along lines of social status, ethnicity and position in the life cycle. Spatial concentration of these groups is later analyzed in order to detect eventual segregation patterns within the city. The second approach aims at characterizing the content of the resident population of neighborhoods without targeting a specific social group but by taking into account the whole population and all descriptors of households at the same time. Unlike these classical approaches, we want to both determine spatial concentration of specific groups of population in the urban space and to take into account all descriptors of households at the same time. This poses the problem of clustering households according to two conflicting criteria: maximum homogeneity of human content and maximum spatial difference within the metropolitan area. Classical clustering can not be directly applied due to optimization of two conflicting criteria. This is the reason why we adapt an evolutionary and a simulated annealing algorithm and apply them to a data set of households of the French Riviera extracted from the CERTU Household Mobility Survey of 2008.

2. OUR FRAMEWORK
Given a set of $n$ households $I = \{x_1, \ldots, x_i, \ldots, x_n\}$ where $x_i = \{x_{i1}, \ldots, x_{ij} \}$ represents the $j$-th household, and each $x_{ij}$ represents its $i$-th feature value. We name $w_i$ the weight associated with the $i$-th attribute and $coem_j$ the weight corresponding to the $j$-th household in the sample.

In this paper we consider the clustering based on medoids: each cluster $C_{i \in 1..k}$ is defined by a center $m_i \in I$. One common measure used for clustering is the intra-cluster distance between medoids and items and can be defined as:

$$Intra(C) = \frac{\sum_{i=1}^{k} \sum_{x_j \in C_{i \in 1..k}} w_i \cdot coem_j \times d(m_i, x_j)}{\#I}.$$  

(1)

where $d \in [0,1]$ represents the distance between two items weighted by $w_i$. Moreover, $\#I = \sum_{j=1}^{n} coem_j$. In the following the cardinality of a subset $A \subseteq I$ will be the sum of the $coem$s of the items it contains, i.e. $\#A = \sum_{x_j \in A} coem_j$.

However, the minimization of equation 1 is not sufficient to determine clusters of households that are spatially opposed within the metropolitan area. In order to ensure that socio-demographic differences among clusters also correspond to...
s
a state
respond to the medoids of the cluster. The neighborhood of choosing NBLOOP
ble with other strategies, we perform 400000 evaluation by
medoids in SA, a state is a vector of different clusters identified within the metropolitan population
weighted average of Duncan and Duncan index over the dif-
metropolitan space. Our Weighted Dissimilarity Index is a
tion that should move in order to spread it evenly within the
spatial difference in sectors of residence, we create a new
criteria based on dissimilarity index by Duncan and Dun-
now to project clustering results in geographic space in or-
determination which categories of population are most opposed
from a spatial point of view. The produced results seem in
good agreement with expert knowledge of the social struc-
der to see what the ID values of the different clusters mean
at the expense of cluster internal heterogeneity.

3. EXPERIMENTS
Simulated Annealing (SA) [4] and Genetic Algorithm (GA)
have been adapted for optimizing a single objective combining
both criteria using $f(S,C) = \frac{WDI(S,C)-Internal(C)}{2}$. For SA, a state is a vector of $k$ distinct elements of $I$ that
correspond to the medoids of the cluster. The neighborhood of a state $s = \{c_1, \ldots, c_k\}$ is obtained by switching one of the medoids in $s$ with an item in $I$. In order to be comparable
with other strategies, we perform 400000 evaluation by choosing $NBLOOP = 2000$ and $NBSTEP = 200$. We fix $t_0 = 0.1$ and $r = 0.995$, $s_0$ is chosen randomly. Results are depicted in figure 1(a). For GA, a medoid-based represen-
tation clearly explained in [3] is used with reset mutation, tournament selection of size 10, a population size of 200 and a one point crossover. We then adapted NSGA-II [1] where objectives are considered independently.

4. DISCUSSIONS
Socio-demographic content of clusters extracted from Para
to front obtained by NSGA-II (PF17, PF12,PF48) is an-
alyzed and presented in figure 1(b). Colors represent both
household configuration and social status of the average clus-
ter profiles in every solution. The combination of the five
configurations with the four social strata produces twenty
cases possible. A few additional cases account for particular
profiles. Cluster labels G0-G9 are followed by the Dissim-
ilarity Index (their weighted average gives the WDI value) and the cluster share within the total population. Interme-
diate Pareto front solutions are robust as WDI grows. For
every configuration of households, two different social posi-
tions are normally identified. However, only PF17 identifies a cluster of couples (sometimes with children) of medium-high social status. Particular profiles with higher DI are de-
picted by PF12 and PF48: couples of retirees of low social
status and very segregated single retirees in social housing, respectively. Extreme solutions on the Pareto front are less
interesting and even less pertinent when WDI is maximized
at the expense of cluster internal heterogeneity.

5. CONCLUSION AND FUTURE WORK
For understanding social specialization on the French Riviera, we have adapted an NSGA-II algorithm and proposed a framework for clustering with a double optimization scope: minimizing intra-cluster distances and maximizing Weighted Dissimilarity Index seems to us the only way to empirically

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