

Robots in the Home: Qualitative and Quantitative Insights into Kitchen Organization

Elizabeth Cha¹, Jodi Forlizzi², Siddhartha S. Srinivasa¹

¹ Robotics Institute, Carnegie Mellon University, Pittsburgh, PA 15213

² Human-Computer Interaction Institute, Carnegie Mellon University, Pittsburgh, PA 15213
{lizcha,forlizzi,siddh}@cs.cmu.edu

ABSTRACT

In the future, we envision domestic robots to play a large role in our everyday lives. This requires robots able to anticipate our needs and preferences and adapt their behavior. Since current robotics research takes place primarily in laboratory settings, it fails to take into account real users. In this work, we explore how organization occurs in the kitchen through a home study. Our analysis includes qualitative insights towards robot behavior during kitchen organization, an open source dataset of real life kitchens, and a proof-of-concept application of this dataset to the problem of object return.

Categories and Subject Descriptors

I.2.9 [Computing Methodologies]: Artificial Intelligence—Robotics; J.4 [Computer Applications]: Social and Behavioral Science – Psychology

Keywords

human-robot interaction, organization, kitchen, design

1. INTRODUCTION

In the future, we envision domestic robots to perform a wide range of tasks, able to assist people with limited mobility or support aging in place [1, 4, 11]. Since the technical challenges associated with this goal are being extensively researched, it is important to understand the difficulties that arise when a human and robot not only share space but have to work together to maintain a home [33].

To identify and address these challenges, it is important to look at real homes and users. However, most robotics research to date has taken place in laboratory settings because the environment is highly structured and experiments are more controllable. As a compromise, many research groups utilize simulated or mock home environments, either built in the lab or as a virtual environment [20, 29, 33]. Unfortunately, these environments often fail to capture the true complexity and dynamics of the home [2, 9].

Recent work in design and human-computer interaction has focused on moving out of the laboratory and into real

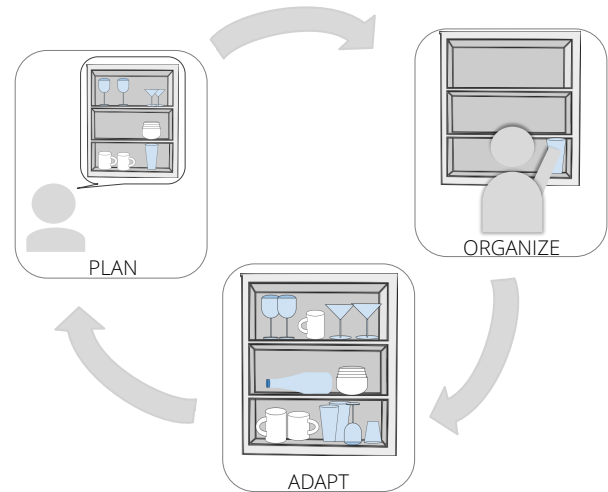


Figure 1: Homes constantly undergo a complex cycle of organization – adapting until they are forced to reorganize.

homes. The benefit of these works is that they go beyond visual observation, providing insight into the complex dynamics of the home [2]. In order to obtain these insights, qualitative techniques such as ethnography or cultural probes are often used [5, 7]. As these works present anecdotal results, it is unclear how roboticists can utilize these techniques in their own research. Therefore, our goal in this work is to translate the results obtained through qualitative studies into tools that accurately represent the home environment and can thus, inform the design of domestic robot behavior.

There are many potential applications for such tools. Imagine a robot in the home with several objects to put back. Without any prior knowledge, the robot will likely choose a location based on the object's geometry which can result in misplaced items. In some cases, such as misplaced medicine, this is more than a minor annoyance. Thus, for robots to truly benefit users, they must anticipate their needs and desires in the home.

The main challenge is that the home is a complex and dynamic space [2, 9, 18]. It continues to evolve as lifestyles change and new technologies emerge. There are also privacy concerns: due to the personal nature of the home, it is undesirable to utilize cameras or other costly sensors that can capture potentially sensitive moments. Alternative methods which send researchers into the home or utilize residents to record data disrupt the dynamics of the home. Therefore, our goal is to find a solution that accurately captures the domestic environment while addressing these concerns.

Since the home is a large and challenging space to design

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for, we focus on the kitchen. This is a more tractable space because most kitchens are prefabricated and contain similar elements across homes [32]. As the kitchen holds many perishable items, regular organization and cleaning are essential. Several prior works have also shown that many users desire robotic assistance with tasks in the kitchen, making it an interesting and important area to explore.

In this work, we present an analysis of organizational habits in the kitchen through an exploratory home study. We make the following contributions:

- 1. Home Study:** We present an exploratory home study focusing on organization in the kitchen. The study consists of a home tour, kitchen tour, interview, and demonstration.
- 2. Dataset:** Using data from our study, we create an open source dataset of organizational preferences in the kitchen that goes beyond simple observation or visual analysis.
- 3. Qualitative Insights:** We present interesting observations from our exploratory study and discuss their design implications for future domestic robots.
- 4. Quantitative Assessment:** We assess the usability of our dataset by applying it to an open robotics problem, object return, and present our initial results.

2. RELATED WORK

The home is a complex space shaped by its residents' needs, experiences, and desires [2]. While early work explored the functionality of the home [12], more recent research has focused at how the evolution of the home and household [2, 14, 27].

This is especially important as the typical household changes: many homes no longer consist of a family and domestic responsibilities are no longer relegated to one person [2]. To support this shift in lifestyle, many new technologies have been introduced to the home. As these technologies increase in complexity, however, researchers must try to anticipate how they will change the home and our everyday lives [9].

2.1 Technologies in the Home

Much prior work explores how new technologies affect our routines in the home [28, 40]. Recent work takes this a step further by trying to anticipate the usage and effects of future technologies, such as the smart home [13, 17, 36, 39, 40].

The idea of a smart home that possesses the intelligence and automation to anticipate and meet users' needs has been around as early as 1930 when the "Home of the Future" was unveiled at the World's Fair [19, 36, 40]. Creating such a home requires the installation of costly sensors and automation still being developed. Hence, a recent drive has been to create sensor-driven, intelligent devices that nearly no home modification, e.g. the Nest Thermostat.

In order to study these complex and integrated technologies, prototypes of home environments such as the Georgia Tech Aware Home, MIT Place Lab, Microsoft MS Home, and the Honda Smart Home have been built [21, 38]. One concern of these environments is privacy: the home is a personal space so continuous monitoring may not be desirable. The impact of these works are also limited, as they take place in research settings where people do not exhibit the same natural behavior and preferences [39].

Along with the smart home, people have also envisioned an intelligent and skilled home robot [1, 11, 34], e.g. Rosie the robot from the 1960's television show, *The Jetsons*. However, even today there are still very few robots in the home due to the technical challenges and high expectations of such systems [11, 24]. Thus, much of our existing knowledge is

from short term studies that take place in laboratory settings limiting their impact.

2.2 Methods for the Home

In order to understand how these technologies will function in real homes, it is necessary to go "in the wild." However, this is generally considered to be a difficult endeavor [2]. Studies in the workplace are more common because it is less private and more easily accessible [9]. Researchers also cite issues such as privacy, intrusiveness, and disruption of the home life as potential difficulties of going into the home [6]. Despite these concerns, there are a growing number of researchers using methods that are well established in the workplace, such as ethnography, in the home.

However, there has been much debate as to whether these methods are suitable for the home. A key challenge in designing for the home is to understand its everyday nature including how people live, what they do in the home, and the potential role of technology. This makes qualitative techniques such as ethnography or cultural probes attractive as they are proven tools for sociologists and designers. However, prior work using these techniques have focused on conveying a sense of the home, rather than shaping these studies into usable tools for design [8].

The advantage of these techniques is that they provide context. Quantitative techniques provide raw information such as the contents of a home, but this knowledge lacks meaning without context. Thus, our goal is to find a way to merge these two approaches to create a tool that is useful to both roboticists and HRI researchers.

2.3 Organization in the Home

In this work, we choose to focus on the domain of home organization because it has been well researched through contextual studies using observational methods. Moreover, the technical challenges of organization have been a popular topic in robotics [33, 41].

Much of the prior work in organization has looked at how organization affects efficiency in the workplace [3, 26]. More recently, researchers have looked at clutter and how it affects the home [10, 37]. The results of these works have mostly been broad conclusions and general design guidelines, e.g. homes are dynamic in nature and organization must be carried out with users' preferences in mind.

Within robotics, researchers have looked at problems like object retrieval, search, and return [23, 35, 41]. Since the technical challenges of are considerable, roboticists have tested their work in mock environments where experiments are more controllable. However, as these challenges are being addressed, there is a need to move away from laboratory settings. Schuster has taken the first step in this direction by attempting to learn organizational preferences using a more data-driven approach: a dataset created via mock paper kitchens and pictures from real kitchens [33]. Unfortunately, this approach fails where contextual research excels, as the mock kitchens lack realism and understanding.

Thus, we attempt to bridge the gap between these works by applying both qualitative and quantitative techniques to organization in the home. Since the home is such a complex and large space, we focus in this work on the kitchen.

2.4 Kitchen

Historically, the kitchen has been the center of the home experience [32]. Since the majority of housewives' time were spent in the kitchen, this started a drive to create more efficient and easy to use kitchens [16, 32]. At the start of

the twentieth century, however, there was a realization that for a kitchen to be efficient, it must also be flexible to the needs and preferences of users [32].

This realization created a drive to understand not only how to improve kitchen activity but how to support the experiences, affects, and desires that affect design in this space. Much of this work has concentrated on comfort, both physical and emotional, in the kitchen [22, 16, 32]. These works usually rely on using techniques in design to evaluate the space and its usage.

Unfortunately, as with the home there is still a gap between traditional kitchen research and robotics and HCI work surrounding kitchen activities. Many of these works look at activity recognition to provide support to users during cooking and cleaning [42] or cooking aids that provide assistance through expert advice or virtual demonstrations [31]. Since these works take place outside of actual kitchens, it is unclear how applicable they are in real homes.

3. HOME STUDY

For years, the home has been a popular research area [2, 9, 39]. As much of this work provides anecdotal results, it is unclear how to utilize the same methods when designing complex robot behavior. As a result, roboticists have mostly relied on mock kitchens or pictures of real homes when researching a variety of human-aware problems ranging from activity recognition to home organization [25, 33]. Yet, these solutions fail to truly represent the complexity of real homes and users. Therefore, our goal in this work is two-fold: 1) gain crucial knowledge of organizational behavior in the kitchen and 2) create a dataset which accurately captures a household’s organizational preferences.

Since few works have attempted to bridge the gap between these different approaches, it is unclear what knowledge is important or necessary when creating such a dataset. For this reason, we first performed an exploratory study consisting of a general tour of the home, an in depth tour of the kitchen, an interview about organizational habits in the home, and a demonstration of organization in the kitchen.

3.1 Participants

For this study, we recruited 7 households with a total of 15 residents. This group consisted of two unmarried couples, two families, two single persons, and one set of roommates living in a house, townhouse, or apartment. All interviewees lived in the Pittsburgh area, spoke English fluently, were between the ages of 24 and 37, and are the primary organizers of the kitchen in their households.

3.2 Procedure

3.2.1 Introduction

Each session started with researchers introducing themselves and giving a brief overview of the study. Participants were told the purpose of the study was to learn about how organization occurs in the home.

3.2.2 Home Tour

After the introduction, participants were asked to give a tour of their home. They were instructed to focus on areas such as the closets where organization is important and to leave the kitchen for the end of the tour.

During the tour, participants discussed how each space in the home is used including the contents of the space and why they were placed in that particular location. This provided us with a general idea of who used each space, who was



(a) Kitchen Tour

(b) Demonstration

Figure 2: During the home study, participants gave a tour of the kitchen and a demonstration of unpacking groceries.

in charge of its organization, and general cleaning habits in that area. Throughout this process, we asked participants to elaborate on anything we found interesting or unclear.

Although the focus of this work is the kitchen, the home tour was still crucial because it gave us a general idea of the household’s organizational habits such as the general state of clutter and how often spaces are cleaned. It also helped us to build rapport with participants and gave them time to become comfortable with the tour structure. Moreover, there are often areas of the home which act as extensions of the kitchen that we wanted to ensure were included.

3.2.3 Kitchen Tour

The home tour ended in the kitchen where participants were instructed to go through each storage container and discuss its contents. The tour was lightly structured to allow researchers to digress and obtain important details.

For each item, participants were instructed to give an overview of the item and its usage:

Item description: What is the item?

Purpose: What is it used for?

User: Who uses it?

Frequency: How often is it purchased and used?

Surplus: Is it extraneous?

Desired Location: Where does it belong and why?

Actual Location: Where is it typically located and why?

A typical description was: “We keep the flour in this cabinet on the bottom shelf with the other baking supplies. X uses it 2-3 times a week to bake stuff. It’s a large bag so we only have to purchase it every month or so. Sometimes it sits on the counter for a few hours after we use it.”

3.2.4 Interview

After the tours, we interviewed participants about their organizational and cleaning habits. We waited until the tours concluded so that we had a good understanding of the entire space and how its different components fit together.

In particular, we probed participants about item placement, especially the reason for choosing a particular location. When participants had no clear reason, we asked what led an item to end up in that location.

When there were several places an item could reasonably be located, we asked participants why one location was chosen over another. For example, one participant stored a wine carafe with cocktail making items but could have alternatively placed it with the drink pitchers or wine glasses.



Figure 3: An example of the 3D layout of a visited kitchen and information contained in its corresponding database.

We also looked at surplus items or items where extras were kept in a secondary location. A common surplus item in most households were paper towels: the roll currently in use is kept in an easy to access location such as the counter while the remaining rolls are kept in a storage container.

During this time, we also attempted to get a better sense of the kitchen usage by asking questions such as how often residents cook or clean, which items they frequently use, and what is located in inconvenient or difficult to access spaces. Since several homes had spaces outside the kitchen which contributed to its organization, we included these spaces as part of the interview and kitchen tour.

We also looked at the history of the kitchen and its organization in both the short and long term. We asked participants how often food and other disposable items in the kitchen are purchased, used, and thrown out and whether the space had undergone any major reorganizations and why.

Finally, we looked at how the household affects the kitchen and its organization. In homes with more than one resident, we wanted to know whether this impacted the everyday level of cleanliness and clutter, how space is divided up, whether conflicts arise due to differing preferences, and what is each person’s organizational role.

3.2.5 Demonstration

After the interview, we asked each participant to demonstrate putting away a bag of groceries. We provided each household with a paper grocery bag containing a jar of spice, a candy bar, a bag of rice, a box of sugar, an apple, a bottle of milk, and a can of chicken broth. We chose only food items since most households purchase kitchenware and housewares less frequently. Items were chosen to vary in as many features as possible (shape, size, container material, usage, refrigeration, shelf life), with some items having ambiguous features such as the apple’s refrigeration requirements.

This process gave us a sense of how participants make decisions on the fly. This is important as most items in the kitchen have short lifespans and are constantly replenished. During the demonstration, participants narrated their thought process and discussed how they normally unpack groceries.

4. DATASET

We also contribute in this work, an open source dataset consisting of the layouts and contents of 7 kitchens that can be downloaded at www.lizcha.com/kitchen_dataset.

Since the home is complex and difficult to visualize in 2 dimensions, we began our analysis by creating a 3 dimensional layout of each kitchen. Using Google SketchUp, we recreated each kitchen, approximately to scale. The layout also functions as a map with every organizational container related to the kitchen assigned a numerical label.

4.1 Terminology

We define an organizational *container* as a unit of storage either found in the kitchen or containing items related to kitchen activities, e.g. cabinets, drawers, and refrigerators. In some cases, such as an extra freezer in the garage, the container is located outside of the kitchen but contains kitchen-related items. Containers can be further segmented into smaller organizational elements, called *subcontainers*. For example, cabinets are often divided into separate spaces using shelves. In our analysis, each shelf in a cabinet is treated as a distinct subcontainer. However, if a shelf exists as an independent unit outside of any other container, such as a wall mounted shelf, it is treated as a container. Extra storage units such as carts are treated as containers. In the layout, each container is assigned a numerical label designating its position in the kitchen. Subcontainers are assigned numerical labels relative to their position in the container.

4.2 Databases

For each home, we created a database containing its kitchen related items and their positions, or the numerical label corresponding to an item’s container and when applicable, subcontainer. For duplicate items located in the same container and subcontainer, only one database entry was included due to the difficulties in obtaining accurate counts of every item.

Most items were identified through visual analysis of the kitchen [33]. Since this approach only captured the current state of the kitchen, we used the kitchen tour and interview to identify items that were missing or out of place. The result was users’ desired kitchen arrangement in which all items are in their proper location, something that rarely occurs in most homes.

4.3 Features

We identified two types of features describing the items: object-related features and user-related features.

4.3.1 Object-Related Features

We define object-related features as characteristics of the object. These features can be discerned without any knowledge of the object’s owner or the kitchen it is located in and are hence, consistent between homes. Some examples are an object’s shape, state, and refrigeration requirements.

Object-related features are commonly used when creating organizational schemes such as ontologies of items found in the home or kitchen [33]. A common method of identifying these feature is by analyzing websites that sell food, kitchenwares, and household items [33]. Several applications within robotics such as object search, object return, computer vision, and activity recognition utilize these features because they can be identified through simple visual analysis. More-

over, these features have been laid out in ontologies, kitchen stores, and past literature in organization [33].

4.3.2 User-Related Features

We define user-related features as requiring knowledge of the user, kitchen, or household the object belongs to. Unlike object-related features, these features typically vary across homes as they represent how a particular household uses an object. Some examples are how frequently an object is used or what type of container it is kept in. In order to discern these features, we must go beyond visual analysis and utilize qualitative methods such as interviews or ethnography. These features have been mentioned in several works that relay this information anecdotally. By transforming these results to a more concrete set of features, we can utilize them when customizing robot behavior. We chose to use an in depth interview to find this information as long-term observation is time-consuming, and invasive. We envision that in the future, a similar process can be used to provide the robot with initial information about the kitchen. The robot can continually refine its knowledge by observing the household and asking questions.

5. ORGANIZATIONAL THEMES

Previous works exploring home organization use qualitative methods that enable researchers to discover information that is difficult to extract from photographs, videos, and other sensor data. However, it is unclear how to utilize these results when designing robot behavior. Pantofaru takes a more structured approach by creating frameworks to act as design guidelines for domestic robots [30]. We employ a similar approach in which we identify general organizational themes found in the kitchen, identify real-life examples, and discuss the design implications for future robots.

Although our focus is the kitchen, we started with a home tour to get a sense of the household’s organizational habits. In most cases, common spaces in the home were a good indicator of how cluttered the kitchen was. We also found that people tended to prioritize the kitchen over other spaces because of its frequent use and perishable contents.

The most significant portion of the study was the kitchen tour in which participants opened each organizational container and discussed its contents and placement. In this section, we present the findings from these tours.

5.1 Object-Related Features

Theme: Item locations are often chosen based on features of the object, as defined in Section 4.3.1. Object-related features were primarily used in 2 scenarios: 1) the object has a feature which limits its location or 2) the object is placed with other objects that have similar object features.

In most homes, several items were placed in locations that satisfied the objects’ constraints. For example, food items such as meat or ice cream often had specific storage requirements to prevent spoilage. Another common constraint was an object’s size or shape: pots and appliances often required larger shelves and cabinets. One household chose a particular shelf for their glassware because it was the only one tall enough to fit their wine glasses.

Participants also attempted to group “similar” items together. It is natural to store certain duplicate item, such as dishes or silverware, together. For different items, however, this is more difficult as it requires users to define similarity between two items. We also found that the object-related features used to group items together often changed depending on the compared items: canned items are stored together

due to their common shape and packaging, while items used in baking such as flour and sugar were grouped together.

Design Implication: Robots designed for the home will likely be tasked with returning items to their correct locations. However, prior work indicates that users do not want to have to give the robot constant detailed instructions [11]. Instead, they prefer the robot to know their preferences and have the intelligence to make reasonable choices, as a human would. This implies that such a robot should be able to readily identify common object features as they play a huge role in determining where items should go. Humans naturally attempt to group items into certain categories (e.g. baking items, frozen foods) and classification techniques may be able to replicate this process using object features.

5.2 User-Related Features

Theme: Knowledge of user-related features, as defined in Section 4.3.2, can help refine our knowledge of an item’s location and often provides deeper insight into a person’s organizational strategy.

We found that although, object-related features gave a general idea of where items should go, user-related features often provided a more precise location or helped explain anomalies. One of the most useful features was frequency of use. Frequently used items tended to be in easy to access locations. In containers, these items were towards the front for easy access. Other frequently used items such as salt were kept on or near the counter, easily within arms reach.

Moreover, user-related features encode the household’s habits which gives context and can explain seemingly out of place items. For instance, one household with a strict organizational scheme had a random assortment of items on the counter. After returning from the grocery store, one resident would leave items she planned to use in that day on the counter which others knew not to put away.

However, many user-related features are not easily observable and can only be found through insight from people in the home. For instance, one home had seemingly random food items isolated in the fridge and cabinets as one person had severe food allergies and separated his food for safety. In homes with children, certain containers held foods for just the child. Without knowing this information, such rules might appear random or out of place.

Design Implication: Prior work shows that people have strong preferences when it comes to the home. A robot which ignores users’ preferences can disrupt the home environment, inconveniencing the user. Thus, understanding users’ needs is essential to the acceptance of a home robot.

Object-related features only give a general sense of where items might belong. Imagine a stranger attempting to put away your groceries. Without any prior knowledge, they will attempt to use what they know about the objects. However, by providing them information about your habits, they can make a more refined guess. Thus, for a robot to adapt to the user, it must be able to learn user-related features. Since many of these features require long term observation or are not observable at all, it may be beneficial to conduct interviews or tours to gather this information. Once the robot has a good sense of the kitchen, it can continue to incorporate new information about the household.

5.3 Ambiguity

Theme: There is a large amount of ambiguity regarding the location of items in the kitchen. Many items have several logical locations resulting in cases where households have multiple “correct locations” that items move between.

This situation frequently occurred in households with multiple people as each resident would choose a different correct location. In homes with one dominant organizer, others would not know the correct location and would guess.

For instance, one participant found a misplaced whisk. She initially determined items locations but failed to communicate this information to the other resident causing several misplaced items. Interestingly, she replaced the items but never corrected the other person.

Other, more transient items are difficult to classify and may not have a set location. We observed several items in the refrigerator that participants' said could go on a number of shelves such as meat or leftovers. More permanent items, such as condiments, had set locations.

Sometimes kitchen and household items had two locations if there were extras of the items. For example, most homes keep a roll of paper towels on the counter and spares in another container. Some homes also stockpiled non-perishable, easy to store items for convenience or to save money.

Design Implication: Even humans have difficulty reasoning where items belong in the kitchen since we tend to view and use the kitchen in different ways. Thus, our priorities skew our beliefs of how a kitchen should be organized. Despite such discord, humans are able to coexist in these shared spaces because we learn, adapt and are willing to accept some error.

This is promising for future robots as we envision them to work autonomously, without constant instruction or help. Expecting a robot to always do what the user wants is an impossible expectation not even humans can meet. However, we found that users are willing to accept some reasonable error: finding a whisk with a measuring cup but not in the underwear drawer. Thus, robots should not ask humans when they are unsure as they will quickly become cumbersome. Instead, they should ask questions only when needed and otherwise make a refined guess.

Prior work shows, however, that people are sometimes more demanding of a robot and less willing to accept failure. This creates an interesting problem, how to adjust users' expectations of robots, that we need to further explore.

5.4 Dynamic

Theme: The kitchen is an extremely dynamic environment—its contents are frequently changing and items often move locations. Many kitchen items, such as fresh foods, are transient. Hence, the kitchen is constantly changing to fit new items and remove old ones.

This is frequently seen in the refrigerator. Its contents are subject to users whim and often have a short shelf life: what is in the fridge one week may not be the next. This is partially because we often desire variety in what we eat. Other items are seasonal and available only certain times.

Design Implication: One of the most challenging technical issues for robots is dealing with dynamic environments. However, the home and kitchen are constantly in flux. This implies for any robot to succeed in the home, it must continually take in new information and adapt its behavior. Thus, current work which looks at understanding human behavior may be useful in dealing with these challenges.

5.5 Reorganization

Theme: Households are often unwilling to reorganize unless it is absolutely necessary. Most participants listed several issues which made their home less efficient and therefore, less usable. However, regardless of whether it is a small or large change, people are unwilling to reorganize since it

is time consuming, requires planning, and they are already accustomed to the current home layout.

Instead, people will come up with alternative strategies to avoid reorganizing. In some cases, they create catch-all spaces for items that do not have a designated place. They may also place items in inconvenient or difficult to reach spaces. One home recently purchased a blender, but when placing it in the kitchen did not remove the cabinet's original contents. Instead, they pushed items above and around the blender, making everything difficult to access.

Participants would wait until a space became unusable before reorganizing. An exception is when a significant change in either the space or household occurs, e.g. changing residents or adding extra storage. One participant reorganized when her significant other moved in because of food allergies.

Design Implication: Since the decision to reorganize is not a straightforward one, a household robot should take many factors into consideration before moving an item. If this is an infrequent occurrence, it may be beneficial for the robot to simply ask users whether it is okay.

However, some works have found that people adapt their habits to new technologies [15]. Thus, people may be more open to reorganizing if a robot carries out the actual task. We observed organizational schemes that were suboptimal, but participants were adamant about their choices for sentimental or personal reasons. Therefore, a robot should always be aware of human users when trying to decide whether reorganization is acceptable.

6. LEARNING USER PREFERENCES

A major contribution of this work is the construction of an open-source dataset of 7 real life kitchens, see Section 4. In this section, our goal is to show how this dataset can be applied to common problems in robotics. We focus on object return, or how to determine an object's correct location.

In the remainder of this section, we present the details of our evaluation and our results using three types of classification algorithms.

6.1 Feature Selection

The dataset we are evaluating contains two types of features: object-related and user-related features, see Section 4. We chose to use only object-related features because to limit the scope of the evaluation as it is only one of the contributions of this work. Furthermore, we wanted to compare our work to Schuster's, which only utilizes object-related features found through a kitchen ontology [33].

As detailed in Section 4, object-related features were chosen from prior literature, kitchen ontologies, and information available on houseware and grocery stores websites. In order to select the most relevant features, we performed simple word analysis on participants' interviews and kitchen tours. We identified terms related to each feature and ranked the feature by its number of mentions. We initially evaluated our classification algorithms with the three highest ranking features. We then continued to expand the number of features until we achieved the highest classification accuracy, which was given by the following features: refrigeration requirements, container material, food state, use, and item type (food, kitchenware, houseware).

6.2 Training and Testing Set

Since it does not make sense to combine data from multiple homes, we evaluated the dataset of each individual home separately. In order to train each classifier, we created a set of training examples. The training set consisted of 85%

of the dataset chosen randomly. We looked at two different sets of examples to test the classifier. The first testing set consisted of the items given to participants during the *demonstration* portion of the home study, see Section 4. The second testing set consisted of a randomly chosen *segment* of 25 items from the dataset not used in the training set.

There main issue with the demonstration testing set is that it is limited in size and consistency: only seven items were used in the demonstration and each item was food.

6.3 Classification

We used the selected features to train a set of standard machine learning classifiers, including Support Vector Machines (SVMs) and k-Nearest Neighbors to predict the location of a kitchen item. We also looked at k-Means as a method of creating item groupings. We evaluated every home using each classification technique and averaged the results across all homes, as shown in Table 1.

6.3.1 Support Vector Machine (SVM)

Support Vector Machines (SVMs) are popular supervised learning algorithms which are widely available in various machine learning toolkits (such as Weka) and software packages (MATLAB) making them relatively easy to use.

We trained a set of SVMs using a linear kernel to predict objects’ container number. Since SVMs are inherently two-class classifiers, we used two common approaches to multi-class classification: one-versus-rest and one-versus-one. In the one-versus-all approach, a single classifier is trained per class with samples from the class, i.e. container, labeled as positive while items from all other containers are labeled as negative. The classifier with the greatest margin is chosen as the predicted label. In the one-versus-one approach, a classifier is trained for every pair of containers. Every classifier is then applied to the testing sample and the container chosen by the highest number of individual classifiers is the predicted label. We found that the one-versus-rest approach performed best, as shown in Table 1.

6.3.2 k-Nearest Neighbors (k-NN)

k-Nearest Neighbors is a non-parametric classification algorithm that takes as its input the k closest training examples. The closest training examples are found by defining a similarity metric in the feature space. Hence, this algorithm mimics humans’ method of grouping similar items. The output of the classifier is determined by a majority vote of the closest training examples with the label most common amongst its neighbors being chosen. Both humans and k-NNs performances are subject to similarity is defined. We evaluated k-NN with a variety of k values and distance metrics. We use the same features as with our SVMs and achieved the best results with $k = 12$ and a Euclidean distance metric, as shown in Table 1.

6.3.3 k-Means

k-Means is a clustering algorithm which can be used to partition objects into k groups, or clusters. We chose to look at k-Means because it is similar to organizing a space from scratch: there are k storage containers and n items that must be divided amongst them. Although k-Means can be used as a classifier by adding new items to pre-existing clusters, we chose to utilize the entire dataset as the testing set. Since features of the kitchen were not used in this analysis, we do not evaluate how many items were in the correct container. Instead, we calculate the accuracy of the algorithm by looking at every pair of items in each cluster and com-

	Segment	Demonstration
Support Vector Machine	93.7%	87.1%
k-Nearest Neighbors	87.9%	79.5%
k-Means	77.5%	77.1%

Table 1: Results for object return using our dataset and 3 classification algorithms

puting how many item pairs are correct, i.e. located in the same container.

6.4 Results

We found, as shown in Table 1, that SVMs perform the best of all three algorithms. The SVMs and k-NNs performed better on the segmented testing set than on the demonstration testing set. This is likely due to the size and bias of the demonstration testing set. The items in the demonstration were also chosen due to their ambiguity for many object-related features. Items in the segmented testing set were greater in number and randomly chosen, resulting in higher variation. Since these items belonged to the participants, the training dataset is more likely to contain similar objects.

For k-Means, the entire dataset was tested and reported in the segment result of the table. We added the additional items from the demonstration and reported the results of k-Means in the demonstration result of the table. Overall k-Means performed worst, but this is to be expected as the entire dataset was clustered.

A drawback to these algorithms is that our dataset excluded duplicate items in the same container and subcontainer. Thus, 10 coffee mugs are treated the same as 1. This can issues as methods such as k-NN use majority voting. Overall, we were able to obtain over 90% accuracy using just an SVM, showing that our dataset does a reasonable job capturing users’ organizational preferences with respect to object locations.

Our goal in this section was not to solve the problem of object return but rather to evaluate the effectiveness of our study and dataset. Thus, we limited our analysis to 3 simple, but easy to use algorithms. Although we achieved good performance with SVMs, it is likely that performance on all 3 algorithms can be further boosted by common methods such as feature weighting. We also limited our analysis to object-related features. In the future, we would like to explore how user-related features can improve our results. It is also worth noting, that our overall performance was negatively affected by one home which contained significantly fewer kitchen items than other homes.

7. CONCLUSIONS

Since we expect robots of the future to have personal roles such as assistant or caregiver, it is essential they learn to meet the needs and demands of everyday users. However, despite the growing interest in domestic robots, there is an absence of knowledge or tools that accurately portray the complex and dynamic nature of the home.

In this work, we take a first step towards the creation of such tools through an exploratory study. From this study, we create an authentic dataset that goes beyond ethnography or visual analysis. We present an analysis of this dataset in the context of object return, an open problem in robotics. We show that we are able to accurately predict where objects go in different kitchens. We also present some common themes surrounding organization in the home, discuss how

these themes appear in real-life kitchens, and their design implications for future robots.

One application which we mention but did not explore in this work is simulated homes and kitchens. Currently, roboticists rely on mock home environments, but these environments are simplistic and lack the complex nature of a real home. In the future, we plan to further explore how to use our work to create more realistic home environments and what metrics can be used to evaluate their quality.

In the future, we hope to further explore how we can better utilize information about the home and household in a quantitative context. One method is to incorporate general patterns found in multiple homes. With the small size of our dataset, it is difficult to identify these patterns. Therefore, we plan to refine our methods to incorporate more homes into our future work. Furthermore, we are excited to continue exploring other problems in robotics that our work can address.

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