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AN ASYMMETRIC LOSS WITH ANOMALY DETECTION LSTM FRAMEWORK FOR POWER CONSUMPTION PREDICTION

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Abstract:
Creating a reliable load forecasting model that minimizes underpredictions is crucial for avoiding potential power outages caused by insufficient electricity generation. However, predicting residential power consumption is challenging due to its inherent fluctuations and anomalies. In this study, we propose several Long Short-Term Memory (LSTM) frameworks incorporating different asymmetric loss functions to apply greater penalties for underpredictions. Additionally, we employ a density-based spatial clustering of applications with noise (DBSCAN) technique for anomaly detection before the load forecasting process to eliminate outliers. We account for the impacts of weather and social factors by performing seasonality splitting on three datasets from France, Germany, and Hungary, which include hourly power consumption, weather, and calendar features. Our results, measured by root-mean-square error (RMSE), demonstrate that anomaly removal effectively reduces both underestimation and overestimation errors across all seasonal datasets. Furthermore, while asymmetric loss functions and seasonality splitting are successful in minimizing underestimations, they may slightly increase the overestimation error. Overall, addressing underpredictions in electricity consumption is crucial for preventing power outages and safeguarding community welfare.

I. Introduction

In the past decade, the rapid increase in electricity consumption has led to the depletion of natural resources and exacerbated environmental pollution. In response, there have been significant efforts aimed at preventing the overproduction of electricity [1]. While addressing overproduction is important, preventing underproduction is equally crucial, as failures in this area can lead to power outages and blackouts, which negatively impact economic growth and industrial development [2], and can even result in severe situations. For instance, in 2021, Lebanon experienced a severe power outage that put hospitals and essential services at risk. To avoid both underproduction and overproduction, power companies are constantly seeking improved load forecasting methods and more reliable energy management strategies [3].Previous research on power consumption forecasting has explored various machine learning techniques, including Recurrent Neural Networks (RNNs) [4], Long Short-Term Memory (LSTM) networks [3], [5], [6], and hybrid approaches that combine Artificial Neural Networks (ANNs) with Support Vector Machines (SVMs) [7].

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Traditionally, these methods have used symmetric cost functions, which perform well when the consequences of underestimations and overestimations are equally significant. However, in scenarios where underestimations can have more severe repercussions than overestimations, there is a growing interest in developing models with asymmetric loss functions [8]–[13]. These asymmetric functions assign greater importance to minimizing underpredictions, aiming to maintain a slight excess in power generation to prevent potential outages or emergency power purchases [12], [13].Power consumption forecasting is particularly challenging due to fluctuations in residential power consumption patterns, which are influenced by weather and social factors [14]. Additionally, anomalies in the data, caused by errors in data collection, incorrect measurements, or exceptional events, further complicate accurate predictions [15]. Previous studies [4] have demonstrated that such anomalies can increase model errors. In this work, we seek to enhance power consumption forecasting for the residential sector by focusing on outlier detection and reducing prediction errors, particularly underestimations. Our approach begins by integrating hourly power consumption data with corresponding weather and calendar information [16]. To account for seasonal variations, we divide each dataset into three seasonal subsets. We then apply the density-based spatial clustering of applications with noise (DBSCAN) algorithm [15] for anomaly detection, replacing outliers with more realistic values to improve forecast accuracy. The seasonal datasets are then used to train three distinct LSTM models: one with a symmetric loss function and two with unique asymmetric loss functions. These models are evaluated based on their performance in minimizing underestimation and overestimation root-mean-square errors (RMSE). Our results demonstrate that the proposed anomaly detection and data substitution techniques effectively reduce both underestimation and overestimation errors across all seasonal datasets. Additionally, while asymmetric loss functions and seasonality splitting are successful in reducing underestimation errors, they do slightly increase overestimation errors compared to symmetric loss functions. The key contributions of this work are: (1) evaluating the effectiveness of various asymmetric loss functions within an LSTM framework for reducing underpredictions and improving load forecasts, and (2) exploring the influence of seasonality on the load estimation process.

The remainder of this paper is organized as follows: Section II reviews related work, Section III details the proposed methodology, and Section IV presents the experiments conducted and the results obtained. Finally, Section V concludes the paper with a discussion of limitations and suggestions for future research.

II. Literature Survey

1. Asymmetric Loss Functions for Time Series Analysis

Authors:[1] Huang, J., & Ling, C. X. (2005**)**

Summary: Huang and Ling investigate various evaluation metrics for machine learning algorithms, emphasizing the use of asymmetric loss functions. They highlight that traditional symmetric loss functions might not be suitable for all applications, especially when underestimations or overestimations have different impacts.

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Relevance: This work lays the groundwork for understanding how asymmetric loss functions can be applied to scenarios where the cost of mispredictions varies, which is a crucial consideration for power consumption forecasting where underestimation can lead to significant consequences.

[2] Asymmetric Loss Functions for Regression Problems.

Authors: Kasy, M., & Sato, M. (2019).

Summary: Kasy and Sato explore asymmetric loss functions in regression tasks, demonstrating their effectiveness in handling cases where errors have different costs. They propose several asymmetric loss functions and show that they can significantly improve model performance in applications like financial forecasting and risk management.

Relevance: This paper's insights into asymmetric loss functions are directly applicable to power consumption prediction, where it is crucial to minimize underestimation errors to avoid potential power shortages.

[3]A Survey on Asymmetric Loss Functions in Machine Learning

Authors: Zhang, C., & Zheng, X

Summary: Zhang and Zheng provide a comprehensive survey of various asymmetric loss functions and their applications. They review the theoretical foundations of these loss functions and discuss their applications in different domains, including anomaly detection and time series forecasting.

Relevance: This survey offers a broad overview of asymmetric loss functions, which is essential for selecting the most appropriate loss functions for enhancing LSTM models in power consumption prediction tasks.

III.System Analysis

Existing System

In traditional approaches to power consumption forecasting, the primary objective is to create models that can predict future electricity demands based on historical data. Common methods include statistical techniques, machine learning algorithms, and time series models that aim to forecast power consumption as accurately as possible. However, these methods often struggle with issues such as predicting exact consumption patterns and managing fluctuations caused by anomalies in the data.

Challenges of the Existing System

Handling Anomalies:

Issue: Existing systems often struggle to manage anomalies and outliers in power consumption data. Anomalies, such as sudden spikes or drops in consumption, can skew predictions and reduce forecasting accuracy.

Impact: These anomalies can lead to suboptimal power generation strategies, resulting in either overproduction or underproduction of electricity.

Symmetric Loss Functions:

Issue: Traditional forecasting models typically use symmetric loss functions, which treat underestimation and overestimation errors equally. This is problematic when underestimations can have more severe consequences, such as power outages.

Impact: Symmetric loss functions fail to address the specific needs of scenarios where minimizing underestimation errors is more crucial than managing overestimations.

Predicting Exact Results:

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Issue: Existing data mining techniques like clustering and classification provide insights into power consumption patterns but often cannot guarantee exact predictions.

Impact: Inaccurate forecasts can lead to inefficiencies in power management, potentially causing disruptions in electricity supply.

Data Quality Issues:

Issue: Inconsistent or missing data can affect the accuracy of forecasts and complicate the analysis.

Impact: Poor data quality leads to less reliable models, which affects the overall effectiveness of the forecasting system.

Algorithms Used:

Data Mining Techniques: Clustering, Classification, Association Rules.

Proposed System

Proposed System Overview

The proposed system introduces an advanced framework combining **Asymmetric Loss Functions** with **Anomaly Detection** and **Long Short-Term Memory (LSTM) Networks** for power consumption prediction. This approach addresses the limitations of existing systems by focusing on minimizing underestimation errors and effectively managing anomalies in power consumption data.

Advantages of the Proposed System

Enhanced Anomaly Detection:

Solution: The proposed system incorporates the **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)** algorithm for detecting anomalies in power consumption data.

Advantage: By identifying and managing outliers, this approach improves the accuracy of forecasts and ensures more reliable predictions for power consumption patterns.

Asymmetric Loss Functions:

Solution: The system utilizes **asymmetric loss functions** to place greater importance on minimizing underestimation errors compared to overestimation errors.

Advantage: This adjustment helps to ensure that predictions are more conservative, reducing the risk of underestimations that could lead to power shortages.

Advanced Forecasting with LSTM Networks:

Solution: The proposed framework employs **LSTM (Long Short-Term Memory)** networks to model temporal dependencies in power consumption data.

Advantage: LSTMs are capable of capturing long-term dependencies and complex patterns in time series data, leading to more accurate and robust power consumption forecasts.

Cumulative Satisfaction Considerations:

Solution: The framework integrates both **prior satisfaction** and **post-recovery satisfaction** to enhance the prediction model.

Advantage: This approach addresses how past data influences future predictions, leading to more effective forecasting and management of power consumption.

Improved Data Quality and Consistency:

Solution: The system includes a data pre-processing stage to handle missing values and ensure data consistency.

Advantage: Higher data quality leads to more reliable forecasts and better decision-making for power management.

Algorithm Used:

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Machine Learning Algorithm: Support Vector Machine (SVM) for churn analysis in the telecom sector, extended here as a reference to emphasize advanced predictive modeling techniques.

Proposed Techniques: Asymmetric Loss Functions, Anomaly Detection with DBSCAN, LSTM Networks.

IV.System Study

Feasbility study

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.Three key considerations involved in the feasibility analysis.

Economical feasibility: This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

Technical feasibility: This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

Social feasibility: The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

V. System Design

We aim to obtain better predictions and most importantly reduce underestimations. Hence, we propose the concept of asymmetry to highly penalize underpredictions and thus reduce the underestimation error. Two asymmetric loss functions are proposed with different penalties for overestimates and underestimates.

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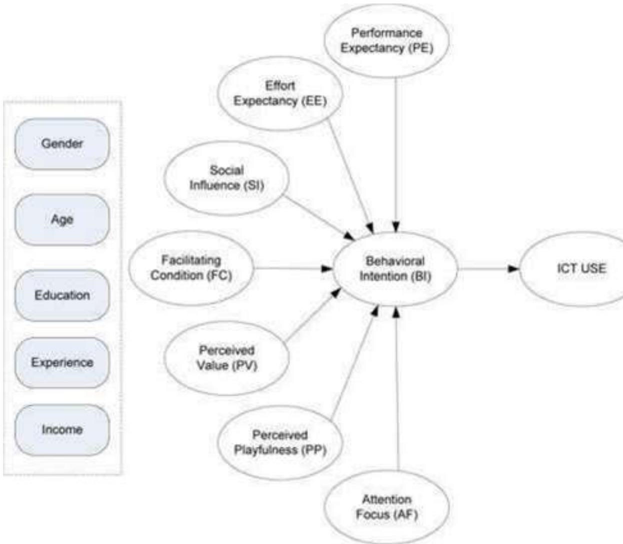
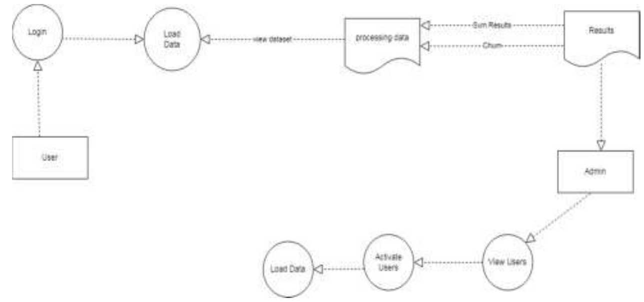


The data flow diagram is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

It is one of the most important modelling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.

It shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.

It may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.



UML Diagrams

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artefacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

Goals:

The Primary goals in the design of the UML are as follows:

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Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.

Provide extendibility and specialization mechanisms to extend the core concepts.

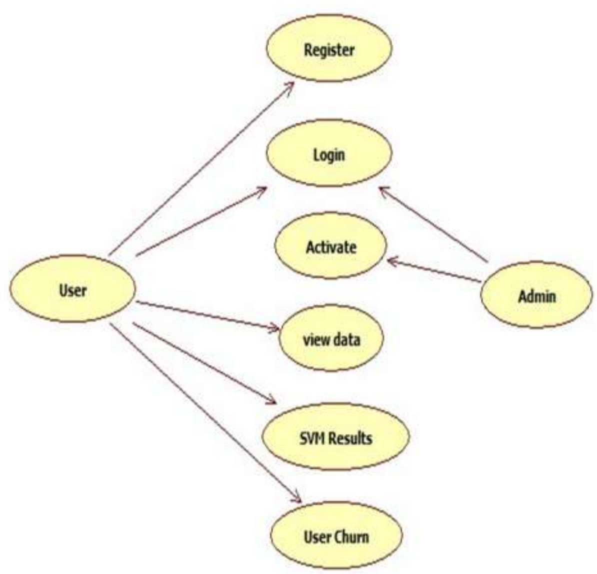
Be independent of particular programming languages and development process.

Provide a formal basis for understanding the modelling language.

Encourage the growth of OO tools market.

Support higher level development concepts such as collaborations, frameworks, patterns and components.

Integrate best practices.

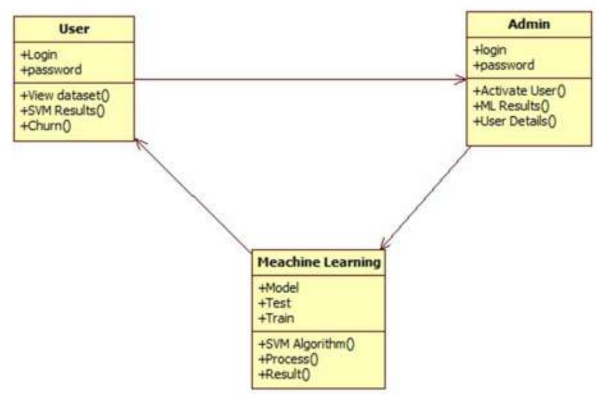


A use case diagram in the Unified Modelling Language (UML) is a type of behavioural diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

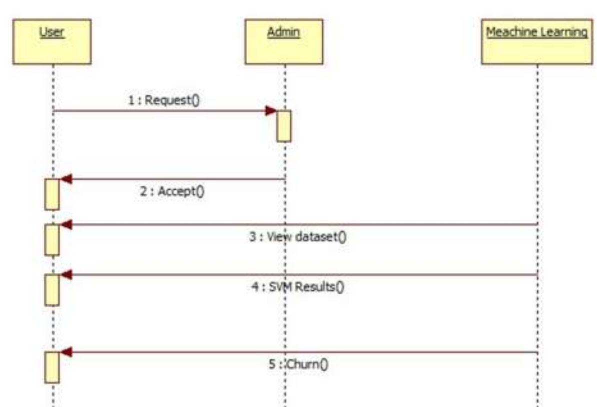
Class diagram:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.



Sequence diagram:

A sequence diagram in Unified Modelling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams



Activity diagram:

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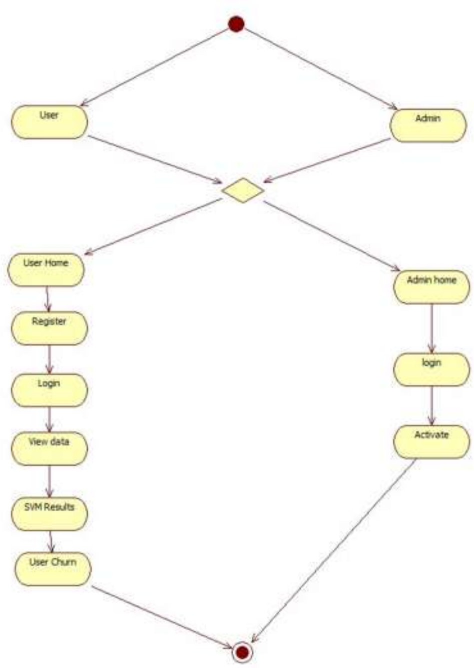
Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



VI.Modules Description

The proposed asymmetric loss functions succeeded to remarkably reduce underestimations, but failed to limit overestimations. Future work might aim to improve the formulation of these asymmetric loss functions to achieve fewer overestimations besides effectively minimizing underestimations.

User:

The User can register the first. While registering he required a valid user email and mobile for further communications. Once the user register then admin can activate the user. Once admin activated the user then user can login into our system. User can upload the dataset based on our dataset column matched. For algorithm execution data must be in float format. Here we took Three Customer Behaviour dataset for testing purpose. User can also add the new data for existing dataset based on our Django application. User can click the Classification in the web page so that the data calculated Accuracy and F1-Score, Recall, Precision based on the algorithms. User can click Prediction in the web page so that user can write the review after predict the review that will display results depends upon review like positive, negative or neutral.

Admin:

Admin can login with his login details. Admin can activate the registered users. Once he activate then only the user can login into our system. Admin can view the overall data in the browser. Admin can click the Results in the web page so calculated Accuracy and F1-Score, Precision, Recall based on the algorithms is displayed. All algorithms execution complete then admin can see the overall accuracy in web page.

Data Preprocessing:

A dataset can be viewed as a collection of data objects, which are often also called as a records, points, vectors, patterns, events, cases, samples, observations, or entities. Data objects are described by a number of features that capture the basic characteristics of an object, such as the mass of a physical object or the time at which an event occurred, etc. Features are often called as variables, characteristics, fields, attributes, or dimensions. The data preprocessing in this forecast uses techniques like removal of noise in the data, the expulsion of

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missing information, modifying default values if relevant and grouping of attributes for prediction at various levels.

Machine learning:

Based on the split criterion, the cleansed data is split into 60% training and 40% test, then the dataset is subjected to four machine learning classifiers such as Support Vector Machine (SVM). The accuracy, Precision, Recall, F1-Score of the classifiers was calculated and displayed in my results. The classifier which bags up the highest accuracy could be determined as the best classifier.

VII. Conclusion

In this study, we introduce two asymmetric loss functions, **AL1** and **AL2**, designed to significantly reduce underpredictions in power consumption estimation tasks using an LSTM model. Our results demonstrate that both AL1 and AL2 effectively decrease underprediction errors, with AL1 achieving the most substantial reduction. However, the trade-off observed is an increase in overprediction errors for both loss functions, with AL1 exhibiting the highest increase.

Additionally, we integrated a clustering approach prior to the load estimation process to detect anomalies in the power consumption data. By substituting these anomalies with more realistic values, we improved the accuracy of the load forecasts across all LSTM models. The inclusion of seasonality as a factor was shown to be beneficial in reducing underprediction errors, particularly in the French dataset, though it slightly increased overestimation errors with both asymmetric loss functions.

While the proposed asymmetric loss functions were effective in significantly minimizing underpredictions, they were less successful in managing overestimations. Future research could focus on refining these asymmetric loss functions to achieve a better balance between minimizing underestimations and controlling overestimations.

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