Using Program Synthesis for Social Recommendations

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ABSTRACT

This paper presents a new approach to select events of interest to a user in a social media setting where events are generated by the activities of the user's friends through their mobile devices. We argue that given the unique requirements of the social media setting, the problem is best viewed as an inductive learning problem, where the goal is to first generalize from the users' expressed "likes" and "dislikes" of specific events, then to produce a program that can be manipulated by the system and distributed to the collection devices to collect only data of interest.

The key contribution of this paper is a new algorithm that combines existing machine learning techniques with new program synthesis technology to learn users' preferences. We show that when compared with the more standard approaches, our new algorithm provides up to order-of-magnitude reductions in model training time, and significantly higher prediction accuracies for our target application. The approach also improves on standard machine learning techniques in that it produces clear programs that can be manipulated to optimize data collection and filtering. [1]

Categories and Subject Descriptors

H.2.8 [**Database Applications**]: Data Mining; I.2.2 [**Automatic Programming**]: Program synthesis

Keywords

recommender systems, social networking applications, program synthesis, support vector machines

1. INTRODUCTION

At a high level, the problem of selecting events or updates of interest to a user in a social media setting appears similar to recommendation problems in other environments, such as offering book or movie recommendations on Amazon and Netflix. In each of these, a user's previously expressed preferences are used to infer new items of interest; every time the user interacts with the site, the system builds a more accurate picture of what she likes and dislikes and uses it to improve recommendations. Social media, however, poses some unique challenges which demand a different approach from the standard *collaborative filtering*, where other users' preferences are used to infer about what the user will like [12, 15].

To illustrate some of the new challenges that recommendation systems face in this domain, we focus on an application called LifeJoin [5]. We designed this application to model the future of social networking, where a person's profile is continuously updated (modulo a privacy filter) by an automatically generated event stream from the user's mobile devices, including her location and activities (e.g., running, sitting on a bus, in a meeting, etc). The system also attempts to discover interesting co-occurrences in friends' event streams, such as a meeting of two of the user's friends in a nearby pub. In order to deal with the data deluge, the system gives the user the ability to "like" and "dislike" both individual and combinations of events. LifeJoin uses the expressed likes and dislikes to infer what kinds of events are of interest to the user, which can then be used to auto-populate the user's newsfeed or notify her of interesting nearby social events. Collecting all sorts of events through a mobile device can consume a lot of energy [7], so LifeJoin uses the inferred user's interest to drive subsequent event acquisition. For instance, if LifeJoin infers that Mary's friends are only interested in the places she goes for a jog, then the system will save power on Mary's device by turning off data collection when she is not jogging. Our initial experiments have shown that implementing the data collection scheme in the scenario above can extend the phone battery life by up to 40% [5]. Thus, the more accurate we can detect the users' real interests, the more energy we can save in data collection as compared to a scheme that collects all data under all circumstances.

More specifically, inferring interests in LifeJoin poses four unique challenges:

1. **Decomposable Models:** For applications such as LifeJoin, models must be decomposable into simple classifiers that can be pushed down to the individual devices to drive event acquisition. One simple way to ensure a model is decomposable is to limit it to only contain boolean combinations of simple predicates over the input features, which can be decomposed in a straightforward way to indicate the required data from phones. Such models are also useful because they allow users to give explicit feedback about whether the system actually understands their true interests, and to manually tune the models to better suit their preferences as discussed in [12]. By contrast, many existing preference learning algorithms produce black box classifiers that are difficult to decompose and understand.

2. **Active Learning:** Given the large number of incoming events, and the large number of ways in which they could be combined, it is unreasonable to ask the user to rate any meaningful fraction of them. Thus, the learner needs to intelligently choose a subset of incoming events that can most improve the current model. In addition, the domain of users mentioned in the incoming events can also change over time as the user's friends network changes.

3. **Noisy, Skewed Data:** Since the ratings are produced by humans, they are bound to contain occasional errors. Users also change their interests over time, so the same event might be given different ratings depending on when it was shown to the user. At the same time, each user's definition of "interesting" is different, so it is difficult to make generalizations about the statistical properties such

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as the anticipated degree of skew in users preferences. In fact, this is currently an active research topic on its own [3].

4. **Personalized Events:** Unlike typical recommendation systems such as those for books, movies, or online ads, where all users rate a common set of items, the events in LifeJoin tend to be highly personalized. For instance, a user might like an event because it involves her best friend Peter, but the same event would be totally meaningless if is shown to another user who does not know Peter. Thus, we believe it is easier to learn a model for each user individually (i.e., event is of interest if it involves Peter, without needing to know the relationship between Peter and the user) rather than trying to discover the relationships between users and design a model that is applicable to all.

These requirements preclude the use of collaborative filtering (CF) techniques which have been successful in other recommendation systems—such as building neighborhood or latent factor models to predict user ratings. In particular, these techniques tend to generate models that cannot be used to drive data acquisition and generate an explainable model to the user to solicit further feedback (req 1). For instance, a neighborhood model-based approach might attribute a new rating based on a set of previously rated events that are deemed similar, but it is unclear how the system can easily generalize from the set of similar events to determine what new events to collect. Furthermore, CF techniques require a similarity measure between users or events. It is unclear how that can be done in a setting where events are highly personalized to a small set of users (req 4); this is an active research topic [13, 14], and the proposed solutions require explicitly modeling all social relationships between users, rather than simply learning a separate model for each user individually, which does not require discovering the relationships among the users.

We avoid the above issues by viewing the problem as an inductive learning problem with an active learning component: given a set of labeled examples, the goal is to learn a set of rules that represents an individual user's preferences, and to choose new events for the user to rate. Unfortunately, standard inductive learning algorithms such as those based on entropy measures (e.g., decision trees and inductive logic programming tools) are known have issues with skewed data (req 3) [4], it is not clear how active learning can be applied, and they also do not provide good generalization guarantees when compared to statistical-based learners such as support vector machines (SVM).

Recently, the programming languages community has been exploring inductive learning problems in the context of software synthesis in programming-by-example systems [9], where the goal is to infer a program from a set of sample behaviors. Unfortunately, the learning problem in Lifejoin is different enough that none of the previous techniques from this community can be applied out of the box. In particular, the active learning problem has not been sufficiently addressed by previous research from this community. Nevertheless, these techniques provide a new set of tools that can be leveraged to attack the problem.

In this paper, we present a new algorithm to infer users' interests; the algorithm combines new techniques in program synthesis with more traditional machine learning approaches to satisfy the unique requirements illustrated by the LifeJoin application. Specifically, we make the following contributions:

1. We show that both the classical machine learning approach and an approach based purely on program synthesis do not adequately address this problem.

2. We describe a hybrid approach that employs program synthesis to generate a number of classifying functions, and subsequently asks an SVM to assign weights to the features in each generated functions. We show that, when compared to pure machine learning or synthesis approaches, this hybrid technique takes up to an order of magnitude less time to encode the training data into a feature space representation, and improves upon traditional learning algorithms by 30% in overall classification accuracy.

3. We show that we can use a program synthesizer to produce more decomposable and human-understandable models than those generated by traditional machine learning techniques, and provide empirical evidence that the generated models are comparable to the original intentions that the user has in her mind.

We have implemented the learning technique in the context of the LifeJoin application. However, we believe that our approach is applicable to other social networking applications as well, where large amounts of data are collected from users, and labels provided by users contain errors or interest drifts. In the next section we give an overview of the various steps in the learning task in LifeJoin, and illustrate our approach with an example.

2. OVERVIEW OF THE APPROACH

In this section, we illustrate the recommendation problem with a concrete example and present an outline of our solution. To frame the problem, consider the LifeJoin event stream, which contains large numbers of events about the activities of a user's friends and family. Out of this event stream, suppose that the user is interested in events where her friend Joe is away from home either late at night or early in the morning:

$$(user = Joe) \wedge (location \neq Home) \wedge (time < 9am \vee time > 9pm)$$

The goal of the system is to infer this interest function based on events the user rates as having liked or disliked. We want the algorithm to produce its interest function in the form of a predicate like the one above because that helps ensure the decomposability described earlier. When the interest function is expressed in this form, it can be easily manipulated and decomposed into predicates that can be pushed down to individual users' phones to optimize the data acquisition process as described. Such expressions are also comprehensible by users, and can be manually adjusted to tune the results the user sees. We are not aware of any statistically-based methods (such as CF or SVM) that can directly generate models like these.

In the absence of additional information about the expected distribution of the events, the most naïve approach to finding an interest function is to exhaustively explore the space of all possible predicates of the desired form until a set of predicates is found that matches all the previously labeled events. The most obvious problem with such an approach is that the space of possible predicates is enormous—on the order of 10^{40} in some of our experiments. However, as we will describe in Sec. 3, new technology from the field of combinatorial synthesis [23] can find a matching interest function in this space in a few seconds. For example, Fig. 1 shows a sample of labeled data and a few interest functions that were found this way to match the data.

A deeper problem with the naïve approach is that predicates found this way cannot be expected to have much generalization power—that is, they are unlikely to correctly classify as yet unseen data items. Individually, they will also not be of much use in optimally determining the next data element to present to the user for labeling. To address this problem, we rely on the idea of boosting [20]. After the combinatorial synthesis algorithm has found K interest functions f_i, each of these functions can be treated as a weak base learner, and the group forms an ensemble.

The standard way of forming the ensemble is to learn a linear function $F(e) = \Sigma w_i \cdot f_i(e)$, where an event is classified as interesting if $F(e) > 0$. The ensemble allows us to follow a standard

user	location	time	preference
Joe	Office	10am	✗
Bill	Home	3pm	✗
Joe	Office	11pm	✓
Joe	Bar	6am	✓

Each line below denotes a potential classifier

$$(User = Joe) \wedge (location = Office \vee location = Bar) \wedge (time < 7am \vee time > 10pm)$$
$$(User \neq Bill) \wedge (time > 10pm \vee location = Bar)$$
$$(User = Joe) \wedge (time < 9am \vee time > 11am)$$

Figure 1: Learning example with labeled data (left) and candidate classifiers that are consistent with the labeled data (right)

approach for active learning, namely, to select those events that are closest to the boundary where $F(e) = 0$ [26]. Normally, the weights w_i are selected based on the training data, but in our case, since all the functions f_i were selected to agree on all the training events, that leads to all functions having equal weight. That means that the ensemble reduces to a majority vote, and the active learning strategy reduces to selecting the event that causes the maximum level of disagreement among all the candidate interest functions. We refer to this pure synthesis based algorithm as the "ensemble" approach. As we will see in Sec. 5, such an approach already outperforms many standard learning techniques, but we can do better.

When defining the space of candidate interest functions, we require the functions to be in disjunctive normal form. This means that every function f_i can be seen as a disjunction of individual predicates $p_{i,j}$. We exploit this structure when building the ensemble; instead of an ensemble $F(e) = \Sigma w_i \cdot f_i(e)$, we build an ensemble of the form $F'(e) = \Sigma w_{i,j} \cdot p_{i,j}(e)$. Finding weights for each predicate is no longer trivial. We use an SVM to find a set of weights for the function, which has the additional benefit that the weights will be set in such a way that the resulting classifier will be maximum-margin one. As we will see in Sec. 5, defining the ensemble in this way significantly improves active learning, and we call this combination of program synthesis and machine learning techniques the "hybrid" approach.

As our experiments show, this approach also copes gracefully with errors in the training data. We can improve its handling of errors by selecting each of the f_i functions to match only a randomly chosen subset of the data. If the rate of errors is low, this ensures that at least some of the f_i will be selected to match only uncorrupted data.

One issue that still has to be addressed is that the SVM may find fractional values for the weights, so the function $F'(e)$ will no longer be a well-formed boolean predicate. Once again, we use combinatorial synthesis technology to find a well-formed predicate $P(e)$ that is closest to the linear function $F'(e)$. Such predicates have the decomposability property we desire.

Now that we have described our basic approach and problem setup, we describe the synthesis technology we use to solve the problem in more detail in Sec. 3, as well as the details of our hybrid approach in Sec. 4. Sec. 5 presents our experiments on a synthetic data set derived from the LifeJoin scenario, showing substantial performance gains for the hybrid approach. Finally, we discuss related work in Sec. 6, and conclude in Sec. 7.

3. CONSTRAINT BASED SYNTHESIS

In recent years, there has been a lot of interest in the programming languages community around constraint-based approaches to program synthesis [23, 22, 10, 24]. At a high-level, this technology provides an efficient mechanism to search a space of candidate programs for one whose behavior satisfies a given specification.

The synthesis problem can be seen as a generalization of traditional curve fitting, where a space of possible curves—say, the space of all polynomials of degree less than k—is explored in search of one that satisfies a given set of requirements. Modern synthesis systems go several steps beyond simple curve-fitting by providing rich languages for describing requirements and spaces of candidate programs. The search for a correct solution in this space is performed symbolically; i.e., the space of candidate programs is described through a set of equations which are solved through a combination of inductive and deductive methods by a specialized solver. LifeJoin uses a synthesis system called SKETCH [23]. In the reminder of this section, we give a brief overview of Sketch, and show how our system uses it to generate candidate solutions to the problem.

3.1 The Sketch Synthesis System at a Glance

Sketch extends a simple procedural language — think C or Pascal — with new constructs that allow users to write programs with *holes*, i.e., missing expressions that must be completed by the synthesizer. The language allows programmers to use recursive definitions to describe the space of expressions that can be used to fill a hole. For example, consider the following program:

```
int foo(int x, int y) { return expr(x,y); }

generator int expr(int x, int y) {
   return {| ?? | x | y | expr(x,y) + expr(x,y) |};
}
```

The program defines an expression expr to be either a constant, a variable x or y, or a sum of similar sub-expressions. In essence, the generator defines a grammar for the possible expressions that can be returned.

Given the grammar, the user can constrain the behavior of the desired expression by writing test harnesses. For example, the test harness below ensures that the value returned by the function is greater than twice the first parameter when the second parameter is greater than zero, and ensures also that when x=5 and y=8 the function produces 10.

```
harness void main(int px, int py) {
   if (py > 0) { assert foo(px, py) > 2*px; }
   assert foo(5, 8) == 12;
}
```

Given such a program as input, the Sketch system discovers that a plausible solution is for foo to return x+x+2.

To understand how the technology works, consider the generator expr which describes a set of possible expressions. One way to understand this generator is that every time it is called, the system has to make a choice about what to return. In order to turn foo into a concrete piece of code, the system needs a strategy to make those choices; i.e., it needs to find a recipe for how to make the choices in expr to ensure that the correct answer is produced every time. Sketch encodes such a recipe as a vector of bits $\hat{c}$, so the test harness can be seen as taking $\hat{c}$ as an additional parameter. The goal of finding a strategy that works every time reduces to finding a value of $\hat{c}$ that satisfies an equation of the form

$$\forall px, py. P_{main}(px, py, \hat{c})$$

The predicate P_{main} is derived from the test harness main automatically by a compiler, and is true if the strategy $\hat{c}$ causes the function to pass the assertions when run with inputs px and py. Sketch translates the equation above into a series of boolean satisfiability problems. Unlike traditional inductive learners such as decision trees (which gives poor results as discussed in Sec. 1 and Sec. 5), the core algorithm in Sketch works by forming an initial hypothesis about the solution, then iteratively finds instances from the harness that fails the hypothesis and incorporates them into the hypothesis itself. The process repeats until the harness is satisfied. In practice, this tends to be quite fast in in terms of solution generation time as our experiments show, and the details of the algorithm are described in [23]. The algorithm itself is NP-complete as it uses a SAT solver as the backend. However, in practice many of the problems, such as those in LifeJoin, can be solved in very short time as our experiments show.

3.2 Encoding the Space of Interests using Sketch

Given the above, we now discuss how we use Sketch to aid in feature selection in LifeJoin. One of the problems with feature selection is that there is an exponentially large space of possible features, so analyzing them one by one to identify those that better predict the labels in the training data is prohibitively expensive. By contrast, constraint-based synthesis allows us to represent the entire space of possible interest functions as a compact sketch that uses a grammar to describe the space of all possible solutions to the classification problem.

As mentioned in Sec. 2, we would like to generate interest functions that select data elements from the stream of events collected from users' phones by returning a boolean value given events from the event streams. To generate the appropriate interest function, we encode its grammar using Sketch similar to that of the example above. LifeJoin currently collects two streams of events from users' phones: a stream that describes a user's activity (walking, running, etc), and another that describes a user's location. Both event streams come with timestamps that describe the start and end time of each event along with the user involved and. Given that, we encode the space of interest functions using a grammar with predicates from the two event streams, as shown in Fig. 2. Each interest function consists of a disjunction of interests and returns a boolean value. Each interest takes in an activity and a location event, and consists of a conjunction of event predicates. Each event predicate is either one that restricts the set of events from either event stream, or is a join predicate that links events from both data streams, for instance the user from the location event has to be the same as the user from the activity event. As an example, a user who is interested in events about Peter running along the Charles River can be represented with the interest function:

$$a.user = Peter \wedge a.activity = running \wedge$$
$$l.location = Charles\ River \wedge a.user = l.user$$

We formulated our grammar based on initial user studies, and further predicates (such as average duration of events) can be incorporated as needed. In our experiments we also bound the maximum number of disjuncts and conjuncts allowed in the interest functions and interests during synthesis, along with the set of users, activities, and locations.

Following the example above, with the grammar for interest functions we use the previously-labeled events from the user as the harness. We then ask the Sketch system to generate an interest function that satisfies the labels on the training events. And each function generated becomes a weak base learner as discussed in Sec. 2.

$$\begin{array}{rcl}
f(a,l) \in \text{interest function} & ::= & \bigvee_k i_k(a,l) \\
i(a,l) \in \text{interest} & ::= & \bigwedge_k \ (ap(a) \mid lp(l) \mid jp(a,l)) \\
a \in \text{activity} & ::= & \{user, activity, start, end\} \\
l \in \text{location} & ::= & \{user, location, start, end\} \\
ap(a) \in \text{activity pred} & ::= & a.user\ op\ \{Users\} \\
 & \mid & a.activity\ op\ \{Activities\} \\
 & \mid & a.start\ op\ N \mid a.end\ op\ N \\
 & \mid & (a.end - a.start)\ op\ N \\
lp(l) \in \text{location pred} & ::= & l.user\ op\ \{Users\} \\
 & \mid & l.location\ op\ \{Locations\} \\
 & \mid & l.start\ op\ N \mid l.end\ op\ N \\
 & \mid & (l.end - l.start)\ op\ N \\
jp(a,l) \in \text{join pred} & ::= & a.user\ op\ l.user \mid a.start\ op\ l.start \\
 & \mid & a.end\ op\ l.end \mid a.start\ op\ l.end \\
 & \mid & a.end\ op\ l.start \\
 & \mid & (a.end - a.start)\ op\ (l.end - l.start)
\end{array}$$

Figure 2: Grammar of Interests

```
learnModel (posEs, negEs) {
  (posTrainEs, negTrainEs) = subsample(posEs, negEs);
  baseFns = callSketch(harness, posTrainEs, negTrainEs);
  preds = extractPredicates(baseFns);
  m = createSVMModel(preds, posTrainEs, negTrainEs);
  return model;
}

generateDecomposableModel (model) {
  supportVectorEs = getSupportVectors(model);
  decompModel = callSketch(supportVectorEs);
  return decompModel;
}

activeLearningRound (posEs, negEs, unratedEs,
                     numSamples) {
  model = learnModel(posEs, negEs);
  for (e in unratedEs)
    ratings[e] = computeRating(model, e);
  sortedEvts = sortByAbsValue(ratings);
  decompModel = generateDecomposableModel(model);
  return (sortedEs[0:numSamples], decompModel);
}
```

Figure 3: Hybrid Algorithm

With this in mind, we next discuss how the weak base learners are combined in the ensemble and hybrid approaches.

4. THE HYBRID APPROACH

In this section we discuss in detail our ensemble and hybrid approaches, and provide insights into why the hybrid one performs better than the ensemble one.

4.1 Hybrid Algorithm

As mentioned in Sec. 2, our classifier works by first generating a number of functions that are capable of fully explaining the training data. Unfortunately, the ensemble approach does not provide any generalization guarantees. However, as we later pointed out in the same section, we can instead break the weak learners into their predicate constituents and treat them as base features, and then use them as features to train a SVM classifier. Classification is then done using the SVM, with events classified as interesting if it returns a value ≥ 0, and is not interesting otherwise. Figure 3 outlines this hybrid algorithm in pseudocode form.

Learning begins by giving the set of positively labeled (i.e., those labeled as "interesting"), and negatively labeled events to learnModel on line 1, which first invokes the Sketch synthesizer to generate a number of functions (the number to generate is a parameter to the algorithm). The functions are then passed to extractPredicates on line 4, which extracts and returns the set of base predicates from each function (e.g., user = John). The base predicates are then passed to the SVM to generate a model that returns a numerical rating ranging from -1 to 1. The model is used in classification of incoming events (not shown in Fig. 3), where the incoming event is negatively labeled if the rating is less than 0, and is positively labeled otherwise.

Then, during each round of active learning, activeLearningRound on line 15 is called with the list of previously rated events, the list of unrated events to choose from for subsequent user querying, and the number of events to choose. It first constructs a model using learnModel on line 17 with the list of previously rated events. Then, for each unrated event, it asks the model to compute its (numerical) rating; events are then sorted according to the absolute values of their ratings, and the ones that are closest to 0 (i.e., the ones that are the most uncertain according to the current model) are chosen to query the user for labels. At the same time, generateDecomposableModel on line 21 is called to create a model representation to drive subsequent data acquisition. In our experiments the time taken to construct models is typically short.

Noisy data might prevent Sketch from generating any candidate function since the ratings might be contradictory. The subsample function on line 2 is used as a means to remove contradicting inputs prior to model training. Even though more sophisticated methods can be used, our experiments have shown that the simple sampling method is good enough to give reasonable performance in presence of noise.

In a sense, one can view the hybrid approach as using the Sketch synthesizer as a feature selection mechanism, and feeding the selected predicates into the SVM to build the resulting classifier. To test that view, we have implemented other standard feature selection algorithms and provide comparisons in Sec. 5.

4.2 Generating Decomposable Models

The output learned by a linear SVM is a model consisting of a linear function made up by a selected set of predicates, and a list of the all the input predicates and weights for each of them. The weights for each predicate are computed using standard methodology from the weights the SVM assigns to each input event instance. Unfortunately such a model does not decompose well into per-device filters usable for further data acquisition. On the other hand, given the input training data, a program synthesizer is able to generate a classifier that is decomposable, but unfortunately program synthesizers do not provide any generalization guarantees. Fortunately, SVM is able to help us in that respect, since it already identifies the subset of the training data that is used to define the separating hyperplane, otherwise known as the support vectors, and in most cases, the number of support vectors is much smaller than the size of the entire training set, thanks to the SVM's regularization feature. Thus, as a post-processing step, we feed the events that are labeled as the support vectors to the synthesizer and ask it to generate a decomposable model. Even though the resulting classifier generated by the synthesizer might not be exactly the same as the one generated by the SVM (for instance, it might pick predicates that have low weights as assigned by the SVM, but nonetheless can still classify the incoming events), in Sec. 5.5 we present empirical evidence that our approach does indeed generate decomposable models that are similar to what the user originally has in mind.

5. EXPERIMENTS

In this section we present our experimental results. The overall goal of the experiments is to compare various aspects of the different learners.

5.1 Methods Compared

We used the LifeJoin platform for experimental purposes. LifeJoin collects events from two different event streams. One of them is about the location of users, with fields (user, location, start time, end time), and the other one about users' activities, with fields (user, activity, start time, end time). As mentioned in Sec. 1, we are interested in composite events where events from the two streams can be combined in different ways, for instance joining them on the user fields, and part of the learner's goal is to learn how to combine the two event streams to generate interesting events. In the following we use loc$F$ as a shorthand for field F in the location event (and similarly for act$F$ for the activity event), and duration is shorthand for the length of the corresponding event (i.e., end time - start time). To simplify the description we represent users and activities using numbers rather than actual names. We use the **unary** features to describe those that involve only one comparison operation, such as locUser = 3, and **conjunctive** features for those that involve multiple comparisons connected with conjunctions, such as (locUser = 3 and activity = 4). In the rest of the section **full** refers to the set of all unary and conjunctive features together.

For the evaluation we implemented eight different learners, as shown in Fig. 4. The **L1** and **MI** methods are both classical machine learning approaches based on an SVM classifier. Here the L1 approach uses the LASSO algorithm for feature selection, followed by a linear SVM for classification. The MI approach performs feature selection by computing the mutual information between each of the features and the output label, and picks the features with the highest scores for subsequent classification using a linear SVM. Both of these methods enumerate the full feature set on the training data before feature selection. The **ensemble** learner represents the program synthesis approach described in Sec. 3, and **hybrid** represents our new hybrid approach described in Sec. 4.

Tree is the learner created by first learning a decision tree using the C4.5 [19] algorithm using the weka [1] toolkit, and then creating features by extracting the path(s) from the root node that leads to the leaves that classify the event as interesting, as in [25]. In order to avoid degenerate trees, we lowered the support for splitting and did not prune the generated tree. We have also experimented with random trees and the results are similar. The resulting features are then used to train an SVM for classification.

Full is an SVM learner that uses no feature selection on the full set of conjunctive features as mentioned above, **unary** is an SVM learner that has no conjunctive features, **poly** uses the same set of non-conjunctive features as unary except that the features are passed through a polynomial kernel. We did not consider other types of kernels such as radial basis kernel as they combine the input features in a way that does not produce decomposable models (req 1 from Sec. 1). For the learners that involve SVMs, we tuned the parameters (e.g., amount of regularization) using crossfold validation, and we set the degree of the polynomial kernel to be 6 after trying all kernels of degree 2 to 8. We applied the polynomial kernel to other learners (full, L1, MI, ensemble, tree) as well, but that did not improve the results.

5.2 Experiment Setup

We generated a synthetic data set in which we modeled 5 users, randomly and uniformly selecting one of 5 location to visit. Each user remains at the location for a random period of time (ranging

Learner	Feature Selection	Classification	Active Learning
full	none	linear SVM	linear SVM
unary	drop all conjunctive features from the full feature set	linear SVM	linear SVM
poly	same as unary	poly kernel SVM	poly kernel SVM
L1	LASSO on full feature set	linear SVM	linear SVM
MI	compute MI on full feature set, and pick features with score above preset threshold	linear SVM	linear SVM
hybrid	10 Sketch iterations on the training set to generate features	linear SVM	linear SVM
ensemble	10 Sketch iterations on training set to generate features	10 Sketch iterations on test set and majority voting	events with the most # of disagreements among the base learners
tree	same as unary, but use decision tree to pick features	linear SVM	linear SVM

Figure 4: Description of the learners used

from 1 to 10 hours), and randomly and uniformly selects one of 5 activities to perform at the location. This is meant to model the type of input data that LifeJoin produces. The experiments were run on a server with 32 cores and 30GB of RAM. We try to execute the experiments in parallel as much as we can. We choose to evaluate our methods on synthetic data rather than actual data since no publicly available large data set is available, and using synthetic data decouples us from the potential errors in data collection or event identification on the phones. The data set is generated randomly and does not favor or disfavor any particular learner.

In addition to a data set, we need a way to generate user interests (for labeling training data and to generate ground truth for purposes of evaluating the performance of the different learners.) To do this, we manually created 6 different interest functions of increasing complexity and used numerical values to represent users, locations, and activities, as shown below.

1. locUser = actUser
2. (locUser = 3 $\wedge$ locDuration $>$ 1 $\wedge$ activity = 0) $\vee$ (locUser = 0 $\wedge$ activity = 2)
3. (location = 3 $\wedge$ locUser = actUser $\wedge$ locDuration $>$ 3) $\vee$ (location = 2 $\wedge$ activity = 1 $\wedge$ actDuration $>$ 2) or (locUser = 1 $\wedge$ locDuration $>$ 4)
4. same as 3. plus disjunct: (actUser = 3 $\wedge$ activity = 2 $\wedge$ actDuration $>$ 1)
5. same as 4. plus disjunct: (actUser = 1 $\wedge$ actDuration $>$ 1)
6. same as 5. plus disjunct: (locUser = actUser $\wedge$ actUser = 2 $\wedge$ locStartTime - actStartTime $<$ 2)

Each of the interests above causes different amount of class imbalance in the input training data. For instance, the first interest function labels about 40% of the events to be positive, whereas the last (most complicated) interest function labels only about 10% of the events as positive. This is to model how class distribution can vary drastically among different user interests.

For all the experiments we allow Sketch to learn a maximum of 14 different interests, and allow each interest to consist of a maximum of 7 different conjuncts. The numbers were picked from initial sampling of 5 users. Obviously limiting to 7 conjuncts is more than needed in order to learn the predicates listed above, but we used that setting for two reasons. First, we believe this level of interest complexity is a reasonable approximation of the maximum complexity of interests a user might have. Second, for the experiments below that contain errors in the training set, limiting the number of interests to be too small could result in Sketch not being able to find a satisfying model.

Learner	Pred 1	Pred 2	Pred 3	Pred 4	Pred 5	Pred 6
full	100%	100%	85.5%	79.5%	77.5%	81%
unary	75%	75%	75%	75%	75%	75%
poly	76%	76.5%	76.5%	76%	75%	75%
L1	100%	100%	92.5%	88%	74.5%	81.5%
MI	100%	100%	83%	82.5%	78%	82%
tree	100%	100%	91.5%	89.5%	91%	81.5%
ensemble	100%	100%	98%	96.5%	93.5%	92.5%
hybrid	100%	100%	97.5%	95%	94%	93.5%

Figure 5: Cross validation accuracies on error-free training data

Learner	Pred 1	Pred 2	Pred 3	Pred 4	Pred 5	Pred 6
full	43k	43k	43k	43k	43k	43k
unary	344	344	344	344	344	344
L1	61.5	118.6	32.6	265.5	482.9	604.9
MI	6708.5	6906.5	6990	6696.7	6430.8	6650.8
ensemble	26.5	40.1	50.2	45.2	40.2	46.7
hybrid	27.9	43.8	43.2	39.4	39.5	41.8

Figure 6: Cross validation feature set sizes on error-free data (poly and tree have the same # as unary)

To generate training data (and validate the performance of our learners), we labeled data points in our data set using each of these interest functions, assigning a positive label to the event for a given interest function if the interest function evaluates to true.

5.3 Cross Validation Experiments

In the first set of experiments, we evaluate the accuracies of the different schemes using cross validation. The goal of this experiment is to evaluate learner performance in the absence of any performance anomalies the active learning methods may introduce.

For each of the predicates we first generated a dataset of 100 positively and 300 negatively labeled events. The events are uniformly sampled from a domain consisting of 5 users, 5 locations, and 5 different types of activities. We ran 10-fold validation on the dataset, where we divide the positive and negative events into 10 partitions. Figure 5 shows the average accuracies and Fig. 6 shows the number of features that are actually used for classification.

The results show that our hybrid learner has similar accuracy as compared to standard machine learning techniques. At the same time, it does not require using the full feature set as in the other learners such as LI or MI. This is particularly important when comparing the number of features that are used for classification. To achieve the same overall accuracy, the number of features used by the hybrid and ensemble learners are an order of magnitude smaller as compared to others, as shown in Fig. 6.

Next, we repeated the same experiment, but this time we introduced an 5% error into the training set. Here error refers to the chance that a given event in the training set if mislabeled, i.e., an event that is labeled as "interesting" is reversed to be "uninteresting" and vice versa, but the test set is error-free. This is to model human error or user interest drifts over time.

The results shown in Fig. 7 is similar to the case without errors, except that the average accuracies of all the learners are lowered, as expected. It also took longer for the experiments to complete (about 1-2 hours per fold) due to the complexity introduced by the erroneous events.

5.4 Active Learning Experiments

In the next set of experiments we evaluate the learners in the

Learner	Pred 1	Pred 2	Pred 3	Pred 4	Pred 5	Pred 6
full	94%	92%	81.3%	69%	70.2%	75%
unary	65%	64%	62%	70%	66.4%	70.2%
poly	75.5%	75%	75.5%	74.5%	74%	75%
L1	92.6%	93.7%	84%	82%	80.5%	74.3%
MI	93.4%	90%	88%	80%	78.4%	76%
tree	90%	90%	85.5%	77.5%	78.5%	74%
ensemble	95%	95%	82.5%	85%	84%	84.7%
hybrid	96%	91%	86%	84.2%	83%	86.5%

Figure 7: Cross validation accuracies on data with 5% error

actual usage setting, where the user is asked to label a few new data points each time she visits her newsfeed. At the end of each round the learner is given the newly rated events along with the previously rated ones to refine its model about the user. The goal of the learner is to select the list of events to present in each round so as to maximize the accuracy of the model, and to do so with as few rounds as possible.

5.4.1 *Basic Setting*

For evaluation purposes we generate 100 positive and 300 negative events as a training set to be presented during active learning. The events are generated using the same settings as in the cross validation experiments. We then generate an additional 10k events and ratings (which are not given to the learners) to use as the test set. The events in the test set are generated randomly without regards to the ratio of positive and negative events (about 10% - 40% of the test events are positive, depending on the interest function). Initially, the learners are given 1 positive and 1 negative event to learn an initial model. Then, during each iteration, the learners choose 5 events from the training pool to query for their ratings to rebuild the model. We measure the accuracy of the model at the end of each round for 20 rounds. Figure 9(a) shows the results on predicate 6, averaged over 10 runs. The results for the other predicates are similar but the learning rates tend to be higher for less complex predicates as explained next.

The focus of these results is the learning rate, i.e., the rate at which the accuracy increases. As the results show, while the learners that use classical feature selection mechanisms (L1 and MI) do have higher learning rates as compared to those that do not (full and unary), our hybrid and ensemble learners have a significantly higher learning rate than any of the others, due to the fact that they are able to pick features with higher predictive power, as discussed in Sec. 4.

Figure 8 shows the number of features that are used for classification in each round for the learners. While they all increase as the number of rounds increases as expected, the growth rate for the hybrid and ensemble learners that use Sketch for feature selection is much slower than the others.

As a note, we also experimented with skewed data, where the training and testing data are biased towards certain users and locations (to model popular events, and thus the class imbalance is less severe), along with another experiment where we varied the number of events to add per round of active learning. The results are similar to those from the basic setting.

5.4.2 *Effect of Errors*

Next, we introduce errors into the training events as in the cross validation experiments and quantify the effect on accuracies. We introduced K% error. We run two sets of experiments where we introduced 5% and 10% error. Fig. 9(b) shows the results running predicate 6, with 5% error, and Fig. 9(c) shows the results with 10% error.

The average accuracy of all the learners is lowered versus the no error case, as expected. Also as expected, the 10% error case is worse than the 5% error case. However, in both cases, the hybrid learner still performs better than the others. The number of features used (no shown) exhibits a similar trend as in the no error case, except that all learners end up using a larger number of features as a result of the introduction of noise. This shows the power of our approach — by not having an implicit assumption about the class distribution of the training data, the hybrid learner performs better than those that do.

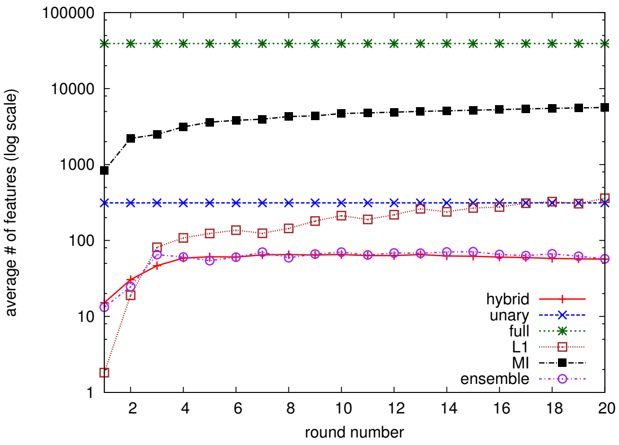


Figure 8: Average feature set sizes used by learners on error-free data (poly and tree have the same # of features as unary)

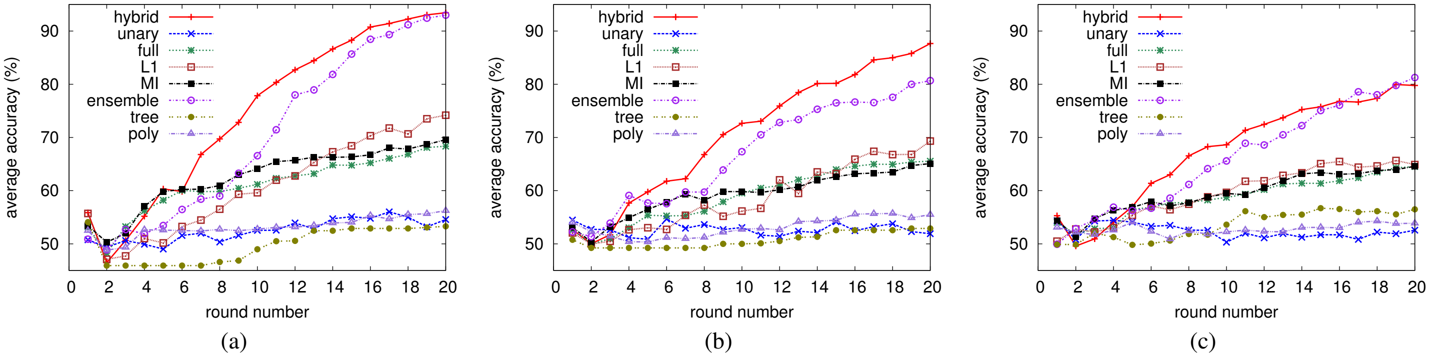
5.4.3 *Making Use of Extended Labels*

One of the advantages of the hybrid learner over the ensemble learner is that the SVM in the hybrid learner is able to make use of extended labels. This is because extended labels simply change the problem from classification to regression, where instead of a binary label (e.g., "like" or "dislike"), the goal is to predict ratings on continuous a scale from -1 to +1. In this experiment, we repeat the same experiment as in the basic setting but with extended labels for events. For events that are of interest, the label remains as +1 as before. For those that are not of interest, the label is negative, but its value is computed in the following way. Given the user's interest expressed as N disjuncts $\vee d_i$, where each d_i is a conjunction of predicates, then if the event e fails all disjuncts, the value of its label is computed as $\mathsf{min}(\#failed(d_i, e)/\#(d_i, e))$, where $\#failed(d_i, e)$ is the number of predicates that e has failed within d_i, and $\#(d_i, e)$ is the total number of conjuncts in d_i. We chose to pick the minimum since this represents the minimal number of changes in e that would make the user happy. We present the accuracy results in Fig. 10 for running on predicate 6, and they show that the learning rate for the hybrid-regression learner is faster as compared to the ensemble and original hybrid-binary learners. This makes sense since the regression learner is able to make use of the extended information that is embedded within the "near miss" cases in selecting better samples during each round of active learning.

5.4.4 *Large Domain*

In the next experiment we increase the number of users and the number of locations from 5 to 50, and the number of activities from 5 to 10. This is to model a user who has more friends and visits more locations. We generated the 100 positive and 300 negative training events from the new domain using uniform sampling as before, and an additional 10k events for the test set. [2] We execute

[2] Since we are learning a separate model for each user, we do not need to scale up to, say 1M for the number of users or locations as it is unlikely that a given user would have that many friends or locations traveled.



(a)

(b)

(c)

Figure 9: Average accuracies of learners using (a) error-free, (b) 5% error, and (c) 10% error data.

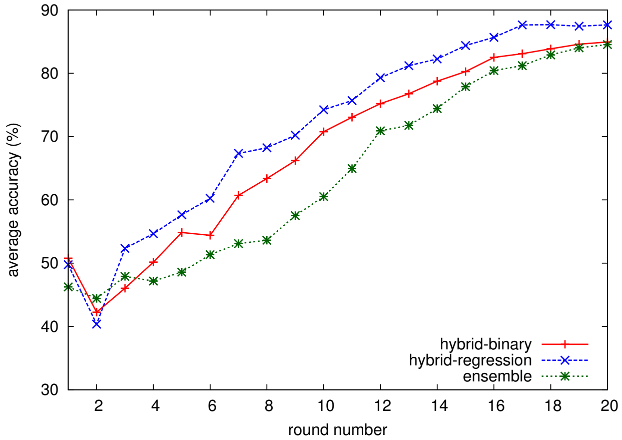


Figure 10: Extended label experiment results

the same active learning experiment as before. Figure 11 shows the results.

On the outset, it seems that all learners achieve high overall accuracies on the test data, but close examination proves that not to be the case. In particular, unlike previous experiments where the ratio of positively and negatively rated events is not heavily skewed, in this case, due to the large domain size, only around 3% of the events in the test set are positively rated, so the learners quickly learn to assign negative to most test events in order to maximize overall accuracy. The result is a model with high precision on the negatively rated events and very low precision on the positively rated ones. The decision tree based classifier, however, decided rather to generalize on the positively labeled events and classifies almost all events as interesting. As a result, it achieves high accuracy on the positive events and poorly on the negative ones, resulting in low overall accuracy. To illustrate this, Fig. 12 show the accuracy results on just the positive events. The figures show that even though the overall accuracies of the learners are comparable, the hybrid and ensemble approaches actually perform much better than the other learners on the positive events.

This experiment raises two important points when comparing among the learners. First, all of the learners except for hybrid, ensemble, poly, and tree require enumeration of the full feature set for all events. In this large domain case, this takes a substantial amount of time (2 hours for conversion into the feature representation) and disk space (300 MB needed to encode 10k events), as compared to the synthesis-based feature selection approach used in the hybrid and ensemble learners, which takes much less time (10 min to finish the Sketch runs and seconds to convert the chosen features into feature-space representation) and negligible disk space (600 kB to encode 10k events). Secondly, the fact that the

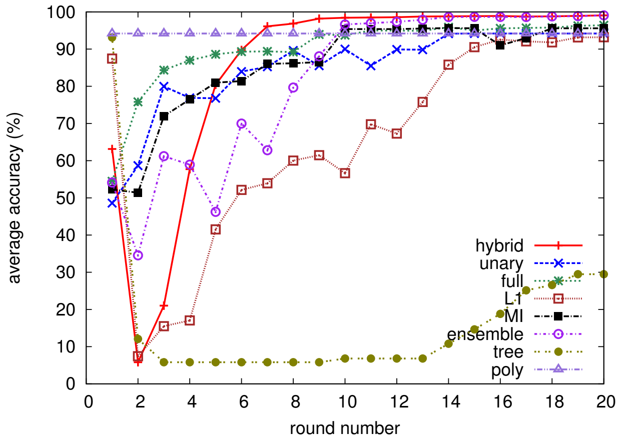


Figure 11: Average accuracies of learners using data from large domain

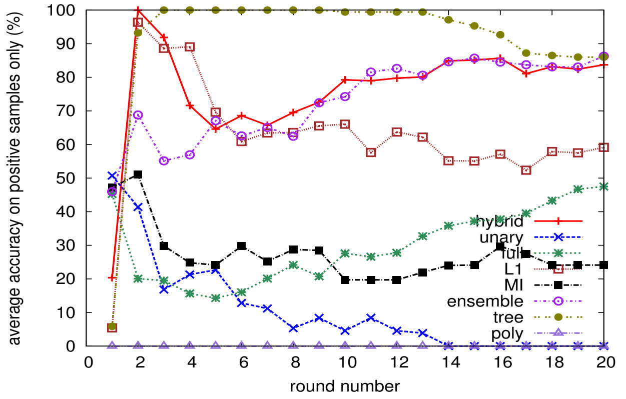


Figure 12: Accuracies of learners on positively labeled events

int	runs	SV	Interest function learned
1	1	21	locUser = actUser
2	4	157	(locUser = 3 ∧ locDuration ≠ 4 ∧ locUser = actUser) ∨ (activity = 2)
3	6	120	(locDuration = 4 ∧ locUser = actUser) ∨ (location ≠ 0) ∨ (locUser = 1 ∧ locDuration > 4)
4	6	146	(location ≠ 2 ∧ locUser = actUser ∧ locDuration = 4) ∨ (location ≠ 2 ∧ activity = 1) ∨ (locUser = 1 ∧ locDuration > 4) ∨ (actUser ≠ 1 ∧ activity = 2)
5	10	183	(location ≠ 2 ∧ locUser = actUser ∧ locDuration > 2) ∨ (location = 2 ∧ activity = 1 ∧ actUser ≠ 4) ∨ (locUser = 1 ∧ locDuration ≠ 2) ∨ (actUser ≠ 2 ∧ activity = 2)
6	16	198	(location ≠ 2 ∧ locUser = actUser ∧ locDuration > 2) ∨ (location = 2 ∧ activity = 1) ∨ (locUser = 1 ∧ locDuration > 4) ∨ (actUser = 3 ∧ actDuration ≠ 5 ∧ locUser ≠ 4) ∨ (actUser = 1)

Figure 13: Model explanations using Sketch

classical machine learning based learners assign negative labels to most events means that they will very likely not be able to identify any interesting events for the user, which is the ultimate goal.

5.5 Model Explanation Experiments

In these experiments we test the effectiveness of using a program synthesizer at producing a decomposable model (which will provide human readability and the ability to be pushed down onto a phone for data acquisition purposes). As discussed in Sec. 4.2, we took the support vectors after model generation and fed them into Sketch. In an attempt to generate a minimal description of the model, we ran Sketch iteratively, first assuming the user has only 1 interest and asking Sketch to generate a description of the model. If that fails we increase the number of interests until Sketch is able to find a description. We took the data from one of the cross validation experiments without error consisting of 400 events. Figure 13 lists the number of iterations needed for each of the predicates to produce the model description, the number of support vectors used as inputs, along with the actual description generated.

Although the learned predicates do not perfectly match with the predicates used to generate the labels for the data, they are quite similar, and are relatively easy to determine what data to subsequently collect on the phones. The results also show the power of using SVM to reduce the number of input events that are needed to feed into the synthesizer, where in the best case (interest 1) we only need to give 5% of the original training events in order to generate a decomposable description that also happens to perfectly match the original interest function.

6. RELATED WORK

Recently, many probabilistic modeling approaches have been proposed that can also be applied to the learning problem discussed in this paper, including Bayesian networks [11], statistical relational learning [8], and probabilistic logic [17]. There are also work in building probabilistic models predicting user behavior [27, 12, 2, 15, 6]. However, as with SVMs, models learned using such techniques tend not to generate decomposable models.

On the other hand, other inductive learning techniques, such as inductive logic programming [18, 16], which aim to learn formulas from the training data, can produce decomposable models. However, such tools still assume the input data to have certain class distribution, and it is unclear how feature selection can be done for such techniques.

There are many feature selection algorithms that have been proposed in addition to mutual information and LASSO. However, our synthesis-based approach differs from classification techniques in that most feature selection techniques focus on the statistical properties of the training data, e.g., approximating the probability distribution of a feature based on the number of data points in the training set in which it appears, as in the MI metric. Such schemes perform well when fed with a sufficiently large amount of training data, as evident in our cross validation experiments, but do not do so well in cases when the training data size is small, as in our active learning scenarios.

In recent years, the programming languages community has been working on programming-by-example problems to synthesize different types of programs [21, 10, 9]. Our work differs from previous tools in that we require a feature selection mechanism in place in order to provide reasonable results. The work of Gulwani in [9] proposes querying the user to provide differentiating outputs when the synthesizer cannot decide between multiple programs that satisfy the same input constraints. Similar ideas appeared in [10]. We generalize this concept and propose the ensemble learning scheme, and further show that a hybrid scheme that combines synthesis-based feature selection with an SVM for classification can provide excellent performance for social networking applications like LifeJoin.

7. CONCLUSIONS

In this paper, we presented a learning algorithm that combines the strengths of classical machine learning techniques with program synthesis tools, focusing on personalized social recommendation applications. We showed that a hybrid approach, which first uses program synthesis to generate base learners, followed by breaking down into individual features and weight assignment with an SVM, significantly improves runtime and classification accuracy. Finally, we showed that using program synthesis on the *output* of an SVM can yield much simpler, and more human readable models, which help users understand system behavior and can drive subsequent data collection.

The experiments show that the hybrid approach can significantly outperform traditional classification schemes on synthetic data, but an important next step is to validate the results on real-world data. Similarly, more research is needed in analyzing the generalization properties of the synthesis-based approach. Understanding its theoretical connections with classical machine learning-based techniques with help develop further algorithms that leverage the advantages of the two in improving results.

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