The Predictive Context Tree: 
Predicting Contexts and Interactions
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Abstract

With a large proportion of people carrying location-aware smartphones, we have an unprecedented platform from which to understand individuals and predict their future actions. This work builds upon the Context Tree data structure [Thomason et al., 2016c] that summarises the historical contexts of individuals from augmented geospatial trajectories, and constructs a predictive model for their likely future contexts. The Predictive Context Tree (PCT) is constructed as a hierarchical classifier, capable of predicting both the future locations that a user will visit and the contexts that a user will be immersed within. The PCT is evaluated over real-world geospatial trajectories, and compared against existing location extraction and prediction techniques, as well as a proposed hybrid approach that uses identified land usage elements in combination with machine learning to predict future interactions. Our results demonstrate that higher predictive accuracies can be achieved using this hybrid approach over traditional extracted location datasets, and the PCT itself matches the performance of the hybrid approach at predicting future interactions, while adding utility in the form of context predictions. Such a prediction system is capable of understanding not only where a user will visit, but also their context, in terms of what they are likely to be doing.

1 Introduction

Much existing work has focused on identifying locations from geospatial trajectories as a basis for prediction, aiming to determine the likely regions that an individual or other entity will visit in the future. While this is a useful component of many services, the identified locations do not necessarily correspond to real-world entities, often spanning multiple buildings or areas. Other avenues of research have focused on identifying activities or contexts that an individual has been immersed in, but these typically require data from low-level sensors (e.g. accelerometers and heart-rate) or video footage, neither of which are commonly available. Aiming to overcome both of these limitations, this work focuses on predicting both the future location and context of an individual, using only geospatial trajectories collected from or about an individual, in addition to data that can be added after the time of collection. The methods presented in this paper are building blocks for the creation of intelligent and tailored services.

Using the Context Tree [Thomason et al., 2016c] data structure as a basis, this paper first discusses substituting existing location extraction techniques with element identification for prediction applications. Elements represent real-world locations and so provide additional insight and information that existing techniques do not consider, such as tags that describe each element’s function. We then present the Predictive Context Tree (PCT), a new hierarchical classification model for predicting future element interactions and the future contexts that the user will be immersed within. An earlier version of the PCT was presented in [Thomason et al., 2016b], however this paper provides a greater level of detail, an expanded evaluation and extends the PCT to predict multiple land usage elements and contexts. We
demonstrate the utility of the PCT through results showing increased predictive accuracies over existing techniques.

We begin with a discussion of related work in location and context identification and prediction in Section 2. Section 3 presents a modification to the context tree generation procedure (discussed in Section 2.4) that allows for the identification of individual elements that represent real-world locations that a user interacted with, and proposes using these locations in lieu of extracted locations as a basis for location prediction using existing machine learning techniques. Section 4 then goes on to present a new technique for location prediction, the Predictive Context Tree (PCT), that uses the information from clustered context trees to identify which identified location the user will visit in the future. The PCT is designed to additionally operate as a context predictor, where contexts instead of locations can be returned as prediction results. A quantitative investigation of predictions made over extracted locations and real-world elements, in addition to those predicted with existing techniques and the PCT is then conducted, with the methodology presented in Section 5 and results in Section 6. Finally, the paper is concluded in Section 7.

2 Related Work

This section introduces existing methods for extracting locations from geospatial trajectories, and then considers predicting future locations and contexts. Finally, the Context Tree data structure and generation framework is discussed, as this provides a foundation for the work in this paper.

2.1 Location Extraction

Locations are typically extracted from geospatial trajectories using two distinct clustering steps. The first step is performed by iterating over the trajectory to identify periods of low mobility. This is followed by a clustering step that groups the extracted visits (or stops) into locations [Montoliu and Gatica-Perez, 2010; Zheng, 2015].

Extracting periods of low mobility, referred to as visit extraction, was initially performed by looking for periods of missing data, which were assumed to correlate to a person being indoors, since early data logging devices did not function in enclosed spaces [Ashbrook and Starner, 2003]. Modern devices, however, can use a combination of techniques to determine their location and are much more resilient. Taking account of this new hardware, time and distance thresholds can be applied to determine the maximum size of visits, where a visit must be longer than a specified duration and contained within a specified radius [Andrienko et al., 2013; Hariharan and Toyama, 2004; Kang et al., 2004; Montoliu and Gatica-Perez, 2010; Zheng et al., 2010a; Zhou et al., 2014]. However, these methods still suffer from a lack of resilience to noise, and so more specialised algorithms have been proposed to analyse the trend of motion of an individual, and determine when they are moving away from a visit location. Such techniques include the Gradient-based Visit Extractor (GVE) [Thomason et al., 2016a].

Once they have been extracted, visits are clustered together using standard approaches, including density-based techniques such as DBSCAN [Andrienko et al., 2013; Ester et al., 1996; Montoliu and Gatica-Perez, 2010] and partitional approaches, such as k-means [Ashbrook and Starner, 2003; MacQueen, 1967]. While both are applicable, DBSCAN is more commonly used because it does not require the number of locations to be known a priori and allows for arbitrary shaped and sized clusters.

2.2 Location Prediction

Making predictions over extracted locations allows for the provision of services that consider where a person will likely be in the future. Although location prediction was originally considered for preparing handovers in cellular telephony networks [Akoush and Sameh, 2007; Bilurkar et al., 2002], recent work has focused on predicting specific locations that will be visited by the user from sets of locations extracted from trajectories [Ashbrook and Starner, 2003; Assam and Seidl, 2013; Chon et al., 2012; Hariharan and Toyama, 2004]. Location prediction has been realised using support vector machines (SVMs) [Wang and Prabhala, 2012], neural networks [Akoush and Sameh, 2007; Bilurkar et al., 2002; Thomason et al., 2015], and Markov models [Ashbrook and Starner, 2003; Assam and Seidl, 2013; Hariharan and Toyama, 2004].
2.3 Context Prediction

While locations provide a basis for understanding users, identifying the context of user actions vastly increases the available information for making decisions about users. The aim of context identification is to detect periods of time in which the user likely had similar goals, or were performing the same task. Existing work has considered context extraction from sequence- and entropy-based approaches [Bao et al., 2011; Lemlouma and Layaida, 2004], used as a basis for adapting computing applications to a current context [Anagnostopoulos et al., 2006; Lemlouma and Layaida, 2004].

Predicting the future context of an individual has also been considered, where location and context predictions are sometimes treated together. Le et al. 2015 use historical contexts to suggest locations a user may wish to visit, while Assam et al. 2014 aim to use interaction histories to predict the types of contexts associated with each location. Aiming to solve the problem of location prediction, but using additional knowledge offered by context extraction, Bhyri et al. 2015 propose a two-step approach to location prediction that first aims to predict the context that a user will be in and then aims to match this context to the most likely location the user will visit to fulfil the context, achieved through classification techniques.

2.4 The Context Tree

Towards the goal of identifying and representing contexts, Thomason et al. 2016c present the Context Tree, a hierarchical data structure that summarises user contexts. Each leaf node of the tree represents a real-world feature or element that the user has likely interacted with, be it a specific building, area, or individual feature (e.g. a bench in a park). These individual elements are joined together through context nodes that represent a context at a specific scale, where time spent within a context means that the user likely had similar aims or goals, and are identified by exploring time the user spends interacting with elements with similar properties, or elements that are interacted with in a similar manner. Figure 1a depicts the structure of a context tree, reproduced from [Thomason et al., 2016c].

The procedure for generating a context tree augments geospatial trajectories with land usage data, filters these augmented trajectories to identify elements that the user was likely interacting with, and then clusters these interactions hierarchically using both features of the interactions and properties of the locations being interacted with. This has advantages over existing work in that it assumes only the availability of geospatial trajectories at time of data collection and therefore does not rely on data from additional sensors.

Part of the work presented in this paper aims to convert the context tree into a predictive model which requires the use of hierarchical prediction techniques. Although hierarchical classification has been considered in other domains before, it still presents several challenges. The largest of these is a
requirement for the model to understand the relationship between the nodes in the hierarchy. There are two primary ways of achieving this, either by maintaining the hierarchy and training a classifier at each node or level, the top-down approach, or by constructing a new model that fully understands the hierarchical relationship [Silla Jr and Freitas, 2011]. The latter category are classed as big-bang classifiers, and have been implemented using Bayesian models [Gopal et al., 2012] and Markov networks [Rousu et al., 2005], while top-down classifiers typically employ support vector machines (SVM) [Cesa-Bianchi et al., 2006].

2.5 Geospatial Datasets

Although geospatial trajectories are becoming increasingly common due to the now pervasive nature of location-aware smartphones, privacy concerns do present challenges for researchers. Available research datasets include Microsoft’s GeoLife Trajectories [Zheng et al., 2010b] and Nokia’s Mobile Data Challenge (MDC) [Kiukkonen et al., 2010; Laurila et al., 2012]. GeoLife was collected in such a way that participants were only rewarded for providing data when they were moving long distances, leading to large periods of missing data. MDC, on the other hand, aimed for continuous collection, but to protect privacy, periods around users’ home locations have been obfuscated by truncating the longitude and latitude values, leading to artificial changes in variance. The MDC dataset contains data collected from the smartphones carried by nearly 200 users over a span of 2 years, and is the most appropriate of the publicly available datasets for evaluating the methods proposed in this paper. However, since it is not clear what impact these truncated periods would have, we opt to treat these periods as missing.

Our primary evaluation data, however, comes from real-world data collected from 10 members of the University of Warwick, collected over 6 months, with a methodology aiming to replicate the MDC data collection process. This provides us with continuous data, without artificially missing periods, to conduct our evaluation. In addition, we use 10 users of the MDC data to verify the trends observed in the Warwick data.

3 Land Usage Extraction

The focus of this paper is using trajectories, collected by smartphones, and augmented with data from a land usage dataset to accurately identify the building or other real-world geographical feature that a person was interacting with at any given time. From this, the identification of meaningful locations becomes the task of grouping together spans of time in which the same element was interacted with. The benefits of this approach, instead of solely using geospatial trajectories as in existing approaches, is that it better captures the relationship between the identified locations and the real-world, with locations being representative in terms of shape, location and properties of the places actually interacted with by the user.

This land usage extraction procedure is designed to be able to replace existing location extraction approaches, where real-world elements replace the arbitrary clusters that would have previously been used. The procedure itself is based on the augmentation procedure used to generate context trees [Thomason et al., 2016c]. The primary difference, however, is that while the augmentation procedure for context trees allows an arbitrary number of land usage elements to be associated with each trajectory point, this process places an upper bound on both the size of elements and the number of elements that can be associated with a trajectory point. If, for example, this limit were set to 1, the resultant augmented trajectories would be synonymous with extracted locations, while higher values for multiple elements associated with each point.

3.1 Element Extraction

A geospatial trajectory relates the location of an individual, entity or device to specific times. For this work, we assume that trajectories are temporally ordered and consist of longitude, latitude and timestamp as well as accuracy, measured in metres:

\[ T = \{(t_1, lat_1, lng_1, acc_1), \{t_2, lat_2, lng_2, acc_2\},...,\{t_n, lat_n, lng_n, acc_n\}) \]
This work requires both trajectories and land usage data, which are assumed to be sets of entities with associated information. Each entity represents a real-world object, feature or area, such as an individual post box, building or farm. Elements are assumed to have a collection of geographical coordinates that represent their location and shape, along with a set of ‘key:value’ pairs that describe its properties. For example, a house may have the tag ‘building:residential’.

The procedure for the extraction of relevant land usage elements, modified from [Thomason et al., 2016c], is shown in Figure 2, where a raw geospatial trajectory (Step 1) enters the system and is overlaid on the land usage dataset (Step 2). The reported accuracy of each trajectory point is then used as a radius to consider (Step 3), such that all elements smaller than a specified size that are partially or wholly within the radius are stored alongside the original point (Table 1). This is achieved by processing each trajectory point in turn automatically until an augmented trajectory is formed. Elements associated with each point are then subjected to a filtering procedure, which identifies the $n$ most likely elements to have been being interacted with by the user. Once this has been completed, interactions with elements are extracted by identifying when elements started and stopped being interacted with, consistent with the visits in existing works. The example from Figure 2 is finished with the summary shown in Table 2.

This procedure differs from the original context tree generation process by introducing a parameter maxradius, which specifies the maximum size of element to consider, preventing very large areas or groups of elements from being identified. Additionally, the parameter $n$ specifies the maximum number of land usage elements that can be associated with any trajectory point.

### 3.2 Filtering

Identifying which land usage elements were most likely to have been interacted with is the task of a filtering procedure, which considers a buffer of points, consisting of a single point under consideration, along with the $\delta$ seconds of data that fall either side of it. Each land usage element within this buffer is then scored according to the number of points the element is associated with, the accuracy of these
Algorithm 1 Summarisation Procedure

1: trajectory ← (p1, p2, \ldots) // augmented trajectory
2: tmax ← 300 // maximum time between consecutive points (seconds)
3: dmin ← 600 // minimum visit duration (seconds)
4: elements ← ElementStore // store of elements and their interactions
5: ongoing ← {} // stores start time of ongoing interactions until they are ended
6: previousTimestamp ← p1.timestamp
7: 
8: while currentPoint ← trajectory.shift do
9:  // If too much time has past between points, end all ongoing interactions
10:  if (currentPoint.timestamp - previousTimestamp) > tmax then
11:    toEnd ← ongoing
12:    toStart ← currentPoint.elements
13:  else
14:    toEnd ← (ongoing - currentPoint.elements) // End finished interactions
15:    toStart ← (currentPoint.elements - ongoing) // Start interactions for new elements
16:  end if
17:  
18:  // Store interactions that are long enough
19:  while element ← toEnd.pop do
20:    if (previousTimestamp - ongoing[element]) > dmin then
21:      elements.addInteraction(element, {start: ongoing[element], end: previousTimestamp})
22:    end if
23:    ongoing.delete(element)
24:  end while
25:  
26:  // Mark the start time of new interactions
27:  while element ← toStart.pop do
28:    ongoing[element] = currentPoint.timestamp
29:  end while
30: 
31:  previousTimestamp ← currentPoint.timestamp
32: 
33: end while
34: 
35: return elements

points, and temporal distance from the point under consideration:

\[ \text{Score}(e) = \sum_{p \in P_e} \left( \frac{1}{a_p} \times \left(1 - \frac{\text{tdist}(p, p_c)}{\delta}\right) \right) \times |P_e| \]

where \( P_e \) is the set of all points that are associated with element \( e \), \( a_p \) is the accuracy value of point \( p \), \( p_c \) is the point under consideration, \( \delta \) is the width of the buffer (i.e. the number of seconds from \( p_c \) to consider) and \( \text{tdist}(p_1, p_2) \) is the temporal distance between \( p_1 \) and \( p_2 \) (in seconds). This equation gives a higher score to elements associated with a large number of high accuracy points (where high accuracy is recorded as a small accuracy radius). From these scored elements, elements can be selected to be associated with each trajectory point, taking the \( n \) elements with the highest scores. In rare cases, it is possible for two or more elements to share the same score, and in these instances, we select the elements closest to the trajectory point for consideration.

3.3 Summarisation

Summarising the augmented trajectories into interactions is achieved through one-dimensional clustering that simply identifies neighbouring points that share the same land usage element, as shown in Algorithm 1. This procedure requires two parameters: \( t_{max} \), which prevents periods of missing data from being included in an interaction by specifying the maximum amount of time that can exist between neighbouring points before the interaction is split, and \( d_{min} \), the minimum duration, required for an interaction to be stored. Upon completion, the procedure outputs a set of land usage elements that contain information about the element in the form of tags and coordinates, but also a set of times during which the user was interacting with the element. In cases where \( n = 1 \), i.e. the maximum number of land usage elements that can be associated with a trajectory point is 1 and, consequently, interactions cannot overlap, these interactions with elements are interchangeable with visits to locations as used in existing work.
4 The Predictive Context Tree

Once the augmentation, filtering and summarising procedures have been completed, we are left with a record of the land usage elements interacted with by a particular user. These interactions become the basis for contextual clustering, forming a Context Tree (described in Section 2.4, and depicted earlier in Figure 1a). In this tree structure, leaf nodes represent individual land usage elements and nodes further up the hierarchy represent contextual clusters that contain all nodes below them. A small example context tree is shown in Figure 1b.

The process of converting a Context Tree into a Predictive Context Tree is the subject of the remainder of this section. As the Context Tree is a hierarchical structure, it contains a vast amount of information pertaining to the relationships between nodes, and so it is desirable to conserve this information. For this work, we opt to maintain this hierarchical structure and train the Context Tree as a hierarchical top-down predictor (as discussed in Section 2.4). The Predictive Context Tree is an extension to the Context Tree data structure that is capable of both summarising a user’s historical contexts as well as predicting their future context as a classification model. Initial Context Trees are trained according to the procedure outlined in [Thomason et al., 2016c] in combination with the augmentation procedure presented in Section 3. The primary difference is that this method allows us to limit the size and number of land usage elements that can be associated with each trajectory point, for example limiting it to 1 element per point mirrors location extraction techniques commonly used in existing work (e.g. [Ashbrook and Starner, 2003; Montoliu and Gatica-Perez, 2010]).

Once constructed, each node of the Context Tree, except the root node, becomes a binary classifier tasked with answering the question “does the instance belong in the subtree rooted at this node?”. Overall classification of an instance occurs by starting at the root node and requesting a classification from each of the root’s children, selecting children to follow based on a criteria until a final classification is reached, again determined by a criteria. The goals of prediction will determine the criteria:

- **Single element**: When predicting specific land usage elements, the predictor must return a leaf node, achieved by following the child with the highest confidence at each stage. This process is shown in Figure 4a.

- **Single context**: When predicting contexts instead of land usage elements, there is no requirement for a prediction to reach a leaf node. Figure 4b shows the procedure for single context prediction, where at each node, the child with the highest confidence is selected providing that the confidence is at least \( T_s \). If no child has confidence of at least \( T_s \), the current node is returned as the class label.
Figure 4: Classification methods for Predictive Context Trees. Classification begins at the root node and selects which children to follow based on the output of their binary classifiers, with different selection schemes

- **Multiple element**: When trained on augmented trajectories that allow more than one land usage element to be associated with each trajectory point, PCTs can be used to predict the multiple land usage elements that will be interacted with next, unlike single element which is limited to 1. This is achieved at each stage by following all classifiers that return confidence $> T_s$ if such exist, otherwise taking the one with the highest confidence, as shown in Figure 4c.

- **Multiple context**: Again, this technique aims to predict multiple elements, but when confidence is low in specific elements, contexts or combinations of elements and contexts can be predicted instead. Predictions are made by taking all children of a node whose confidence is above $T_s$, and returning the node when no child fulfils this criteria, as shown in Figure 4d.

Single element and multiple element are examples of mandatory leaf node prediction, in that the predictive model is required to return only leaf nodes from the tree. Similarly, multiple element and multiple context are examples of hierarchical multi-label classifiers in that they can return more than one class label to a given test instance [Silla Jr and Freitas, 2011], although they can still return leaf nodes (i.e. elements) if confidence is high.

4.1 Training a PCT

Training a PCT takes a set of instances as the training set, with known class labels. The PCT can be used for next-location or next-context prediction where the class label is an identifier pointing to the next location or context of the user after finishing with their current context or location. In contrast, future-location or future-context prediction may generate training instances for each time step and the class label is simply which location or context the user was in during that time window. These instances are fed into each classifier in turn, with the class variable modified to become binary in the following ways:

- If the instance’s class represents this node, it is used as a positive training example.
Figure 5: Example of how a training instance is treated by each classifier when the class label is associated with the node labelled ‘class’. All nodes labelled ‘+’ treat this instance as a positive example, nodes labelled ‘-’ treat it as negative, while nodes without a label ignore this instance for training.

- If the class represents a node in the subtree rooted at this node, it is positive
- If the class represents a sibling of this node, or a descendant of one, it is negative
- If the class represents an ancestor of this node, it is a negative example
- If the class represents any other node, it is ignored and not used for training

Figure 5 shows how each node treats a particular instance. Training through this process ensures that the hierarchical links between elements and contexts are learnt by the PCT, as each node’s classifier is trained to return yes if the instance belongs to itself or one of its descendants, or no if the instance belongs to a sibling or one of their descendants (i.e. following this particular child would be a mistake). Other nodes are ignored because they do not relate to the current problem.

Each node can now be trained as a binary classifier using standard techniques, such as decision trees or k-nearest neighbour approaches. However, using support vector machines, which are tailored to the task of binary classification, and have been shown to be applicable to the specific area of location prediction, are likely to be a good candidate here [Frohlich and Zell, 2005; Wang and Prabhala, 2012].

5 Experimental Setup

The evaluation begins by considering the predictive accuracies that can be achieved when using existing location extraction techniques to identify locations visited by a user as the basis for prediction. We then consider the effects of replacing location extraction with element extraction (as presented in Section 3). Finally, we use the PCT (presented in Section 4) to replace the standard machine learning techniques as predictors. This section provides details of the experiments performed to evaluate the techniques proposed in this paper, with results presented in Section 6.

5.1 Data

For this work, we use both geospatial trajectories collected from 10 members of the University of Warwick over a period of 6 months in 2014, and data from 10 users of the MDC dataset [Kiukkonen et al., 2010; Laurila et al., 2012] for evaluation. As we are unable to publish the Warwick data, for privacy and consent reasons, we use the MDC data for comparative purposes, despite the drawbacks discussed in Section 2.5. Land usage data is provided by OpenStreetMap (OSM)\textsuperscript{1}, a community-maintained map of the world that contains information pertaining to real-world entities, including their geographical coordinates and a set of tags that describe the entity.

\textsuperscript{1}https://openstreetmap.org/
5.2 Location Prediction

The first stage of our evaluation considers location extraction and prediction using existing techniques, to provide a baseline for comparison. As discussed in Section 2, identifying visits, or interactions as we will refer to them, is typically achieved using three thresholds: distance and time, which specify the maximum size and minimum duration, and \( t_{\text{max}} \), the maximum time between two consecutive points to consider them part of the same interaction. Although less widely used than thresholding, the GVE algorithm has also been proposed for identifying such interactions, with the advantage that it can better handle noise in the data, and so we use both Thresholding and GVE for this task. We set the maximum distance parameter for Thresholding to 50m, to aim to extract locations no larger than a building. A value for \( t_{\text{max}} \) of 1 hour allows for short periods of missing data, but will prevent longer periods from being included in interactions where the user may have left and returned some time later. For the MDC data, where longer periods of missing data are expected, we ignore this parameter. Finally, the time parameter, equivalent to the \( d_{\text{min}} \) parameter in land usage extraction, is left open and its impact explored as part of the evaluation. The parameters for GVE allow for tuning the algorithm, but do not map neatly to the real-world properties of the extracted interactions (e.g. size and duration). To get around this, and produce comparable results, we first extract interactions using Thresholding and then select parameters for GVE that extract locations of approximately the same size, using the simulated annealing based methodology proposed in [Thomason et al., 2015], where the distance metric is taken to be the difference in average location sizes between the data clustered with Thresholding and that clustered with GVE.

In both cases, interactions are clustered into locations using DBSCAN with \( \text{minpts} = 0 \), i.e. a single interaction can be considered as a location, and \( \text{eps} = 15\text{m} \), ensuring that interactions must be within proximity to be considered as part of the same location. Once locations have been extracted, prediction is considered using established techniques: support vector machines and hidden Markov models, both of which have been demonstrated to achieve high predictive accuracies for location prediction [Akoush and Sameh, 2007; Bilurkar et al., 2002; Thomason et al., 2015; Wang and Prabhala, 2012].

5.3 Land Usage Extraction

Trajectories augmented with land usage information are to be used both as a foundation for prediction using existing techniques, and as a basis for contextual clustering and prediction using the PCT. In order to produce a representative comparison, parameters are selected that aim to mirror the extracted locations as best as possible. To this end, the maximum element size is constrained to be 50m across, \( t_{\text{max}} = 1\text{hr} \) is specified for the Warwick dataset (and ignored for the MDC data), \( n \), the maximum number of elements to be associated with a trajectory point, is set to 1, and the same values of \( d_{\text{min}} \) as used to extract locations (Section 5.2) are used for exploring its impact on predictive accuracy. The only additional parameter required by this procedure is \( \delta \), specifying the width of the buffer to consider during the filtering stage of trajectory augmentation [Thomason et al., 2016a]. We set \( \delta = 5\text{min} \) for this task, a value selected empirically that produces representative results. Predicting over land usage elements is performed using the same machine learning techniques as in extracted locations, namely support vector machines and hidden Markov models.

5.4 Instance Generation

For both the extracted location and land usage datasets, training instances must be generated. This is achieved by selecting interactions with locations or extracted features that last longer than \( d_{\text{min}} \) minutes. Instances are then generated by summarising interactions into a set of features: day of year, day of week, start hour, start minute, duration, current identifier (element or location), and class (next identifier).

5.5 Multi-element Land Usage

In addition to the land usage extraction procedure already discussed, we explore the potential of allowing overlapping and parallel interactions where multiple land usage elements may be associated with each trajectory point. These may be useful if, for example, a person is interacting with a building that is contained within a larger building (e.g. a shop in a shopping centre), and so we also utilise the land
usage extraction procedure with different values of $n$. For multi-element land usage extraction, we set the maximum element size to be 100m, instead of 50m for single-element, allowing larger buildings to also be extracted. Generating training instances for these datasets uses the same features as before, however the class label becomes the set of elements that the user interacts with next. This is defined as taking the next interaction in the dataset, selecting all other interactions that overlap, and combining the identifiers of all such elements into a single string value that represents the complete set of elements.

5.6 Constructing Predictive Context Trees

Context trees are constructed from the land usage datasets, both single and multi, according to the procedure presented in [Thomason et al., 2016c], and using the Hybrid Contextual Distance (HCD) metric with $\lambda = 0.5$, an empirically selected value that produces representative results. The HCD metric is a similarity measure that balances semantic and feature similarities into a single score used for clustering context trees, where $\lambda$ specifies the weighting towards semantic similarity.

The task now becomes that of converting the generated Context Trees into Predictive Context Trees and evaluating the predictive ability of such a hierarchical model. Each non-root node in the context tree is trained as a binary classifier using a support vector machine (SVM) with the modification of instances as described in Section 4.1.

5.7 Evaluating Predictions

For all location and element prediction approaches (extracted location, land usage, and single element PCT), the training data’s class label represents the next extracted location or land usage element that the user interacted with. Evaluating the correctness of a prediction can simply be performed by comparing the output of the predictor against the known class, referred to as an element correct prediction. For context prediction, in some cases the PCT will return a leaf node which can then be compared to see if it is element correct. In other cases, a non-leaf node will be returned which requires the introduction of the notion of context correctness:

**Definition 1** A prediction is context correct if the node represented by the predicted class label is an ancestor of the actual class node.

For trees constructed over multi-element land usage datasets, predictions take the form of a set of elements or contexts, and so we require evaluative methods to differentiate between these predictions. For this, we define several tests, applied in order:

- **Fully element correct** The set of predicted land usage elements matches the set of actual elements exactly

- **Fully context correct** Every member in the set of actual elements is represented in the predicted set either by itself or an ancestor in the tree. Additionally, every element in the predicted set is either contained within, or an ancestor of, at least one element in the actual set

- **Partial element correct** Some elements were correctly predicted: the union of the predicted and actual sets is non empty

- **Partial context correct** Some contexts were correctly predicted: the union of the predicted set and the set of all ancestors of members of the actual set is non empty

- **Incorrect** There is no overlap between the predicted and actual set, or the predicted and ancestors of members of the actual set

6 Results

Evaluating the performance of the PCT requires a baseline from existing approaches. Figure 6 provides insight into the accuracies that can be expected from existing prediction models (support vector machines and hidden Markov models) when predicting over locations extracted using existing clustering techniques.
and land usage elements extracted using the procedure presented in this paper. The figure demonstrates that increasing $d_{\text{min}}$ leads to predictions of higher accuracy, as $d_{\text{min}}$ controls the minimum duration of an interaction to consider, with shorter interactions being ignored as noise. A larger value for $d_{\text{min}}$ only considers locations at which the user has spent significant amounts of time, thereby making predictions more accurate with fewer possible locations the user will visit. Additionally, the results show that support vector machines outperform hidden Markov models in all cases. Of most relevance, however, is the relative performance of the predictors operating over land usage elements when compared to those operating over extracted locations. For short interaction durations, extracted locations provide the foundation that affords more accurate predictions, but as $d_{\text{min}}$ is increased beyond 30 minutes, extracted land usage elements provide the better foundation, as demonstrated by the higher predictive accuracies observed.

Figure 7 shows summaries of different properties of the extracted location and identified element
datasets for the different values of $d_{min}$, to understand how comparable the results are. Specifically, Figure 7a shows the number of interactions present in each dataset (averaged across the 10 users), and Figure 7b shows the number of different extracted locations or identified land usage elements associated with these interactions. Figure 7c shows the total time contained within these interactions, and Figure 7d shows the average area of locations and land usage elements. The graphs show that higher values of $d_{min}$ lead to fewer interactions, locations or elements and a lower coverage of total time. The average area is least impacted by $d_{min}$, but also the most varied among the techniques. GVE and Thresholding have similar values, as parameters for GVE were selected specifically to extract locations with similar sizes to those identified through Thresholding, while the land usage elements are consistently larger. Larger land usage elements are to be expected as extracted locations only consider regions where users actually spent time, while land usage elements consider entire buildings or features where a user may have only interacted with part of. Figure 7b also helps to understand why the predictive accuracy for GVE is lower than Thresholding (as shown in Figure 6): for each value of $d_{min} > 30$, GVE consistently extracts more locations than Thresholding, which would result in more possible class labels and therefore more complex models, and consequently lower predictive accuracy.

With comparative baselines in place, the task becomes that of understanding the relative performance of the PCT. Figure 8a shows the predictive accuracies achieved when using the PCT to predict which land usage element a user will interact with, the same task performed by the SVM in Figure 6a, and so the performance of the SVM predictor is shown as a comparison. The figure demonstrates that the PCT produces comparable predictive accuracies to SVM when predicting the next element a person will interact with. The PCT is also designed to predict contexts as well as elements, and the accuracies achieved for context prediction are shown in Figure 8b. A comparison of the performance of all techniques are shown in Figure 9 for $d_{min} = 20\text{min}$ and 1hr, where location extraction was performed by Thresholding, since it gives the highest predictive accuracies. For $d_{min} = 20\text{min}$, predicting over extracted locations using SVMs provides the highest element correct accuracy (i.e. it is best able to predict the exact location or element to be interacted with), however, when allowing for contextual prediction, the PCT outperforms this existing approach. With larger values of $d_{min}$, such as 1hr, shown in Figure 9b, predicting over identified land usage elements, as proposed in this work, provides higher accuracies than predicting over extracted locations for both the existing SVM based approach, and the PCT. Again, allowing for contextual prediction, the PCT outperforms the other approaches.

The impact of two of the remaining parameters, $T_s$ and $\lambda$, for context prediction using the PCT are shown in Figure 10. $T_s$ is the Selection Threshold, specifying the predictive confidence required to follow a node through to its child when traversing the context tree. A higher value for $T_s$ will mean that children are less likely to be followed, instead returning contextual predictions, leading to fewer element correct predictions, but more context correct ones. The Semantic Weighting parameter, $\lambda$, is used when clustering context trees. A value of 0 uses only the feature similarity for determining contextual clusters, while a value of 1 uses only the semantic similarity [Thomason et al., 2016c]. When
considering primarily feature similarity, the element prediction decreases in accuracy, but the context prediction increases. This indicates that the contexts identified are far less meaningful as they do not provide a good basis for predicting specific elements. Increasing $\lambda$ both increases the accuracy of element prediction and decreases the accuracy of context prediction. As more accurate element predictions are seen, the contexts become more representative and useful as an indicator of what the person is doing, leading to a more useful predictive model.

As Section 5.1 discusses, the results presented so far have all come from the Warwick dataset as this has a high level of coverage. In order to demonstrate the applicability of the PCT to other data, we also use a subset of the MDC dataset for comparison, shown in Figure 11. Although the MDC data contains truncated latitude and longitude values in parts, the trends are consistent with previous results. Contextual PCT prediction outperforms the other approaches, with SVM and the PCT in element prediction mode performing similarly. Finally, when using SVMs over extracted locations, the accuracy starts slightly higher than over identified land usage elements (as with Figure 6), but with $d_{\text{min}} > 30$, land usage elements provide higher predictive accuracies.

6.1 Pruning

The context tree generation procedure ([Thomason et al., 2016c]), includes an approach to pruning superfluous nodes to reduce storage and processing requirements. This process takes two parameters: $\theta$ and $\xi$, where $\theta$ specifies a threshold between 0 and 1 for a node to be pruned, and $\xi$ assigns a
storage overhead to each node in the tree. Figure 12 shows the impact of these parameters on predictive accuracy. A larger value of \( \theta \) (Figure 12a) leads to more nodes being removed from the tree, resulting in fewer element correct predictions (as the leaf nodes corresponding to the elements are removed), but an increased number of context correct predictions. The effect of \( \xi \) is similar as its value is increased. A higher overhead assigned to storing a node makes it more likely that the node will be pruned. If using the context tree for predictive applications, through the PCT, these results indicate that a reduced size tree comes at a trade-off of reduced element correct predictive accuracy.

### 6.2 Multi-element Prediction

The PCT is capable of predicting multiple elements and contexts at the same time. This may be useful in instances where a user is within, for instance, a building that is contained within another building (e.g. a shop within a shopping centre). Evaluating predictions made by trees that allow multiple such elements to be associated with a single time is conducted in accordance with the metrics defined in Section 5.7. Multi-element prediction is shown in Figure 13a for different maximum numbers of elements per point. Increasing the number of elements decreases the ability for the PCT to identify exactly which elements are being interacted with, however, the partial value remains fairly consistent, demonstrating that the PCT typically gets some of the predictions correct in times when it cannot predict all elements correctly. Figure 13b shows the same graph, but for multi-context prediction where fully element correct indicates that the set of elements being interacted with was predicted correctly, fully context correct represents
times when a prediction covers all correct elements through a parent context. **Partially element correct** indicates that some elements were correctly predicted, but either additional elements were included in the prediction or some elements were overlooked, and **partially context correct** means that some contexts that were predicted were correct, but again, not all elements are covered by a context or additional contexts are predicted.

7 Conclusion

This work has explored the potential for replacing extracted locations with land usage elements that represent real-world features for prediction applications. After demonstrating the improved accuracies that this technique affords, the work has also extended the Context Tree data structure to create the Predictive Context Tree, a hierarchical classification model that is capable of both predicting future land usage interactions with comparable accuracy to existing techniques, but also predicting future contexts that users will be immersed in. Focusing on context prediction in a manner that requires only geospatial trajectories to be collected from the users provides the basis for a wealth of smart applications and services without the invasive data collection typically required by existing context identification work.

Through an evaluation over real-world data from two datasets, and a comparison to existing approaches, we have demonstrated the utility afforded by the PCT. Furthermore, properties of the predictions and the impact of the parameters have been explored. The primary contributions of this paper have been: (i) the proposal and evaluation of replacing extracted locations with identified land usage elements through a modified identification procedure, (ii) the PCT classification model, (iii) an evaluation of the PCT over real-world data demonstrating its ability to predict both interactions and contexts, and (iv) a parameter exploration to understand how properties of the PCT impact predictions.

This work has demonstrated many advantages of predicting over identified land usage elements, in addition to the advantages offered by the PCT. Future work, however, should explore the possibility of using techniques other than SVMs to further increase the predictive accuracy of the PCT, aiming to achieve even higher accuracy for element and context correct predictions.

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References

Sherif Akoush and Ahmed Sameh. 2007. Bayesian Learning of Neural Networks for Mobile User Position Prediction. In Proceedings of the 12th International Euro-Par Conference on Parallel Processing, pages 1234–1239, Honolulu. ISBN 978-1-4244-1251-8.

Christos Anagnostopoulos, Athanasios Tsounis, and Statthes Hadjieftymiades. 2006. Context Awareness in Mobile Computing Environments. Wireless Personal Communications, 42(3):445–464.

Gennady Andrienko, Natalia Andrienko, Georg Fuchs, Ana-Maria Olteanu Raimond, Juergen Symanzik, and Cezary Ziemlicki. 2013. Extracting Semantics of Individual Places from Movement Data by Analyzing Temporal Patterns of Visits. In Proceedings of the ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pages 5–8, Orlando.

Daniel Ashbrook and Thad Starner. 2003. Using GPS to Learn Significant Locations and Predict Movement Across Multiple Users. Personal and Ubiquitous Computing, 7(5):275–286.

Roland Assam and Thomas Seidl. 2013. BodyGuards: A Clairvoyant Location Predictor Using Frequent Neighbors and Markov Model. In Proceedings of the 10th IEEE International Conference on Ubiquitous Intelligence and Computing, pages 25–32, Vietri sul Mere.

Roland Assam and Thomas Seidl. 2014. Context-based Location Clustering and Prediction using Conditional Random Fields. In Proceedings of the 13th International Conference on Mobile and Ubiquitous Multimedia, pages 1–10, Melbourne. ISBN 9781450333047.

Tengfei Bao, Huanhuan Cao, Enhong Chen, Jilei Tian, and Hui Xiong. 2011. An Unsupervised Approach to Modelling Personalized Contexts of Mobile Users. Knowledge and Information Systems, 31(2):345–370.

Nitin Bhyri, Gautham V Kidiyoor, S K Varun, Subramaniam Kalambur, Dinkar Sitaram, and Chid Kolengode. 2015. Predicting the Next Move: Determining Mobile User Location Using Semantic Information. In 2015 International Conference on Advances in Computing, Communications and Informatics, pages 2359–2365, Kochi.

Pradeep Bilurkar, Narasimha Rao, Gowri Krishna, and Ravi Jain. 2002. Application of Neural Network Techniques for Location Prediction in Mobile Networking. In Proceedings of the 9th International Conference on Neural Information Processing, pages 2157–2161, Whistler.

Nicolò Cesa-Bianchi, Claudio Gentile, and Luca Zaniboni. 2006. Hierarchical Classification: Combining Bayes with SVM. In Proceedings of the 23rd International Conference on Machine learning, pages 177–184, Pittsburgh.

Yohan Chon, Hyojeong Shin, Elmurod Talipov, and Hojung Cha. 2012. Evaluating Mobility Models for Temporal Prediction with High-Granularity Mobility Data. In Proceedings of the IEEE International Conference on Pervasive Computing and Communications Workshops, pages 206–212, Lugano. ISBN 978-1-4673-0256-2.

Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. 1996. A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In Proceedings of the 16th International Conference on Knowledge Discovery and Data Mining, pages 226–231, Portland.

Holger Frohlich and Andreas Zell. 2005. Efficient Parameter Selection for Support Vector Machines in Classification and Regression via Model-based Global Optimization. In Proceedings of the IEEE International Joint Conference on Neural Networks, pages 1431–1436, Montreal. ISBN 0-7803-9048-2.

Siddharth Gopal, Yiming Yang, Bing Bai, and Alexandru Niculescu-Mizil. 2012. Bayesian Models for Large-scale Hierarchical Classification. In Advances in Neural Information Processing Systems 25, pages 2411–2419. Curran Associates, Inc.

Ramaswamy Hariharan and Kentaro Toyama. 2004. Project Lachesis: Parsing and Modeling Location Histories. In Proceedings of the 3rd International Conference on Geographic Information Science, pages 106–124, Adelphi. ISBN 978-3-540-23558-3.
Jong Hee Kang, William Welbourne, Benjamin Stewart, and Gaetano Borriello. 2004. Extracting Places from Traces of Locations. In Proceedings of the 2nd ACM International Workshop on Wireless Mobile Applications and Services on WLAN Hotspots, pages 110–118, Philadelphia. ISBN 1-58113-877-6.

Niko Kiukkonen, Jan Blom, Olivier Dousse, Daniel Gatica-Perez, and Juha Laurila. 2010. Towards Rich Mobile Phone Datasets: Lausanne Data Collection Campaign. In Proceedings of the First Workshop on Modeling and Retrieval of Context, Berlin.

Juha K Laurila, Daniel Gatica-Perez, Imad Aal, Jan Blom, Olivier Bornet, Trinh Minh Tri Do, Olivier Dousse, Julien Eberle, and Markus Miettinen. 2012. The Mobile Data Challenge: Big Data for Mobile Computing Research. In Proceedings of the Nokia Mobile Data Challenge (MDC) Workshop in Conjunction with Pervasive, Newcastle.

Truc Viet Le, Siyuan Liu, Hoong Chuin Lau, and Ramayya Krishnan. 2015. Predicting Bundles of Spatial Locations from Learning Revealed Preference Data. In Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems, pages 1121–1129, Istanbul.

Tayeb Lemlouma and Nabil Layaida. 2004. Context-aware Adaptation for Mobile Devices. In Proceedings of the IEEE International Conference on Mobile Data Management, pages 106–111, Berkeley.

James MacQueen. 1967. Some Methods for Classification and Analysis of Multivariate Observations. In Proceedings of the 5th Berkeley Symposium on Math, Statistics, and Probability, pages 281–297, Berkeley.

Raul Montoliu and Daniel Gatica-Perez. 2010. Discovering Human Places of Interest from Multimodal Mobile Phone Data. In Proceedings of the 13th International Conference on Mobile and Ubiquitous Multimedia, pages 12:1–12:10, Limassol. ISBN 978-1-4503-0424-5.

Juho Rousu, Craig Saunders, Sandor Szedmak, and John Shawe-Taylor. 2005. Learning Hierarchical Multi-category Text Classification Models. In Proceedings of the 22nd International Conference on Machine Learning, pages 744–751, Bonn.

Carlos N Silla Jr and Alex A Freitas. 2011. A survey of hierarchical classification across different application domains. Data Mining and Knowledge Discovery, 22(1-2):31–72.

Alasdair Thomason, Nathan Griffiths, and Victor Sanchez. 2015. Parameter Optimisation for Location Extraction and Prediction Applications. In Proceedings of the 2015 IEEE International Conference on Pervasive Intelligence and Computing, pages 2173–2180, Liverpool.

Alasdair Thomason, Nathan Griffiths, and Victor Sanchez. 2016a. Identifying Locations from Geospatial Trajectories. Journal of Computer and System Sciences, 82:566–581.

Alasdair Thomason, Nathan Griffiths, and Victor Sanchez. 2016b. Predicting Interactions and Contexts with Context Trees. In Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, San Francisco, To Appear.

Alasdair Thomason, Nathan Griffiths, and Victor Sanchez. 2016c. Context Trees: Augmenting Geospatial Trajectories with Context. ACM Transactions on Information Systems, pages 14:1 – 14:37.

Jingjing Wang and Bhaskar Prabhala. 2012. Periodicity Based Next Place Prediction. In Proceedings of the Nokia Mobile Data Challenge (MDC) Workshop in Conjunction with Pervasive, Newcastle.

Vincent W Zheng, Yu Zheng, Xing Xie, and Qiang Yang. 2010a. Collaborative Location and Activity Recommendations with GPS History Data. In Proceedings of the 19th International Conference on World Wide Web, pages 1029–1038, Raleigh. ISBN 978-1-60558-799-8.

Yu Zheng. 2015. Trajectory Data Mining: An Overview. ACM Transaction on Intelligent Systems and Technology, 6(3):1:1–1:41.

Yu Zheng, Xing Xie, and Wei-Ying Ma. 2010b. GeoLife: A Collaborative Social Networking Service Among User, Location and Trajectory. IEEE Database Engineering Bulletin, 33(2):32–39.
Jun Zhou, Qinpei Zhao, and Hongyu Li. 2014. Integrating Time Stamps into Discovering the Places of Interest. In Proceedings of the 10th International Conference on Intelligent Computing Methodologies, pages 571–580, Taiyuan. ISBN 978-3-319-09338-3.