1-1-2016

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Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 83 (2016) 1244 – 1249

Procedia Computer Science

The 3rd International Workshop on Machine Learning and Data Mining for Sensor Networks (MLDM-SN)

Forecasting Internal Temperature in a Home with a Sensor Network

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Abstract

We forecast internal temperature in a home with sensors, modeled as a linear function of recent sensor values. The Smart* Project provides publicly available data from an inhabited home over a three month period, reporting on 38 sensors including environmental readings, circuit loads, motion detectors, and switches controlling lights and fans. We select 13 of these sensors that have some influence on the internal temperature, and create forecasts that are accurate to within about $1.6°F$ ($0.9°C$) over the next six hours. Temperature prediction is important for saving energy while maintaining comfortable conditions in the home.

Peer-review under responsibility of the Conference Program Chairs

Keywords: Home Sensor Network, Temperature Forecasting, Smart* data

1. Introduction

According to recent studies, about 40% of energy produced worldwide is consumed by buildings, and more than half of this is used by Heating, Ventilation and Air Conditioning (HVAC) systems.[9,10] Accurate temperature forecasts can reduce energy usage in buildings in two ways. First, as Pan *et al.*[13] state, due to thermal inertia, it is more efficient to maintain temperature in a room or building than to heat or cool it, so an HVAC controller can simply apply heating or cooling to counteract forecasted temperature swings and avoid contributing to those swings. Second, Model Predictive Controllers (MPC), which produce a control signal for HVAC systems, minimize a cost function based on energy consumption. The cost function takes into account a prediction horizon and a control horizon[7]. The prediction horizon used in practice depends on how much data is needed by the HVAC controller to achieve acceptable comfort while reducing energy consumption. For instance, Moreno *et al.*[16] achieve estimated energy savings of 20%. Thus, a rough estimate of potential savings arising from forecasting temperature in buildings is 4% of all energy produced.

The Smart* Project[14] provides publicly available data from several different houses showing various data for each house, specifically electrical load and environmental readings including temperature, humidity, wind and rain readings. One of the homes, Home A, has readings from 38 sensors including environmental readings, circuit loads,

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Peer-review under responsibility of the Conference Program Chairs
doi:10.1016/j.procs.2016.04.259

motion detectors, and switches controlling lights and fans, over a three month period. We predict temperature in this home over various horizons, *i.e.* a temperature estimate and an estimate of its accuracy 15 minutes in the future, 30 minutes, and so on, up to six hours. Our forecast accuracy decreases gradually as the forecast horizon increases, with mean absolute error estimated at $0.11°F$ $(0.06°C)$ for the 15 minutes-ahead forecast, and at $2.7°F$ $(1.5°C)$ for the six hour-ahead forecast. Accordingly, the average error over all 24 forecasts is estimated at $1.6°F$ $(0.9°C)$. [1]

We contend temperature forecasting systems should use recent data from a wide variety of sensors, when that is available. Previous work has relied on time series analysis from a long series of data taken over several days from just a few sensors. For example Zamora-Martinez *et al.*[2] use internal temperature and solar radiation, while Mechaqrane *et al.*[15] use indoor and outdoor temperature, solar radiation, and auxiliary heating power. However, where people are living, their activities may be variable and unpredictable. Events that can affect temperature, such as motion detected in the kitchen area, may occur at varying times. Moreover, the chance of a sensor malfunction over a long period is higher, which may lead to interruptions in the forecast until sufficent data is available, which may interrupt any energy saving that depends on forecasts.

In the remainder of this paper, we describe the data made available by the Smart* Project[14], we review statistical methods applied to this data, and explain our findings when forecasting internal temperature.

2. Background: Smart* Data and Statistical Methods for Temperature Forecasting

The Smart* Project[14] provides environmental and electrical load data from four houses that are actively inhabited, one of which,“Home A” also contains a sensor network. Data records are about the environmental factors including inside and outside temperature and humidity, wind speed and rain, about the electrical load on circuits including the master outlets and the furnace, about the motion within the home including corners near the master bedroom, the living room, the kitchen, and the bedroom, and about switches, including the living room dining lights, and many others. We named these variables: enviromental varliables inT, outT, inH, outH, WS, R, circuit variables MOC, FC, motion variables MM, ML, MK, MB, and the switch variable LRDL. We chose the six environmental factors and these seven additional ones because they add predictive value. [2]

The data provided on the Smart* website cover May, June and July 2012, and report either at specific times, or as energy demand is made, depending on the sensor. In our process we accumulate all data into 15 minute intervals. The environmental data is averaged over all readings with the interval and reported at the end of that interval. Each day has intervals 0,...,95, where interval 0 occurs at 12 midnight and reports on readings from 11:45PM to midnight, and is given the date of the day about to begin. Interval 95 reports the data from 11:30PM to 11:45PM. Similarly, we group all of the readings from the MasterOutlets and the Furnace and average it over each period. For the motion detector, we add up the number of motion events detected over the interval, and for the switch, we take the average over the interval of each power estimate. Power is computed by multiplying the maximum wattage of the switch by the proportion that it was dimmed.[3]

Given the constraints of this workshop venue, we refer to a recent paper[17] for a comparison with previous work in temperature forecasting . We are not aware of any previous work forecasting temperature from Smart* sensor data.

We provide a sequence of forecasts for each future 15-minute interval, up to six hours. We perform a separate linear regression to forecast the temperature in each interval. The model selection method we use is a variant of linear resolution known as forward stepwise linear resolution, as presented by Hastie *et al.*[4], and provided the `leaps` package, using the R method `regsubsets`. As with any linear regression problem, we are given a set of independent variables $x_1, ..., x_n$ and a dependent variable y of interest that we want to forecast as a function of the independent variables. Specifically in our case, we seek parameters $\beta_0, ..., \beta_n$ so that $\beta_0 + \Sigma_{i=1}^{n} \beta_i x_i$ is a good approximation of y. When presented with a set of m instances of each x_i, called $x_{i,j}$ and the corresponding instances y_j, we select the β_i parameters so that either root mean squared error (RMSE) function $\sqrt{1/m \sum_{j=1}^{m} (\beta_0 + \sum_{i=1}^{n} \beta_i x_{i,j} - y_j)^2}$ or mean

[1] Units used here are the units of the given data. Quantites in imperial units are shown with international equivalents.
[2] Model selection using the six environmental factors with each of the 32 others individually, show only these seven factors improve the models.
[3] For example, on June 16, at Interval 80 which represents 7:45 PM to 8:00 PM, the values of the 13 variables are, respectively: $76.8°F$, $77.6°F$, 43.1%, 43.5%, 0.13 fps, no rain, 441.2 watts, 612.2 watts, 3 events, 23 events, 11 events, 2 events, and 0 watts.

absolute error (MAE) function $1/m \sum_{j=1}^{m} \left|\beta_0 + \sum_{i=1}^{n} \beta_i x_{i,j} - y_j\right|$ is minimized, depending on the situation. In this paper we minimized RMSE. Stepwise forward regression initially sets β_0 to $\bar{y}$, and all other $\beta = 0$. Then it repeatedly selects a value for β_i so that the error function is reduced as much as possible among all such choices. Once a value of β_i is selected it is not changed further. After all such β_i are selected, stepwise regression halts with the model.

Minimizing a model's error over training data is an important indicator of a model's error over validation data, but overfitting can occur if this is the only criterion. An important measure of a model is the Bayesian Information Criteria (BIC)[8], defined as $1/n\ (\mathrm{RSS} + log(n)\, d\, \hat{\sigma})^2$ where n is the number of observations, and d is the number of dimensions of the model, in our case the number of non-zero β's. $\hat{\sigma}^2$ is an estimate of the variance of the internal temperature, and RSS is $\sum_{j=1}^{m}(\beta_0 + \sum_{i=1}^{n} \beta_i x_{i,j} - y_j)^2$ over the training data. BIC penalizes larger models, and thus balances model size against error on the training data. A model with a smaller BIC is better, and is more likely to be accurate on the validation data.

3. Experiments and Results

We generate forecasts for the next six hours, based on present readings and readings gathered over the previous two hours. As each interval is 15 minutes, we build 24 separate models to predict the internal temperature at each of $f = 1, \ldots, 24$ intervals into the future. Our models are based on the readings from the 13 sensors for nine previous intervals, including the present time and the previous $b = 8$ intervals. Expressed in regression terms, we create one model for each future interval, and each model can forecast the temperature f intervals into the future. Such a model is based on 13 sensor observations taken at $0, ..., b$ intervals into the past, so we have $13 * (b + 1)$ predictor variables. Thus $1 + 13 * (b + 1) = 118$ coefficients are produced, including the intercept. Those observations recalled from previous times are called *lagged* observations.

Let the lag l vary across the intervals 0 through b into the past, and let k vary across the 13 sensors. Let $x_{k,t}$ be the t^{th} observation for the sensor k counting from the earliest observation in the data at $t = 1$. Let y_t be the mean internal temperature of the house at time t. For each f we seek the $1 + 13(b + 1)$ values for the intercept $\beta_{f,0}$ and the coefficient $\beta_{f,k,t}$ for the value of the k^{th} sensor at time t. We want to minimize the residual sum of squares $\sum_{t=b+1}^{m}(\beta_{f,0} + \sum_{l=0}^{b} \sum_{k=1}^{13} \beta_{f,k,t-l} x_{k,t-l} - y_{f+t})^2$. In this equation, t starts at $b+1$ because there are no lagged observations for the first b data points.

The model for a given f and b is built using 2/3 of the data available, called the *training* data and then validated using the remaining 1/3 of the data, called the *validation* data.

Because we use stepwise forward regression, initially $\beta_{f,0}$ is the mean temperature $1/(m-b)\,\Sigma_{j=b+1}^{m} y_{f+j}$. All other β are initially zero, and they are estimated one by one until all are estimated, as described in Section 2. However, many of these steps actually provide no real improvement to the forecast. We want an estimate the BIC for the model of each size, where size is number of steps that the foreward regression has made. We use 10-fold cross validation, where we run the stepwise regression once for each fold. That is, we choose 9/10 of the training data to build a model, leaving out 1/10 of the training data. This gives us 10 estimates of the BIC for each model size. Based on Hastie *et al.*[4]. we consider the mean of these BIC estimates as a good predictor of the BIC for a given model size on the test data. Since BIC reduces and then increases as the number of non-zero β's increases, we can identify the model size with minimal mean BIC. But since the BIC decreases slowly as it approaches the minimal, we are interested the model size whose mean BIC is within one standard error of this smallest BIC. See Figure 1, where the BIC for each model size is shown for $f = 1, ..., 6$ periods forward, and marked with a confidence interval spanning one standard error, based on the BIC's of the models of that size over the 10 folds. Normally, one tries to select a model smaller than than the model with lowest BIC. The model with the lowest mean BIC is shown labeled green, and a smaller model whose BIC is larger by at most one standard error is labelled red. The size of this red model is recorded as the appropriate size for a regression model for this data. One can judge how well this heuristic works by examining how the BIC drops as the model size increases. In the model for IntTempPlus1, (top left of Figure 1) the model size reduced from 29 to 20 by using this heuristic with a small increase in BIC, which is good. In the model for IntTempPlus3 (top right), the heuristic dropped the model size from 23 to 17 which looks good, but we could probably have gone to 15, since there is a big drop in BIC from 14 to 15 and small drops from there. Maximally 118, the selected sizes vary from 8 to 21, which is a good reduction although there may still be some overfitting. The models sizes periods are, respectively, 20, 21, 17, 15, 13, 16, 15, 11, 13, 12, 12, 12, 11, 10, 9, 10, 9, 9, 9, 9, 8, 9, 10, 10.

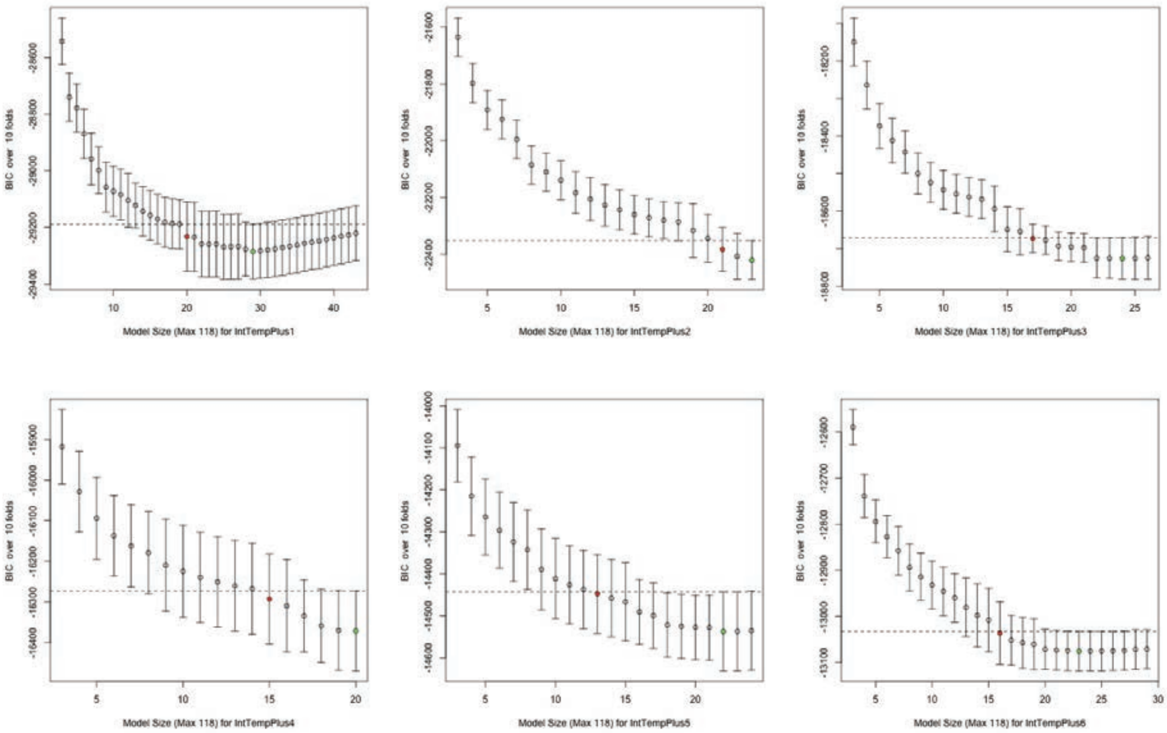

Fig. 1: Selecting the number of predictors for the first six periods. The plots for the remaining periods are similar.

Shown in Table 1 are the predictors selected for the models for each of the 24 periods, the root mean squared error (RMSE) and the mean absolute error (MAE) for each model over the validation data. The variables are in four sets. The environmental variables consist of the internal and external temperature and humidity *inT, outT, inH, outH*, wind speed and rain: *WS, R*. The circuit loads report on the master outlets and the furnace: *MOC, FC*. Motion sensors count the number of motion events in the master bedroom, the living room, the kitchen, and the bedroom: *MM, ML, MK, MB*. Of the switches, we report only the load observed for the living room dining lights: *LRDL*. Since MAE is a difference between two temperatures on the Fahrenheit scale, we can interpret it as the number of degrees by which the forecast is expected to be off. We can see that the best information is given by the temperature and humidities, where the external humidity seems to give benefit only for forecasts in intervals 4 through 24. Wind speed and rain do not help for this experiment. The furnace helps but not for forecasts beyond five hours. Motion detectors in the kitchen and living room are most helpful, and the living room dining lights are helpful for about four hours.

Table 2(a) shows the forecast errors over the validation set for the remaining 1/3 of the data, both as MAE and RMSE. This table can be used to predict expected forecast error. In Table 2(b-f) we can see that by ignoring different set of sensors we lose some accuracy in forecast, which supports our contention that temperature forecasts should use a wide variety of sensors. Table 2(g) shows that a single hour of observations of just the internal and external temperatures and humidities provides forecasts with good accuracy.

4. Conclusion and Future Work

Our goal is to generate forecasts of the internal temperature in a home with access to data from a variety of sensors. Our main success criterion is forecast accuracy, which is maintained at about 1.6°F (0.9°C) for six hours using two hours of readings, using models that have been created with three months of data. This is acceptable in comparison

Table 1: Variables selected for predicting each interval: six enviromental variables (inside and outside temperature and humidity, wind speed, rain) two circuit loads (furnace and master outlets) five motion detectors (bedroom, living room, kitchen, and master bedroom), and one switch (living room dining lights). The model selection procedure choses various lags for each variable. Interval further into the future exhibit more error.

Interval	*inT*	*outT*	*inH*	*outH*	*WS*	*R*	*FC*	*MOC*	*MB*	*MK*	*ML*	*MM*	*LRDL*	RMSE	MAE
1	0, 1, 2, 4, 6, 7, 8	0, 1					2, 3, 5, 7, 8	0, 3	7				0, 4	1.856	0.112
2	0, 1, 2, 3, 4, 6, 8	0					1, 3, 5, 7	0, 1	7	5		1	0, 3, 4	4.804	0.248
3	0, 1, 8	0	0, 1				1, 7	0	7	4		1	0, 3, 4, 5	8.037	0.386
4	0, 1, 8	0					1, 7	0	7	4		1	0, 2, 3, 4	11.975	0.546
5	0, 1, 8	0, 5	0, 1					0		3			0, 3, 4	14.936	0.673
6	0, 1, 8	0	0, 1				1, 7	0		3		1	0, 2, 3, 4	19.088	0.83
7	0, 1, 8	0, 5	0, 1				7	0	4	3			2, 4	23.401	0.981
8	0, 1, 8	0, 6	0, 1					0	3	3				27.61	1.127
9	0, 1, 8	0, 8	0, 1					0	1, 3	2			2	31.572	1.263
10	0, 1, 4, 8	0, 8	0, 1					0	1, 3	3				35.884	1.404
11	0, 1, 3, 8	0, 8	0, 1					0	1, 3	3				40.075	1.537
12	0, 2, 8	0, 8	0, 1					0	1	2				44.379	1.662
13	0, 1, 8	0, 8	0, 1					0	1	1				47.966	1.766
14	0, 1, 8	0, 8	0, 8					0	1	3				52.03	1.881
15	0, 1, 8	0, 8	0, 8						1					58.154	2.066
16	0, 1, 8	0, 8	0, 8								6			61.982	2.159
17	0, 1	0, 8	0, 8						1		5			65.913	2.251
18	0, 1	0, 8	0, 8					0		2				65.141	2.242
19	0, 1	0, 8	0, 8						1	1				68.75	2.324
20	0, 1	0, 8	0, 8						0	2				72.413	2.407
21	0, 1	0, 8	0, 7							2				76.127	2.518
22	0, 1	0, 5, 8	0, 6							1				79.612	2.588
23	0, 1	0, 8	0, 5	0, 8						8				80.894	2.631
24	0, 1	0, 4, 8	0, 5							8	0			84.826	2.701

Table 2: Mean Forecast Errors up to each time horizon, using all sensors, varying subsets of sensors, varying the amount of history. Fewer sensors and less history generally result in more error.

	(a) All Sensors		(b) All but Circuits	(c) All but Motion Dectors	(d) All but Switches	(e) Only Environmental	(f) Ony Temp and Humid	(g) 1 hour of Temp and Humid
Horizon	RMSE	MAE	MAE	MAE	MAE	MAE	MAE	MAE
1	1.8561	0.1121	0.1144	0.1135	0.1136	0.1165	0.1165	0.118
2	3.6413	0.1801	0.1851	0.1786	0.1824	0.1875	0.1875	0.1881
3	5.5109	0.2489	0.2556	0.2478	0.252	0.2578	0.2575	0.263
4	7.6566	0.3231	0.3311	0.3167	0.3249	0.3332	0.3329	0.3386
5	9.5659	0.393	0.406	0.3913	0.4023	0.407	0.4068	0.4119
6	11.7032	0.4659	0.482	0.4652	0.4754	0.4835	0.4833	0.487
7	13.9863	0.5394	0.5584	0.5395	0.5491	0.5599	0.5598	0.5639
8	16.3224	0.6128	0.6336	0.6142	0.6215	0.6351	0.635	0.6375
9	18.6424	0.685	0.7072	0.6874	0.6936	0.7091	0.709	0.7109
10	21.0121	0.7569	0.7803	0.758	0.7627	0.7801	0.78	0.7842
11	23.3944	0.8277	0.8538	0.8301	0.8332	0.8498	0.8497	0.8566
12	25.802	0.8972	0.9265	0.9015	0.9042	0.9211	0.921	0.9276
13	28.1325	0.964	0.9971	0.9709	0.9717	0.9902	0.9901	0.999
14	30.4656	1.0295	1.0656	1.0387	1.0372	1.0573	1.0573	1.0679
15	33.0394	1.0985	1.1305	1.1053	1.1057	1.1197	1.1196	1.1351
16	35.5437	1.1647	1.195	1.1669	1.1715	1.1804	1.1804	1.1999
17	38.0054	1.2285	1.2549	1.227	1.2349	1.2397	1.2396	1.2638
18	39.997	1.2848	1.3106	1.2854	1.2908	1.2974	1.2974	1.3243
19	42.0021	1.3394	1.3648	1.3421	1.3451	1.3535	1.3535	1.384
20	44.022	1.3927	1.4174	1.3972	1.3981	1.408	1.4079	1.4406
21	46.0588	1.4463	1.4698	1.4506	1.4514	1.4609	1.4609	1.4967
22	48.0923	1.4981	1.5206	1.5024	1.503	1.5122	1.5121	1.551
23	49.9657	1.5473	1.5688	1.5515	1.552	1.5609	1.5619	1.6046
24	51.8855	1.5953	1.6159	1.6004	1.5998	1.6085	1.6102	1.6545

with other studies[17]. This technique can be used in conjunction with a temperature control unit that decides to apply heating or cooling depending on the current temperature and the forecast temperature. Such controllers have been shown to reduce energy consumption by HVAC systems by 20%[16], which itself is estimated to be 20% of all energy used[9,10]. Thus potential savings may approach 4% of all energy produced. Our technique relies on a sequence of regression steps that are guided by a greedy algorithm: forward stepwise linear regression. Model size is limited by estimating its BIC over 10-fold cross validation. The BIC metric balances smallness against accuracy. We conservatively choose the minimal sized model with BIC within one standard error of the minimal BIC estimate. High out-of-sample accuracy over a holdout set of 1/3 of the data indicates we meet our main criterion.

We can restart forecasts quickly after a sensor failure so that energy savings are not delayed. Since only two hours of readings are needed, forecasts can resume within two hours of any sensor malfunction or data miscommunication. We consider the tradeoff between forecast horizon and forecast accuracy. If we need the MAE to be below 0.9° F (0.5° C), we would use a forecast horizon of 12 intervals, or 3 hours, according to Table 2(a). We would not forecast for 13 intervals since the error will be 0.96° F (0.53° C). We also consider the adaptability of our technique when different set of sensors may be available. Considering again that we require forecast accuracy to be 0.9° F (0.5° C), if we had only the temperature and humidity data, as in Table 2(f), we could guarantee sufficient accuracy only for forecasts 2.75 hours into the future. Thus, depending on the forecast horizon and precision needed, one can decide from this table what sensor readings need to be given to the modeling system. Another tradeoff is how long the readings are collected. If we had only one hour of temperature and humidity readings, i.e. 4 readings consisting of the current and three lagged, the error is slightly higher, but we could still forecast 2.75 hours while achieving an accuracy of 0.9° F (0.5° C), shown in Table 2(g). In this case we can restart the forecasting sooner. One may want to keep models with fewer sensors and fewer observations on hand, in the case one or more of the sensors fails, to use in the interim until that sensor is repaired and more observations are available.

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