LEARNING CUSTOMER BEHAVIOURS FOR EFFECTIVE LOAD FORECASTING

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Abstract

Load forecasting has been deeply studied because of its critical role in Smart Grid. In current Smart Grid, there are various types of customers with different energy consumption patterns. Customer's energy consumption patterns are referred as customer behaviors. It would significantly benefit load forecasting in a grid if customer behaviors could be taken into account. This paper proposes an innovative method that aggregates different types of customers by their identified behaviors, and then predicts the load of each customer cluster, so as to improve load forecasting accuracy of the whole grid. Sparse Continuous Conditional Random Fields (sCCRF) is proposed to effectively identify different customer behaviors through learning. A hierarchical clustering process is then introducedto aggregate customers according to the identified behaviors. Within each customer cluster, a representative sCCRF is fine-tuned to predict the load of its cluster. The final load of the whole grid is obtained by summing the loads of each cluster. The proposed method for load forecasting in Smart Grid has two major advantages. 1. Learning customer behaviors not only improves the prediction accuracy but also has a low computational cost. 2. sCCRF can effectively model the load forecasting problem of one customer, and simultaneously select key features to identify its energy consumption pattern. Experiments conducted from different perspectives demonstrate the advantages of the proposed load forecasting method. Further discussion is provided, indicating that theapproach of learning customer behaviors can be extended as a general framework to facilitate decision making in other market domains.

1. INTRODUCTION

Load forecasting aims to predict the energy demand of customers under the influence of a series of factors, such as time, price and weather conditions. Load forecasting can benefit Smart Grid in several aspects. Accurate load forecasting helps to determine the amount of energy to produce, thus to improve the efficiency of energy usage and keep the grid away from the risk of too much surplus energy. Brokers in Smart Grid markets rely heavily on load forecasting to make decisions on how much energy to purchase, in order to keep a good supply-demand balance and make more profit. This study focuses on short-term load forecasting, i.e. prediction of hourly power demand over the next 24 hours of a smart grid with various types of customers. Formally, the input data $\mathbf{X} = [\mathbf{x}1; \mathbf{x}2; \cdots; \mathbf{x}n]$ is a $n \times D$ matrix, representing n steps and D features in each step. The output $\mathbf{y}$ is a n-dimension vector, corresponding to n hourly power usages. The input feature $\mathbf{X}$ is shared by all customers, and $\mathbf{y}$ is predicted by the learned model. The most widely used short-term load forecasting is to predict the hourly power usage in the coming 24 hours [24]. Therefore, time step n is set as 24 in this study. In current Smart Grid, there have been various types of customers with different energy consumption patterns, which brings great challenges to accurate load forecasting of a grid system. Customer's energy consumption patterns under the influence of a range of factors (such as time and weather conditions) are defined as *customer behaviors*. The complexity of customer behaviors come from two aspects: vast types of customers and irregular behaviors of each customer type. In Smart Grid, the concept of "customer" has been extended to include not only general energy consumers, but also interruptible consumers, consumers with storage capacity and even small renewable energy producers. We give two instances to illustrate the irregular customer behaviors. Example 1: more and more householders have acquired photovoltaicpower generation systems, which may lead to variable power usages under the influence of weather factors [10], [40], such as cloudiness and humidity. Example 2: some customers with storage capacity may recharge or supply power according to varying prices at different times of the day (Time-of Use [33], a pricing mechanism used in Smart Grid markets). Due to complex customer behaviors, traditional load forecasting methods, which model the whole grid or a particular customer, face challenges to precisely forecast the load of a grid. Intuitively, if customers with similar behaviors could be aggregated into groups, the predictions towards customer groups would improve the accuracy of final load fore casting. We therefore propose the method that identifies customer behaviors through learning to aggregate similar customers. This method is calledLoad Forecasting through Learning CustomerBehaviors, named as LFLCB for short. In LF- LCB, sparse Continuous Conditional Random Fields (SCCRF) is proposed to identify customer behaviors through supervised learning. Then allcustomers can be hierarchically clustered according to the identified customer behaviors. For each customer cluster, a representative SCCRF is fine-tuned to predict its load. Finally, theload of the grid system is obtained by summingthe loads of all customer clusters. The prominent novelty in LF-LCB is the aggregation of various customers through learning. It is challenging toeffectively cluster different customers due to complex customer behaviors. LF-LCB introducesa sparse learning model (SCCRF) to select and weigh the features related to the customer's energyconsumption, and consequently uses a hierarchicalclustering method to aggregate different customers. The hierarchical clustering circumvents the "curse of dimensionality" and obtains stable customer clusters. Customer aggregation can achieve two advantages.

2. LITERATURE SURVEY

Cloud computing is speedily growing and lots of a lot of cloud suppliers area unit rising. value potencyand resource value maximization become 2 major issues of cloud suppliers to stay competitivewhereas creating profit. The profit maximizationdrawback in united cloud environments collaborate to extend the degree of multiplexing has been investigated. define novel economics-inspired resource allocation mechanisms to tackle Existing abstractions for in-memory storage on clusters, like distributed shared memory, key worth stores,databases, and transverse flute, provide AN interface supported finegrained updates to mutable state (e.g., cells in an exceedingly table). it's fine- tuned to predict the load of its cluster. the ultimate load of the entire grid is obtained by summing the hundreds of every cluster. The projected methodology for load prediction in sensible Grid has 2 major benefits. 1) Learning client behaviors not solely improves the prediction accuracy however conjointly incorporates a low procedure value. 2) SCCRF will effectively model the load prediction drawback of 1 client, and at the same time choose key options to spot its energy consumption pattern. Cloud computing providing unlimited infrastructure to store and execute client knowledge and program. Customers don't ought to own the infrastructure, they're simply accessing or renting they'll ante cede cost and consume resources as a service, paying instead for what they use. edges of Cloud Computing: reduced cost. Location and Device independence. Utilization and potency improvement. terribly high measure. High Computing power. employing a wealthy set of operators. the most challenge in coming up with RDDs is shaping a programming interface which will offer fault tolerance expeditiously. Existing abstractions for in-memory storage on clusters, like distributed shared memory, key worth stores, databases, and transverse flute, provide associatedegree interface supported finegrained updates to mutable state (example cells in an exceedingly table). the sole ways that to produce fault tolerance are to duplicate the information across machines or to log updates across machines. Both approaches overpriced for data-intensive workloads, need repetition massive amounts of information over the cluster network, whose information measure is much less than that of RAM, and incur substantial storage overhead. The cloud consumer’s necessary challenge is to seek out the foremost economical thanks to utilize the rented cloud resources. Virtualization is that the necessary method that permits the sharing of computing resources in on-line. The computing resources square measure of various varieties. These includes Infrastructure as a service (Iaas) that provides the aptitude to the buyer to provision network, storage and process. It will embody the software and applications. Example., Amazon EC, Open New, Eucalyptus. Platform as a service (Paas)provides the aptitude to the buyer to accumulate applications created mistreatment programming languages, deploy onto the cloud infrastructure and tools supported by the supplier. Software as a service (Saas) provides the aptitude to the buyer to use the applications of the supplier that runs on cloud infrastructure. Example Google apps, SalesForce.com, Eye OS. Cloud suppliers provides these resources on demand to the users. once there's any requirement for the users within the cloud, the cloud system provides the desired resources to the users by making virtual machines (VM) within the host machine. The tasks of the users square measure within the type of advancement dead by the advancement programming

3. SYSTEM ANALYSIS:

EXISTING SYSTEM

- As an active research topic, there have been several novel methods for load forecasting. Liu et al. [30] proposed a new way that performs quantile regression averaging on a set of sister point forecasts for probabilistic load forecasting. Zheng et al. [49] used Long-Short-Term-Memory based recurrent neural network to capture the dynamic factors in Smart Gird for effective short-term load forecasting.
- Dong et al. [12] proposed Convolutional Neural Networks for large scale load forecasting. They first clustered the data from different regions by K-means to alleviate the data imbalance, and then input regional data into deep neural networks. Those newly proposed methods have achieved improved results on loadforecasting, but they still targeted at the whole grid, without consideration of customer behaviors.
- Recently, researchers have conducted some work on aggregating customers to improve load forecasting. Srinivasan [38] manually divided different customers in a power grid into six groups, and introduced a group method of data handling (GMDH) neuralnetworks for load forecasting. In contrast, our method learns customer behaviors and thus clusters different customers adaptively.Alzate et al. [2] used spectral clustering to cluster customers with respect to the historical load data and reported improved accuracy in load forecasting.
- Alzate and Sinn [3] further explored kernel spectral clustering to aggregate customers, while their method was still limited to the unsupervised cluster of load data. Gulbnaset al. [21] segmented the energy usage data and constructed energy usage profiles to classify building occupants. They also defined energy-use efficiency, entropy and intensity to facilitate energy usages. Different from the previous work, our proposed method uses supervised learning to discover the relations between loads and external factors, which can provide moreaccurate descriptions of customer behaviors.
- Fiot and Dinuzzo [16] used multi-taskkernel learning to predict long-term load.Their method tried to discover the similarityof nodes in Smart Grid, thus to improve the prediction of each node (customer).

In predicting the long term load, only time and calendar features are considered. Differently, our method introduced supervised learning to discover the customer behaviors under the influence of a series of external factors, and aggregate similar customers to improve the accuracy of load forecasting.

Disadvantages

- In the existing work, only the closestneighboring variables were considered.
- There is less effective due the accuracy ofload forecasting in a grid is slow.

PROPOSED SYSTEM

- In the proposed system,the system proposes Sparse Continuous Conditional Random Fields (sCCRF) that considers the theoretical constraints on parameters. Secondly, $L1$-CCRF [43] only models the closest neighboring variables in load sequence data to analyze customer behaviors.
- In the proposed system, the system extends sCCRF to model multiple close neighboring variables to provide more accurate descriptionsof customer behaviors. Thirdly, we improvethe fine-tuning step in LF-LCB to result in a fast convergence. Fourthly, the additionally provides load forecasting in uncertain environments to extend the application of LF- LCB. In experiments, we explore more external features to improve the accuracy of load forecasting.
- The system also conducts new experiments to compare LF-LCB with state-of-the-art methods. In the end, the system further discusses the potential to apply learning customer behaviors to wide market domains.
- This paper proposed sCCRF, which improves $L1$- CCRF [44] in two aspects. Firstly, sCCRF constrains the parameters in a theoretical view. Secondly, sCCRF extends to consider multiple neighboring variables. Experimental results demonstrate the effectiveness of sCCRF in prediction and feature selection.
- LF-LCB substantially improves load forecasting with learning customer behaviors in our previous work. The extensive analysis of learning customer behaviors can facilitate the research work in other market domains.

Advantages

- The system simples to fetch customer behaviors in which Customer aggregation tries to “smooth” the random behaviors of customers by clustering similar customersinto the same group.

The system extends our previous work to take m neighboring variables into account. With theconsideration of multiple neighboring variables, the system can model the load forecasting for each customer more accurately, and hence improve the accuracy of load forecasting in a grid.

MODULE IMPLEMENTATION

- **Admin**

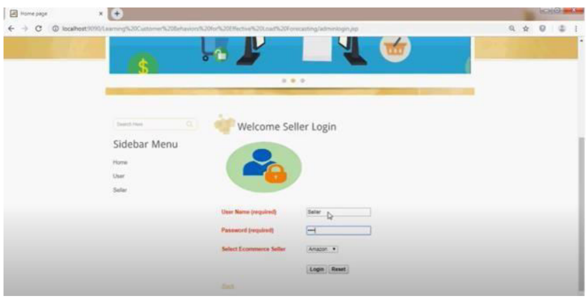
In this module, the Admin has to login by using valid user name and password. After loginsuccessful he can perform some operations such as View All Users and Authorize ,Add and View Filter Details, Add Products, View Uploaded Products ,View Customer Purchased Behavior,View Customer Search Behavior, View CustomerReview Behavior, View Customer Positive Behavior, View Customer Negative Behavior, View Product Score, View Keyword Score

- **User1**

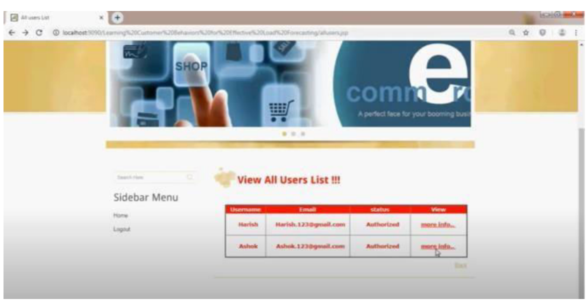
In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorizeduser name and password. Once Login is successfuluser can perform some operations like View Profile, Manage Account, Search Products,View Purchased Transactions

4. OUTPUT RESULTS:

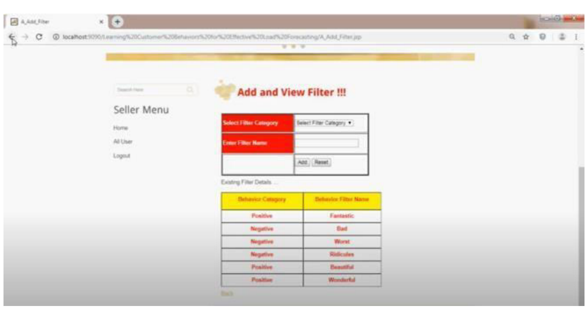
Home Page



View All Users Page



Add & View Filter Page



5. CONCLUSION

This paper proposed a load forecasting method through learning customer behaviors (LF-LCB), which utilized the proposed SCCRF to analyze customer behaviors by using the learned weights to reflect different energy consumption patterns of various customers. The results of experiments conducted from several perspectives supported the following two conclusions: 1) Learning customer behaviors to aggregate customers can improve the prediction precision and lead to a reasonable computation cost. 2) The proposed SCCRF is an efficient learning tool with feature selection capacity.

Our work can potentially facilitate research in related domains. Learning customer behaviors to aggregate customers in fact can supply a general methodology to assist better decision making towards various customers in a complex market environment. This is worth further exploration in other market domains. Evaluation results also indicate that the proposed SCCRF is effective in feature selection and prediction. Thus, SCCRF canalso be applied in other related research fields.

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