

# Smart City Analytics: Ensemble-Learned Prediction of Citizen Home Care

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## ABSTRACT

We present an ensemble learning method that predicts large increases in the hours of home care received by citizens. The method is supervised, and uses different ensembles of either linear (logistic regression) or non-linear (random forests) classifiers. Experiments with data available from 2013 to 2017 for every citizen in Copenhagen receiving home care (27,775 citizens) show that prediction can achieve state of the art performance as reported in similar health related domains (AUC=0.715). We further find that competitive results can be obtained by using limited information for training, which is very useful when full records are not accessible or available. Smart city analytics does not necessarily require full city records.

To our knowledge this preliminary study is the first to predict large increases in home care for smart city analytics.

## KEYWORDS

Ensemble Learning, Home Care, Smart City Analytics

### ACM Reference format:

Casper Hansen, Christian Hansen, Stephen Alstrup, and Christina Lioma. 2017. Smart City Analytics: Ensemble-Learned Prediction of Citizen Home Care. In *Proceedings of CIKM'17, Singapore, Singapore, November 6–10, 2017*, 7 pages.

<https://doi.org/10.1145/3132847.3133101>

## 1 INTRODUCTION AND RELATED WORK

In many countries, older citizens are a rapidly growing proportion of the population, and many of them need varying levels of home care, such as help with medication or surgery rehabilitation, for instance. Predicting how much home care will be needed, and by whom, is important for at least two reasons: (1) it allows for preventive measures to be taken in order to forestall or curb health deterioration, leading to better quality of life for citizens; (2) it facilitates better planning of the city's resources, leading to reducing the overall financial cost of healthcare to the city, while also improving efficiency in response time and waiting lists. Both of the above are necessary actions towards creating *smart cities*.

We present a method for automatically predicting citizen home care. Specifically, our method uses ensemble learning to predict

large increases in the amount of home care needed by citizens. The method creates a new prediction model each month using 3 months of prior information, and the collection of models is combined to a single prediction through meta learning. We focus on predicting large increases as those developments are the most costly and hard to manually predict.

To the best of our knowledge no research has been done on predicting large long term increases in home care on the individual level, and generally research on home care prediction is scarce. Lanzarone et al. [8] proposed a stochastic model to represent a citizens' care pathway, and based on historical data they trained and evaluated the models ability on predicting the number of visits 1 week ahead. Their focus was on providing a support system in the short term, while our work focuses on predicting long term increases before they happen. Generally, a large increase in home care corresponds to a decrease in a citizens' capabilities, either through natural causes such as ageing or from sudden illness. As such, this line of research is similar to that of predicting hospital re-admission, where recent model comparison studies achieve AUC scores ranging from 0.68 to 0.73 [3, 9] depending on the used data.

Our work contributes a new application of ensemble learning for smart city analytics, which can predict large increases in citizen home care with high accuracy and robustly across reduced amounts and types of training data.

## 2 ENSEMBLE LEARNING FOR HOME CARE PREDICTION

We formulate predicting large increases in home care as a binary classification problem. Given a citizen's past, the task is to predict whether the number of provided home care hours goes up by at least 6 hours in the next 3 months. We do the prediction using ensemble learning, which consists of forming an ensemble of level 0 models trained over time, and then combining the level 0 predictions into a single prediction using a level 1 meta model. We consider data to be separated in chunks, such that at time  $t$  a training dataset  $D^t$  arrives as instances (vectors)  $x^t(i)$  and target variables  $y^t(i) \in \{-1, 1\}$  for  $i = 1, \dots, |D^t|$ , where  $x^t(i)$  and  $y^t(i)$  are sampled from an unknown distribution, which is potentially changing at each time step. At each time step  $t$  we train a model  $h_t$ , such that we at a given  $t$  have an ensemble of level 0 models  $\{h_1, \dots, h_t\}$ . To combine the prediction of each level 0 model, we build a new set of instances by computing  $x_h^t(i) = [h_1(x^t(i)), \dots, h_t(x^t(i))]^T$  for all  $i$ , i.e. a vector consisting of each level 0 model's prediction for each instance. These instances are used to build the final level 1 model.

We experiment with two types of models for both level 0 and level 1. The first is a linear logistic regression model, and the second is a nonlinear Random Forest model [1]. Training either level 0 or level 1 models is done notationally in the same way when we use the

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CIKM'17, November 6–10, 2017, Singapore, Singapore

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ACM ISBN 978-1-4503-4918-5/17/11...\$15.00

<https://doi.org/10.1145/3132847.3133101>

notation defined above, so when describing the models we simply refer to a dataset consisting of  $(x, y)$  pairs.

**Logistic regression** in its regularized form is defined as the minimization of:

$$\min_{\vec{w}} \sum_{x, y} \log(1 + \exp(-\vec{w}^T x \cdot y)) + \lambda \|\vec{w}\|^2 \quad (1)$$

consisting of a weight parameter  $\vec{w}$  and a regularizations parameter  $\lambda$ .  $\vec{w}_0$  denotes a bias term such that  $x_0 = 1$ .

**Random Forest** is an ensemble method and consists of a combination of weak classifiers in the form of tree predictors. It consists of three parameters [1]: the number of trees, the number of features to consider in each split, and the minimum number of samples for splitting and creating leaves.

The rationale of experimenting with these two models is that, while logistic regression is only able to capture linear relationships, it is a less complex model and thus requires fewer samples to train in order to expect good performance. This may be beneficial since data is not plentiful in this domain. Random Forest is able to capture nonlinear relationships and was recently empirically shown in general to be among the best families of classifiers [2]. However, it is a more complex model thus requiring more samples to train than logistic regression.

Ensemble learning methods [7, 10] focus on how to combine the level 0 models to obtain the final prediction, and most often do not assume a specific level 0 model. Different combination strategies exist [7], and we have employed the *dynamic* strategy where the learned level 0 models are kept unchanged over time, and the ensemble adapts via a combination phase where a weighting or selection of the level 0 models is learned. Our approach resembles the Dynamic Ensemble of Ensembles (DE<sup>2</sup>) method [10], that also employs interim ensembles of the level 0 models.

### 3 EXPERIMENTAL EVALUATION

#### 3.1 Data

We evaluate our approach on the following data provided by the city of Copenhagen: from April 2013 to April 2017 (inclusive), records of all citizens of Copenhagen who have received home care (27,775 citizens in total). We adopt the definition of home care used by the city, which covers a wide variety of services, spanning from daily help with e.g. pills and laundry, to rehabilitation at home after surgery. The contents of this data are displayed in Table 1. The feedback is reported by the care taker after each visit, and potential hospitalization is reported by the hospitals. The provided services are tracked on an individual basis.

#### 3.2 Training and baselines

The aim is to predict large increases in the hours of homecare provided to citizens. We define large increases as monthly increases of at least 6 hours within the next 3 months. We aggregate the data over 3-month periods: for each month, we aggregate the home care services of the current month with that of the previous two months. We do this for each citizen, with increments of 1 month, such that each month occurs in three 3-months periods. This produces 423,909 historical past records for individual citizens, which can be grouped by month to create the chunks described in section 2. We associate

**Table 1: Our dataset of home care citizen records in Copenhagen from 2013 - 2017.**

Category	Features
Basic	gender, age, zipcode, date, civil status of citizen
Living type	own residence, senior housing, assigned residence
Time	day, evening, night, weekday, weekend
Type	public, private
Health Care	generic activity, emergency care stay, dementia care, reoccurring visit, dental care, palliative care, personal care, practical help, rehabilitation, sick care
Feedback	citizen home, citizen not home, citizen hospitalized, other
Length	number of home care hours, number of large increases of at least 6 hours within the last 3 months
Financial	financial cost of service

**Table 2: Cumulative information levels (IL)**

IL	Description
IL1	Basic, Length, and Living type categories from Table 1
IL2a	IL1 + binary Time category from Table 1
IL2b	IL1 + binary Health Care and Type categories from Table 1
IL3	IL2a+IL2b
IL4	Contains IL3 but with the full distribution (instead of binary) Time, Health Care, Feedback and Financial categories from Table 1

a binary target variable to each record indicating if the provided home care increases by at least 6 hours in the next 3 months, or not. This choice corresponds to 88.05% negative classes and 11.95% positive classes.

Our training data consists of historical past records from September 2013 to February 2017, with the associated target variables representing if a large increase happens in the following 3 months. We use logistic regression and random forests, presented in section 2, interchangeably as level 0 and level 1 models. For logistic regression,  $\lambda$  is tuned in  $\lambda \in [10^{-4}, \dots, 10^4]$ , testing 100 evenly distributed values in logarithmic scale. For random forests, the number of trees is tuned  $\in [100, 200, \dots, 1000]$ , the number of features in each split is tuned  $\in [0.1, 0.15, \dots, 0.9]$ , and the minimum number of samples for splitting and creating leafs is tuned  $\in [2^0, 2^1, \dots, 2^6]$ . At all times, 3-fold stratified cross validation is used for training. At each time point data from 3 months ago is used for training and validation, and tested on the current month.

For level 0 models, we experiment with two variations: 1) using the same level 0 model on all previous available data; and 2) using the data from the last month for the level 0 model.

Performance is evaluated by measuring the area under the receiver operator curve (AUC). AUC was chosen as opposed to e.g. accuracy, because our dataset is highly imbalanced (88.05% negative classes and 11.95% positive classes). As AUC measures the trade-off between the true positive and false positive rate, it is not affected by an imbalanced dataset, whereas accuracy is.

By learning the combination strategy of level 0 models we assume that the best prediction is not just based on the most recent model, but found by utilizing multiple previously learned models.

There are no established domain-specific baselines to compare our work to. Even the city of Copenhagen, who provided the data, did not have an automatic or manual method for predicting increases in home care, despite acknowledging the importance of this type of prediction. So we created the following two baselines to evaluate our method: predicting that today's increase in home care hours is the same as 1) that of one year ago; and 2) that of three months ago.

We further experiment with reduced amounts and types of training data, and study their impact on prediction effectiveness. We structure our data into five *cumulative* information levels, shown in Table 2.

### 3.3 Findings

Table 3 displays the AUC of our ensemble method with different combinations of logistic regression (LR) and random forest (RF) as level 0 and level 1 models, as well as the baselines. The AUC values are the average over all months. We see that the highest AUC (0.715) is obtained from using logistic regression on all previous training data. This means that isolating only the most recent context is not necessary for this type of prediction. We also see that using logistic regression as both level 0 and 1 learners performs similar with an AUC of 0.714. Thus surprisingly the data stream remained similar during the 5-year period, such that an online ensemble did not provide an improvement.

Figure 1 shows the two best performing models for each month, as well as the two baselines. The best performing methods clearly outperform both baselines, where predicting the same as the year before achieved 0.548, and doing the predictions based on if increases occurred during the last 3 months achieved 0.634.

The results when doing the same experiment as above on the five cumulative information levels can be seen in Table 4 as averages over all months, and visualized in Figure 2 where the best performing models are shown for each month. The best AUC score for the lowest information level was 0.677, which increases to 0.697 at the next level, but the remaining three levels perform very close to each other - however with small increases as the levels increase. All information levels outperform the baselines. We see that the more information we use for the prediction (increasing Information Levels (IL)), the better the prediction. However, we also see that prediction is not notably lower when using only basic information (IL1). This implies that good predictions can be achieved by using only basic citizen records, which most cities are likely to log.

## 4 DISCUSSION AND CONCLUSION

Our choice of using records from the last 3 months to predict increases in home care was motivated from the assumption that recent policy changes on behalf of the city could have an effect on the amount and level of provided home care. Similarly, changes in who the responsible care taker is could have an effect as well. However, we see that using a model trained on all available data gave the best AUC of 0.715.

**Table 3: Average AUC for models and training data with information level 4 (IL4). The last four columns correspond to our method. Level 1 models using level 0 models trained on last month (1) or all previous data (2) are shown in the last 3 rows.**

Trained on/Method	Baseline	RF	LR	RF+LR	RF+RF	LR+RF	LR+LR
3 months baseline	.634	-	-	-	-	-	-
12 months baseline	.548	-	-	-	-	-	-
(1): Last month	-	.562	.709	-	-	-	-
(2): All previous data	-	.572	.715	-	-	-	-
Models from (1)	-	-	-	.605	.578	.570	.711
Models from (2)	-	-	-	.617	.582	.571	.714
Models from (1)+(2)	-	-	-	.618	.575	.572	.714

**Table 4: Average AUC for the best performing model on different information levels (IL) of training data. Level 1 models using level 0 models trained on last month (1) or all previous data (2) are shown in the last 3 rows.**

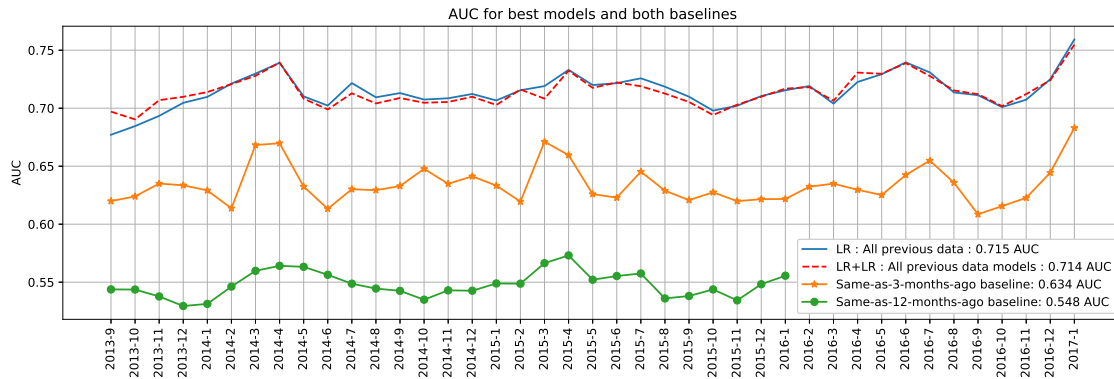
Trained on/Level	IL1	IL2a	IL2b	IL3	IL4
(1): Last month	.669	.696	.710	.711	.709
(2): All previous data	.665	.697	.709	.712	.715
Models from (1)	.677	.696	.711	.712	.711
Models from (2)	.676	.699	.711	.712	.714
Models from (1)+(2)	.677	.698	.711	.713	.714

Our methods were compared against two baselines, one where we predict that an increase will happen if it happened a year before, and another where we predict an increase if it happened within the last 3 months. These baselines serve as heuristic real-world ways of planning ahead. With baseline AUC scores of 0.548 and 0.634 respectively, we were able to outperform them by a large margin, thus providing a considerable improvement.

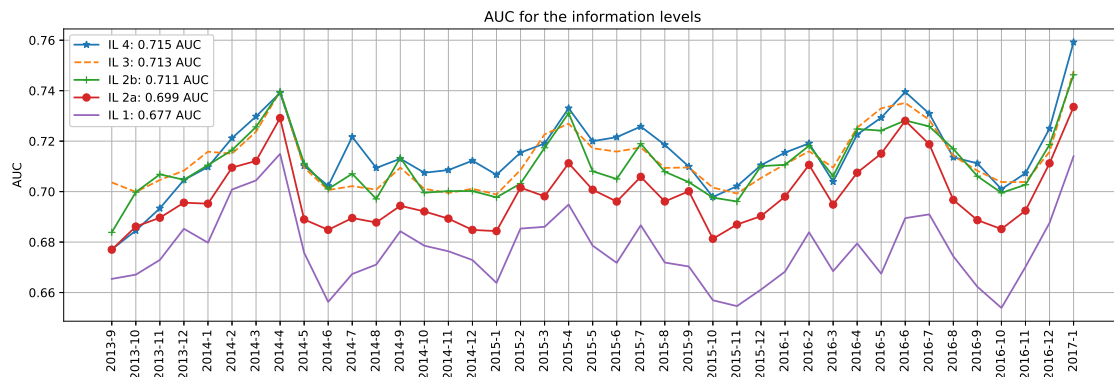
When inspecting the weights of the model trained on all previous data in the last time step we find that the five most discriminative features and their absolute weights are: the number of large increases in the last 3 months (0.38), if the citizen was hospitalized (0.22), if the citizen received sick care (0.21), if the citizen received home care in the weekend (0.21), and the age of the citizen (0.14). Interestingly the most important feature, by a large margin, was the number of times a citizen had their home care hours largely increased in the past 3 months, which corresponds to the best performing baseline. This could correspond to an initial under-evaluation of the new level of required home care for a citizen when their circumstances change, or that a decline in a citizens' capabilities happens fast over a relatively short time span.

We argued in section 1 that the problem of predicting large increases in home care is similar to that of predicting hospital readmissions, where recent model comparisons shows the highest AUC scores of 0.68 to 0.73 [3, 9] depending on the data. The purpose of those studies has been to obtain financial savings and to put extra focus on patients likely to be re-admitted. The purpose of our work is similar, and may be used as a tool for long term planning for both financial and health related benefits.

We considered our data at five cumulative information levels in order to understand what level of detail is needed to obtain good performance. While we had very detailed data available as described in Table 1, we found that simply using binary information about



**Figure 1: AUC scores for the best two performing models and training data, as well as the baselines. The dashed line correspond to our method.**



**Figure 2: AUC scores for the best performing models and training data in the five cumulative information levels.**

the received services on each citizen (IL2b) performed similar to using all available information, which is beneficial since this data is extremely cheap to produce since no daily logging is needed. The binary information about the received services correlates with the general health of citizens, and can therefore also be seen as a derived feature based on their actual medical conditions. Since the largest performance increase comes from knowing which services the citizens receive, a very plausible hypothesis is that knowing the actual conditions of each citizen would lead to further performance improvement. However, this kind of information is not always easily accessible.

This has been a preliminary study into smart city analytics, where we focused on using a well known machine learning methodology for making predictions, namely ensemble learning, in order to predict one of the major health expenses for a city: large increases in home care hours received by citizens. In the future we plan to use natural language processing in order to extract meaningful semantics from the journals of the carers (e.g. nurses, doctors, or other staff) and investigate its usefulness to smart city predictions that can improve welfare. This work complements wider efforts in smart health analytics using Machine Learning [5, 6], and Ensemble Learning [4] in particular.

## ACKNOWLEDGMENTS

Funded by the Innovation Fund Denmark, DABAI project.

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