Agent Technologies for Post-Disaster Urban Planning

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ABSTRACT

Urban planning is a complex decision making process which must compensate for the various interests of multiple stakeholders with respect to physical, social, and economic constraints. Despite growing interest in using A.I. in urban design and planning this community remains a field dominated by human experts. Recent catastrophic disasters such as hurricane Katrina, however, have underscored the need for increased automation and more efficient urban design processes. One particularly urgent decision making in post-disaster urban planning is that of finding good locations for temporary housing. As an illustrative example of the potential of agent technologies in post-disaster planning contexts we propose an agent-based decision support system that can identify good candidate locations for a specific purpose. We showcase an application of our decision support system in pre-disaster mode that identifies a set of ideal locations for potential revitalization. We then discuss how this system can be extended to solve a problem of finding good locations for temporary housing in post-disaster mode. Our preliminary experimental results show promising potential of using agent technologies towards solving real life problems in the urban planning domain.

Categories and Subject Descriptors

[**Decentralized agent-based architecture**]; [**Multiagent learning**]

Keywords

Urban planning, decision support systems, machine learning, intelligent survey

1. INTRODUCTION

Recent catastrophic disasters have brought urgent needs for diverse technologies for disaster relief. In this paper we explore opportunities of A.I. research for solving real-life problems in aid of post-disaster recovery and reconstruction. Among various complex problems in post-disaster situations we mainly focus on reconstruction of the community, specifically from the urban planning perspectives.

Urban planning is a complex decision making process which must compensate for the various interests of multiple stakeholders with respect to physical, social, and economic constraints. Planners need to collect and thoroughly analyze large amounts of data in order to produce robust plans towards both short-term and long-term goals. This is normally a careful and time-consuming task, due in part to limited financial resources but also because design decisions often generate cascading effects contingent on both pre-existing physical urban structures and future design decisions. Resolving the conflicting interests of multiple entities has been an important issue in urban design decision making. Particularly in the post-disaster planning case, understanding persisting local constraints as well as the issues newly introduced by the crisis is a key to a successful recovery and reconstruction plan, i.e., a good coordination among various stakeholders is a necessity. In reality, however, a lot of necessary coordination is conducted only at a superficial depth. Due to limited time and resources, many important decisions are made by high level officials and various stakeholders' responses are collected subsequently, often through hasty paperwork.

Although agent-based modeling is gaining popularity in urban planning research community [12, 2] little has been done for domain experts to recognize benefits of utilizing agent technologies in this domain, and this domain still remains a field strictly dominated by human experts. Recent catastrophic disasters such as hurricane Katrina, however, have underscored the need for increased automation and more efficient urban design processes.

In pre-disaster mode planning tasks are ordered by priority and resource availability and only a small number of tasks are handled at a time. In the post-disaster situation, however, an overwhelming number of high priority tasks are produced overnight and planners must make thousands of complex decisions in a very short time. Various types of new and updated information, such as damage assessment and resource availability, arrive in an arbitrary order and decisions must be made dynamically. It is unlikely that all of the necessary information is available at the time of decision making, thus decision support systems that can provide timely data estimation and inference capability are desperately desired.

One good example of the kind of decision making that could benefit from the timely assistance of autonomous agents is the problem of finding good locations for temporary housing after crisis. Location hunting is a complex constraint optimization problem that must compensate for various case-specific local constraints as well as a set of well-defined legal constraints, such as NEPA (National Environmental Policy Act) guidelines. Due to the urgency of the task and limited resources, candidate selection is hurriedly made, paying little attention to many crucial local constraints.

In this paper we focus on the specific task of location finding in urban planning as our initial target problem. In particular, our system model is based on *urban typology* practice, which is a typical methodology in the urban planning decision making process that classifies urban components according to their various structural and socioeconomic aspects. We present an agent-based framework that utilizes machine learning for intelligent decision support in this domain, and consider applications for both pre-disaster and post-disaster urban planning problems. First, we present an example application of finding good locations for potential revitalization in urban planning in pre-disaster mode. Our preliminary experiments show promising results that agent-based approach can boost the performance of urban planning. We then propose how to apply the same framework to the problem of finding good locations for temporary housing in post-disaster mode, and discuss further issues situated in a distributed environment of a larger scale disaster management.

2. DISTRIBUTED DECISION SUPPORT SYSTEMS

An agent is an autonomous entity that can make decisions through its own reasoning process. The reasoning criteria can be as simple as a set of precoded rules, or a complex utility function to be used to trade off various options. In the problems of interest in our research the purpose of an agent system is to assist human users in such a way that the agent acts as if it is a shadow play of its human master by learning the user's decision criteria.

An assistant agent that is customized to a specific human user can perform certain tasks on behalf of the user. For example, calendar management agents can free up busy users so that the users can spend time more efficiently on serious tasks. CMRadar [10] is a distributed calendar scheduling system wherein individual CMRadar agents assume responsibility for managing different user's calendars and negotiate with other CMRadar agents to schedule meetings on their users' behalf. A CMRadar agent learns its master user's scheduling preferences using passive machine learning algorithms only through observing several meeting scheduling episodes.

Unlike the meeting scheduling problem, where each participant is treated more or less equally important, many important decisions are made exclusively by a group of authorities in post-disaster mode due to the urgency of pressing issues. Many case studies emphasize the importance of involving local community residents in decision making[13], thus efficient methods of incorporating local objectives and constraints have been sought. We propose a distributed de-

cision support system that can provide better insights to decision makers by learning representative decision models for a specific issue by means of an intelligent survey system. Whereas personal assistant agents have convenient access to the user's daily activities that provide training data for passive learning methods, a representative agent system must actively participate in learning process in order to collect geographically distributed training data. In the next section we illustrate a high level architecture of a representative agent system.

3. REPRESENTATIVE AGENTS

Diverse interest groups are involved in the urban planning decision making process. In pre-disaster mode, we consider four major groups of people: urban planners (designers), government officials or other related authority groups, investors, and community residents. It is often true that the voice of actual community residents is weak due to two main reasons: 1) lack of a representative organization, and 2) difficulty of collecting their broad needs and constraints. Common ways of collecting such opinions are passive methods such as voting and surveying. In pursuit of a better balance among various stakeholder groups, e.g., by raising the voice of community residents, it would be ideal to have representative agents that can quickly learn the decision model of a group of people given a specific issue, e.g. whether a given location is a good site for temporary group housing.

A survey is a traditional method of estimating the opinions of a large group of people by asking predefined questionnaires to a group of randomly selected people. A survey provides a snapshot of collective opinions of a group for a specific issue, but often limited to high-level questionnaires. We attempt to induce more general decision criteria for location specific issues by linking a survey with physical and socioeconomic information that is associated with the region under consideration.

We have designed RAISE (Representative Agents in Intelligent Survey Environment), an agent-based survey system that learns a representative model of a large group of people for a location specific issue. We aim to take advantage of vast amounts of local information available from various GIS information sources and high-performing machine learning algorithms to efficiently utilize such data in conjunction with an intelligent survey system. As opposed to using static questionnaires we also use an active learning algorithm that interactively chooses more informative examples as the next questions to ask to guide the learning process.

Figure 1 illustrates a high level architecture of RAISE. The target problem of RAISE is supervised learning in a distributed environment which contains two distributed subproblems: 1) data is distributed in multiple sources, and 2) labeling is conducted by multiple people through various types of user interface.

RAISE provides two types of agents, information agents and survey agents, in order to address each subproblem, respectively. Information agents collect data from various sources to produce a data set that can be used by the learning component. A large amount of urban planning data is available in GIS (Geographic Information System) data format from
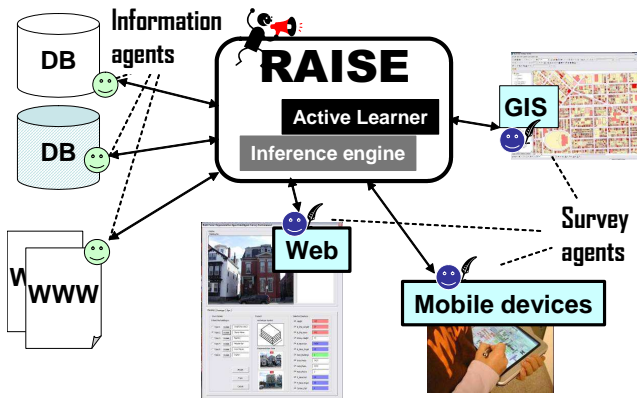
Figure 1: RAISE (Representative Agents in Intelligent Survey Environment) architecture

various information sources. GIS is a powerful tool that integrates a geographic map with semantic information using a multi-layered structure. Internally, these layers of information is stored in a relational database.

The most crucial task of RAISE information agents is data integration from multiple information sources. For instance, if some subsets of information sources need to be aligned multiple information agents must coordinate with one another in order to produce a seamlessly integrated data set. In addition, agents must be able to learn to recognize more reliable information sources because some information sources may contain conflicting data.

Another important class of agents are survey agents. From the learning component's perspective survey agents are the entities that provide correct labels for a given unlabeled data example. The level of expertise varies depending on subject groups participating in a survey. The way of presenting a data example as a question in a survey to human subjects is an important user interface research issue. For instance, just a set of numeric values in raw form is obviously not a good representation of an architectural component, such as a building, even to domain experts.

Community residents might be able to identify a given entry just by the name of a building or visual information such as a picture of the building. They make decisions using their local knowledge as opposed to what the system presents as features. In other words, the features used by non-expert users are unknown to the system. Hypothetically, we assume that the feature space modeled based on domain knowledge can represent a decision model that is equivalent to the user's decision model containing hidden features. We illustrate this issue again in section 4.1 using another example.

Domain experts, such as urban planners, would want to see more detailed information in addition to what is needed for mere identification, e.g., land use code, number of tax entries, whether the building is used for multiple commercial purposes, etc.

- Location of temporary housing
- Sitting of temporary business location
- Sites for dumping disaster debris
- Road closure and reopening
- Bridge closure and reopening
- Restoration of critical infrastructure
- Permitting the reoccupation of damaged homes

Table 1: Short-term decision making issues

The necessity of decision support systems in this domain is far greater in post-disaster mode than normal mode due to the importance of safety issues and urgency of emergent tasks. The target problems we try to solve using RAISE after a crisis are short-term planning solutions with careful consideration of long-term reconstruction goals. Some examples of short-term decision making problems are listed in Table 1. In this paper, we target a specific example of short-term decision making problems: location hunting. For instance, one of the most urgent problems in post-disaster situation is identifying a set of good sites for temporary manufactured housing such as trailers. Since temporary housing sites tend to remain longer than the initially intended period, the location must be carefully chosen and must not interfere with long-term reconstruction.

The short-term issues in Table 1 are directly related to community's daily activities thus it is crucial to incorporate community residents' opinions. Ironically, those people who actually live in the community are often ignored when a decision is being made. In hope of raising the voice of community residents we propose an agent-based system, RAISE, that collects data from multiple information sources and learns a representative decision model of community residents in the form of an interactive survey.

4. URBAN DESIGN PLANNING PROBLEMS

The integrated perspective of form and function in urban studies is not an innovative notion. In fact, it has been the core subject of urban matters for a long time [5], Previous work, however, has primarily focused on one dominant aspect of either form or function from a particular view point, e.g. architecture, psychology, sociology or economics. Furthermore, the range and definition of form and function varies according to diverse disciplines. For instance, while architects regard form as three dimensional shape of space and building components in the intimate detail, economists rather view it as two dimensional shape of cartographic plane at the regional or national scale. Architects consider function as activities in individual building spaces and the in-betweens, whereas policy makers consider function as performance of parcel or zone in the whole system of the city.

Resolving multiple views has been an important issue in urban design decision making. The urban design profession contributes to shape the city through designing physical structures; however, it has generally been an execution of

form-based policy in this respect [1]. Recognizing the importance of considering interdisciplinary aspects of a problem, urban designers have developed methodological frameworks to investigate urban morphology in a manner that combines interdisciplinary aspects [11]. Our research contributes to this effort, by applying AI techniques to develop improved representations and methods for reasoning about urban design issues in an integrated fashion. We focus on an important methodological framework, *typology*, which represents the understanding of urban settings by classification based on present architectural and socioeconimic elements [5].

In general, urban typology analysis is a long term project that requires careful data analysis and field studies. For instance, the ARTISTS (Arterial Streets Towards Sustainability) project in Europe was developed to identify types of streets in order to provide better insights to urban planners and economists. This 2.2 billion euros budget project involved 17 European countries and took three years to classify five categories of streets [15]. Their major contribution includes statistical analysis of street functions and summarization of results in a two-dimensional classification table that can be used as a general decision criteria. Although their classification rules were drawn from statistical analysis human experts were the main forces of this project. The experimental results show how they classified 48 streets into 5 categories based on their decision rules. Our attempt is to carry out similar classification task but in an automated way using machine learning techniques in the hope of assisting decision makers heavily loaded with urgent tasks.

We project a typical typology analysis into a simplified three-step process: data analysis, field study, and decision making. Among these three steps, the field study is the most expensive procedure in terms of both labor cost and time. Our experiment shows potential usage of machine learning techniques in urban typology problems. We also stress that active learning algorithms are especially beneficial by reducing the number of labeled examples in training phase. In practice, this means labor cost is reduced by avoiding less informative field studies.

Supervised machine learning techniques have been successfully applied in various domains such as text categorization [17]. Most of machine learning algorithms expect data to be a well defined set of tuples, but in reality this is rarely the case. For example, if data is stored in relational database with multiple tables the data must be preprocessed into a giant single table. Building an inference network from a relational database is an interesting area of research [7] and we also anticipate that our future work may be in this area. For the sake of simplicity we assume in what follows that we already have the data formatted into a set of tuples in our experiments.

4.1 Modeling
Modeling an urban typology as a machine learning problem is based on two important assumptions: 1) a set of relevant features that define an input to a learning algorithm are known in advance, and 2) data that describe the features are a well-structured set of vectors. Applying machine learning algorithms to a well defined set of data is a straightforward task. However, a major difficulty of formulating urban ty-
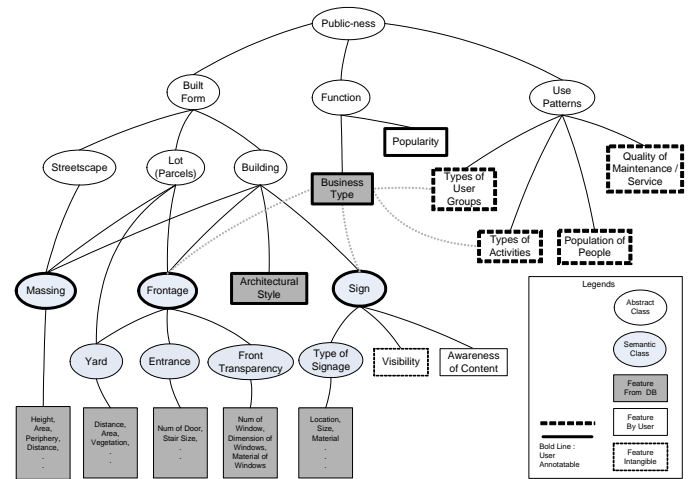

Figure 2: Features determining public-ness of urban component

pology into a machine learning problem resides in feature space modeling and compiling a set of relevant data.

The human experts' elicitation of relevant features is often vague and incomplete. We exemplify a modeling of feature space in Figure 2. This example depicts the feature dependency graph that represents a perception of publicness. Public-ness is a meaningful concept in urban design and relates to how people perceive whether a given urban component is public or private. We modeled this example based on a survey that was given to both domain experts and non-experts. Although this example does not directly address our specific target problem of location finding the features in the graph, such as Massing, are commonly used as urban decision criteria, and thus they are relevant to our discussion.

Among these features the entries that are drawn in bold-face in Figure 2 are the set of features that users considered important in decision making. Because the system can only recognize well-structured data, e.g., features stored in databases, only the features shown in grey are included in our model. This example illustrates our modeling assumption that domain experts' model of relevant features are often abstract semantic concepts that depend on descriptive features that are available in low level databases.

Massing, for instance, is a feature that differentiates buildings by their structural size information. In our information sources Massing is represented as multiple features, height, area, periphery, distance to nearest neighbor, etc. Our survey result also reveals the existence of hidden features that are completely isolated from what is available in low level database. These hidden features were denoted by intangible features in the picture, e.g., features related to "Use Patterns". We learn from this example that a majority of features in a human user's model are abstract concepts, whereas the system only has access to low level databases. We make a specific assumption that abstract concepts that human experts consider relevant in fact depend on low level

Common features	number of buildings, land use, building height, perimeter, lot size, stories, shape length, shape area, gross area, living area
Main Streets	parcel business type, built year, renovation year
Temporary Housing Site	cost, past land use history

Table 2: Available features for site selection

features in databases. We also assume that the system has access to such domain specific information sources. The challenge then is to infer the mapping from low level features to abstract concepts.

5. FINDING MAIN STREETS

This section describes our preliminary experiment on a prototypical example of location finding process to demonstrate the efficiency of using A.I. techniques in this problem domain. We chose the specific problem of identifying a certain type of urban setting, *Main Streets*, based on architectural and socioeconomic features of its vicinity. Although this may appear a semantically different problem we note that post-disaster location hunting is conducted through a similar procedure when selecting potential candidate sites suitable for different purposes. Some examples of common features that are used for site selection for different purposes are listed in Table 2[1] .

The concept of Main Street Approach is introduced from the city revitalization projects dated back in 1970s, which was an attempt to identify commercial districts that have potentials for revitalization. The idea behind this wave was to combine historic preservation with economic development to restore prosperity and vitality to downtowns and neighborhood business districts. Suffering from declined prosperity against the regional mall and rapid urban development [8], Main Street became the major issue of community planning. The criteria of choosing a right commercial district varies from city to city, thus it is hard to find a generalized set of rules to distinguish Main Streets from rest of districts. Since one cannot apply one standard that works on a city to another a local organization is entitled to perform their own data analysis for each city.

The Main Street approach is, as many urban design subjects are, usually pursued in partnership between public and private sectors. For instance, the city of Boston has the Main Street program in the department of neighborhood development in the city hall. Such a team of public sectors collaborates with private sectors, e.g., local Main Street directors who are usually elected or hired by the community. In a city or regional level, the Main Street is a vital strip within the whole vessel network of the city. At the same time, the Main Street is the center of the local area in a local neighborhood level. Since each Main Street has unique characteristics and problems identified by the neighborhood in which it belongs, it is important to understand and identify the local context of the community. Additionally, along with the consideration of historical preservation, the Main Street

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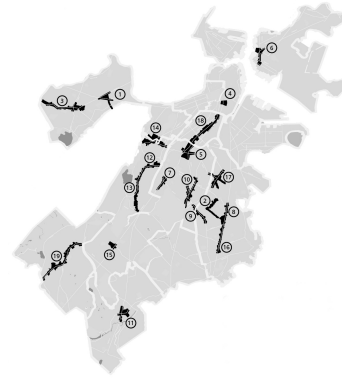[1]This list contains only the features that are available through local GIS information sources.

Figure 3: Main Streets in Boston, Massachusetts

approach conveys reallocation of existing architectural and socioeconomic resources, as opposed to urban renewal, in the neighborhood.

Accordingly, Main Streets raise an important issue that stems from the complexity of communications among multiple actors. The set of actors involved in Main Street design process includes city officials, local directors, design professionals, communities, developers, investors, etc. The key to a successful Main Street design lies in resolving diverse interests and constraints of multiple actors from architectural, social, economic, and historical perspectives. We propose a systematic way to work out the "multiple views" problem of urban typology by providing an intelligent decision support system that can learn various actors' typology decision criteria.

We investigated Main Streets in the city of Boston for this study (Figure 3). Boston provides an ideal testbed for evaluation because a complete set of ideal districts were already identified as Main Streets by field experts. We used relational database tables exported from GIS information sources that are available from the city of Boston. The data was then preprocessed to be suitable for general classifiers. Initially we started with two database tables: buildings and parcels. Note that a data entry in these tables represents a building and a parcel, respectively, whereas our target concept, Main Streets, is defined as a district which is usually composed of several hundreds of buildings and parcels.

First, we applied unsupervised learning methods to group buildings and parcels into a set of candidate districts. We used a single-linkage clustering algorithm in which every data point starts with a separate cluster and merges with the closest neighboring cluster until a given proximity threshold is satisfied. The proximity threshold was chosen empirically to generate reasonable size clusters.

Our algorithm for identifying district candidates consists of two clustering steps. Since the backbone of Main Streets is a strip of commercial buildings we first clustered buildings that are associated with commercial land use code in order to retrieve strips of commercial buildings. At this step, small clusters that contained less than 5 commercial buildings were filtered out. In the second step, the commercial

strips identified in the first step were treated as a single cluster when the second round of clustering started, i.e., the set of initial clusters in the second round was the union of commercial strips, non-commercial buildings, and all of parcels. The number of buildings and parcels in the resulting district candidates were in the range of hundreds.

For simplicity, we used Euclidean distance between the two centers of buildings as the distance measure. In order to refine cluster boundaries we need to incorporate more accurate separator data, e.g., geographic obstacles such as mountains or rivers, and man-made obstacles such as bridges and highways. This will be an interesting topic for a future work. Using a raw data set containing 90,649 buildings and 99,897 parcels (total around 190,000 data points) our algorithm identified 76 candidate districts. Each candidate cluster corresponded to one data row for a classifier, and aggregated characteristics of a candidate cluster, such as average height of the buildings, were used as features.

In our initial experiment, we tried a set of classifiers to determine the best-fitting classifier in our particular problem solving. Among a set of Decision Trees, a Nave Bayes classifier, a kNN (k-Nearest Neighbors) classifier, and an SVM (Support Vector Macine) classifier, an SVM classifier best performed [17][2]. In general, SVM is considered one of the best performing classifiers in many practical domains. Despite SVM's high quality performance users outside A.I., such as designers, tend to prefer Decision Trees or generative models due to the fact that their results are more comprehensible. As a proposed resolution for explaining SVM results to human users we learn a decision tree that is equivalent to the learned SVM classifier in terms of classification results on the test set. That is, after training an SVM classifier using a set of training data the system labels the remaining set of data with SVM's prediction. Finally we train a decision tree using the original set of training data plus the remainder of data labeled by the learned SVM.

Interfacing a classifier with human users introduces many interesting research issues in both ways, i.e., from human users to classifiers and from classifiers to human users. For instance, difficulty of explaining the rationale of classifier to human users is described in the SVM example above. It is also an interesting issue how to tell the system domain expert's "tips". One simple way is to generate simulated training examples based on the rules given by human experts and retrain the system using augmented training data.

Labeling is an expensive process in this domain because labeling one district requires thoughtful analysis of huge data and it further involves field study. This cost-bounded domain constraint leads us to favor learning algorithms that work well with relatively small number of training examples. One such idea is active learning in which learning system actively chooses the next training example to be labeled. We took Tong and Koller's approach over SVM [16]. The basic idea is to suggest data points that are near the separation boundary, which is quite intuitive and is also proven to be very effective in other practical domains such as text classi-

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[2]Due to limited space we omit formal definitions of various classifiers and refer to Yang's work [17] that extensively evaluates various types of classifiers.
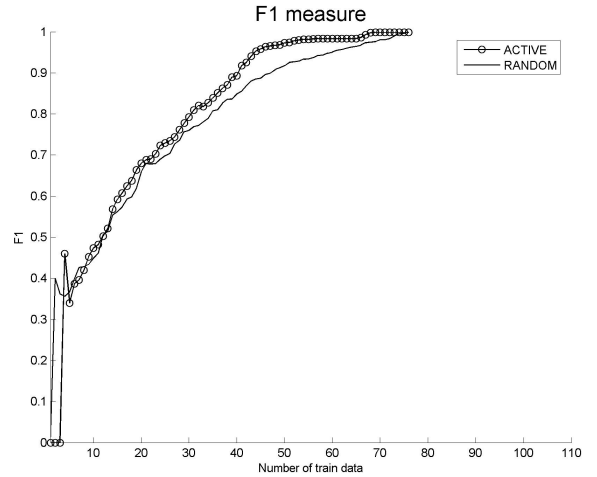

Figure 4: **Active learning algorithm vs. Randomized algorithm**

fication.

Semi-supervised learning is another approach that is useful when the number of labeled data is small. This approach utilizes distribution of a large amount of inexpensive unlabeled data to guide supervised learning. For example, co-training method [3] learns two classifiers using disjoint sets of features, i.e., two different views over the same data, and admits only those predictions upon which both classifiers agree. A more recent approach includes incorporating clustering into active learning [9]. Using prior data distribution their system first clusters data and suggests cluster representatives to active learner. Their algorithm selects not only the data points close to classification boundary but also representatives of unlabeled data. We adopted their idea to find the initial samples to be labeled. This technique, however, didn't make much difference in our experiment mainly because the size of unlabeled data was not large enough (After preprocessing we had only 76 district candidates). We would expect higher impact on performance if we had a larger set of data.

We used precision, recall, and their harmonic mean as evaluation metrics. In our example, precision p is the ratio of the number of correctly identified Main Streets to the total number of trials. On the other hand, recall r is the ratio of the number of correctly identified Main Streets to the total number of Main Streets in Boston. Because the two measures are in inverse relation their harmonic mean is often used as a compromising measure. $F1$ measure, which is a harmonic mean of precision p and recall r is defined in equation (1).

$$F1 = \frac{2pr}{p+r} \qquad (1)$$

Since we had a relatively small sized data set after preprocessing we used Leave-One-Out-Cross-Validation (LOOCV) to evaluate the general performance of Main Streets classifier. LOOCV is a cross validation technique where one data

	Precision	Recall	F1 measure
LOOCV	0.842	0.762	0.800

Table 3: Leave-One-Out-Cross-Validation Result

point is left for testing while a classifier is trained using the rest of data points. The LOOCV results in Table 3 shows promisingly good performance by achieving high F1 measure of 0.8. The results read that the system made 6 correct predictions out of every 7 trials, identifying 76% of Main Streets.

We also compared the performance of the active learning strategy to the performance of the random learning strategy. Under the random learning strategy the system also learns an SVM classifier by incrementally taking more training examples. Whereas the active learning strategy takes advantage of the distribution of unlabeled data in selecting a next data point, the random learning strategy chooses an arbitrary data point. We evaluated the performance of the two approaches in terms of their learning speed.

Figure 4 shows the performance of active learning strategy and random learning strategy. The experimental results in Figure 4 are average performance over a set of 20 independent trials. The experimental results first indicate that finding Main Streets is a class of urban design decision making problems that can be developed by using a machine learning approach. The results also show that the active learning algorithm significantly[3] outperforms the random learning algorithm, achieving high classification accuracy after given a relatively small number of examples.

6. LOCATION HUNTING FOR TEMPORARY HOUSING

At an abstract level, the decision making process in post-disaster mode is not different from the pre-disaster mode. Planners seek good solutions that optimize the interests and constraints of multiple entities. The scale of the problem, however, is far greater. There are several important factors that increase the difficulty in post-disaster mode. First and foremost, time is precious. Fast temporary recovery is desired, but short-term solutions must be in harmony with long-term reconstruction plans. Second, the load of tasks is overwhelming, for instance, over 150,000 properties were damaged or destroyed as a result of hurricane Katrina in 2005[4]. Third, a much larger group of entities are involved due to crisis, including external aid groups such as emergency management team, telecommunication services, transportation services, utility services, education systems, economic development agencies, environmental agencies, etc. Fourth, it is unlikely that planners have all required information at hand. Damage assessment is part of on-going process while planning for reconstruction is being done. The planning team should expect dynamic update of information thus robustness and flexibility should be included in planning objectives.

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[3]This is statistically significant with a strong evidence of p-value 0.01.

[4]This is based on the estimate made by RMS (Risk Management Solutions) on September 2, 2005.

Demand for temporary housing in that area
Site topography
Property owner willingness
Cost
Past land use
Existence of conflicting redevelopment plans
Access to existing utilities
Engineering feasibility
Environmental/cultural resource sensitivities

Table 4: Temporary Housing Site Selection Criteria

Providing temporary housing for those who have been displaced in the aftermath of disasters is one of the most urgent issues in disaster management. When the demand for emergency housing exceeds what existing housing facilities can accommodate, new temporary housing sites are constructed for a group of manufactured homes and mobile trailers, e.g. FEMAville – FEMA (Federal Emergency Management Association) trailer park.

Six months after hurricane Katrina only half of around 130,000 requests for temporary manufactured housing and mobile trailers were fulfilled, leaving tens of thousands of residents without a place to live [14, 6]. The major problem was not in the shortage of trailer supply, but in the failure to find proper locations to install the trailers. In addition, the poor quality of lot specification on paperwork hindered the installation process, dropping the daily installation rate down to 65%. A more fundamental problem that has been seriously criticized is rooted in the lack of public involvement, i.e., the opinions of local community residents were not reflected in decision making [4].

As shown in the failure of the Katrina temporary housing project, finding good locations for emergency group housing is a complicated problem. First, designated officials such as FEMA's contractors choose a set of candidate sites by reviewing local information: aerial photos, maps, site reconnaissance field surveys, and local officials' comments. Factors considered in selecting a site are listed in Table 4 [6]. For a selected site that satisfies the site selection criteria an in-depth analysis of Environmental Assessment (EA) is conducted before a final decision is made. Usually a complete EA is limited to one or two sites at a time due to limited resources and the searching for alternative sites continues in parallel. The result of EA is either a positive confirmation that the construction of temporary housing in the selected location does not have significant impact on surrounding environment, or a rejection due to potentially significant impact. The resulting EA reports are posted for public response, but only for a brief period of time, e.g., typically 2 days, due to emergency nature of this action. It has also been criticized that expertise of local community members has been poorly incorporated in site selection process.

We design another application of RAISE to assist the site selection process. As we have shown in the Main Streets example, we can model this temporary housing site selection as a distributed classification problem. The major difficulty in modeling urban planning problem as a machine learning task lies in feature space modeling and availability of relevant

data. In order to address the multiple views problem further we model RAISE agents for three stakeholder groups: government officials who make final decisions, disaster victims who needs emergency housing, and property owners. The government officials are working on behalf of disaster victims to maximize social welfare, thus they need to coordinate to understand supply and demand of each other. The property owners in this model have priority to act selfishly to maximize their own benefits. In fact, the failure of the Katrina temporary housing project is attributable to such selfish actions, the so called NIMBY (not in my backyard) problem. We aim to help resolving this problem with a multiagent system approach by assisting policy makers to design a better mechanism.

7. CONCLUSION AND DISCUSSION

Recent disasters have brought increased concerns for post-disaster recovery and reconstruction. The baseline motto during planning for post-disaster recovery is that post-disaster planning is an extension of a long-term community development plan, thus, incorporating local information and the city's comprehensive plan is the key to successful planning.

Although it is easy to consider post-disaster planning as an independent task case study shows that post-disaster recovery plans that are well integrated with community's comprehensive plan are more effective in finding creative solutions [13]. In addition, it provides opportunity to utilize resources more efficiently in order to contribute to problem solving in a larger picture. For example, sometimes scare resources suddenly become available after the disaster and good plans maximize resource utility by identifying long waiting tasks that have been in the queue for these scare resources. Post-disaster planning also provides opportunities to fix existing problems due to previous suboptimal planning decisions. The decision making policy of designated emergency managers, such as FEMA officials, is primarily based on safety and urgency of tasks. They develop their own urgent operations that are focused on immediate response and recovery functions following a disaster. However, local community's coordination with emergency managers is crucial for successful plans, because community members are the ones who actually monitor and implement the plans.

In this paper we discussed agent-based modeling of urban planning problems both in pre-disaster mode and post-disaster mode. We presented a framework, RAISE, to build a representative agent in the form of an intelligent survey system. Our preliminary experiment on a location prediction project, Finding Main Streets, provides a good showcase example of the opportunities that agent technologies provide towards solving real life problems, in particular in post-disaster management problems.

8. ACKNOWLEDGEMENTS

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