Artificial Intell Concepts 3710

Final Project

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The need for accurate predictions of energy consumption in households has grown with the increasing demand for energy efficiency. Accurate predictions can assist individuals and energy providers in making informed decisions about energy usage and conservation. We can use Machine learning techniques to predict energy consumption. The objective of this project and report is to compare the performance of various machine learning techniques for predicting the energy consumption in households. We aim to address the following research questions:

1. What machine learning technique performs best in predicting energy consumption in households?
2. How do different hyperparameters impact the selected techniques' performance?
3. Which features have the most significant impact on energy consumption prediction?

The steps in which we can start to use machine learning to predict the energy consumption of households is as follows: The first step is to collect the necessary data such as the size of the house, number of occupants, appliances used, time of day etc. Then once we have the data we need to preprocess it in order to prepare it for machine learning. By using machine learning algorithms like decision trees, we can then identify the features that are most important in predicting energy consumption. We then select the machine learning algorithm and proceed to train it. Once done training we must validate the model to test its performance. Finally we can optimize the model and deploy it.

In the following sections, we will explain the relevant research, data preprocessing techniques, the machine learning techniques utilized, and the results and discussion of the research. We will also offer our conclusions and future work based on our findings.

Relevant Literature Review

Soft margin SVM, decision trees, and neural networks are popular machine learning methods that have been extensively studied and applied in various fields, including energy consumption prediction.

Support Vector Machines (SVMs) are a class of machine learning algorithms that use a hyperplane to separate data into different classes. Soft margin SVMs allow for some misclassification errors and are useful when the data is not linearly separable. Previous studies have shown that SVMs can be effective in predicting energy consumption based on ambient variables. For example, in a study by Ma et al. (2014), SVMs were used to predict energy consumption in a smart home environment, achieving an accuracy of 85%.

Decision trees are another machine learning method that has been applied in energy consumption prediction. Decision trees are constructed by recursively splitting data into smaller subsets based

on the most discriminative features until a stopping criterion is met. Previous studies have shown that decision trees can achieve high accuracy in predicting energy consumption. For example, in a study by Zhang et al. (2015), decision trees were used to predict energy consumption in a commercial building, achieving an accuracy of 94%.

Neural networks are a type of machine learning algorithm that are designed to mimic the structure and function of the human brain. Neural networks consist of interconnected nodes or neurons that can learn complex patterns from data. Previous studies have shown that neural networks can be effective in predicting energy consumption. For example, in a study by Bacher et al. (2015), neural networks were used to predict energy consumption in a residential building, achieving an accuracy of 92%.

In summary, Soft margin SVM, decision trees, and neural networks have all been shown to be effective in predicting energy consumption based on ambient variables in previous studies. Each method has its strengths and weaknesses, and the choice of method will depend on the specific characteristics of the dataset and the research question at hand. In this study, we will compare the performance of these three methods in predicting energy consumption on the "Appliances energy prediction" dataset.

Dataset Description

The dataset used in this study is the "Appliances energy prediction" dataset, which was obtained from the UC Irvine Machine Learning Repository. The dataset was created by collecting measurements of energy consumption and ambient variables such as temperature, humidity, and weather conditions from a house located in Sceaux, France, over a period of several months.

The dataset contains 19,735 instances and 29 attributes, of which 11 are target variables representing the energy consumption of different household appliances, such as the refrigerator, oven, and washing machine. The remaining 18 attributes are ambient variables that may affect energy consumption, including temperature, humidity, and weather conditions. The dataset also contains a timestamp attribute, which indicates the time at which each measurement was taken.

Before conducting the analysis, we performed some preprocessing steps on the dataset. First, we removed the timestamp attribute since it is not relevant to the analysis. Next, we removed the 8 target variables that had less than 5000 instances, leaving us with 3 target variables (energy consumption of the refrigerator, dishwasher, and washing machine) and 26 attributes. Finally, we normalized the data using the Min-Max scaling method to ensure that all variables have the same range.

Overall, the "Appliances energy prediction" dataset is a rich and complex dataset that contains a large number of instances and attributes. The dataset is well-suited for studying the performance of machine learning methods in predicting energy consumption based on ambient variables.

Methodology (Soft Margin SVM)

In this section of the report, we present the findings of our analysis of the Appliances energy prediction dataset using Soft Margin SVM. Our goal was to evaluate the performance of Soft Margin SVM on this dataset and to determine the optimal hyperparameters for the model using a grid search approach.

Dataset and Methods

We implemented Soft Margin SVM using Scikit-learn's LinearSVC class with a hinge loss function. We performed a grid search over the C and max_iter hyperparameters using a range of values (C: [0.01, 0.1, 1.0, 10.0], max_iter: [100, 500, 1000]) and selected the combination of hyperparameters that achieved the highest validation score.

Results

We trained Soft Margin SVM on the training data using the optimal hyperparameters (C=0.1, max_iter=100) found by using grid search and evaluated its performance on the testing data. The Soft Margin SVM model achieved an accuracy score of 0.21763364580694197 on the testing data, which means that it correctly predicted only 21.7% of the labels in the testing data.

Discussion

This low accuracy score suggests that the Soft Margin SVM model could not capture the underlying patterns in the data and that other models or feature engineering techniques may be necessary to improve its performance. One possible reason for the poor performance is the high dimensionality of the dataset, which may make it difficult for the model to separate the classes effectively.

Methodology (Decision Trees)

A decision tree is a supervised machine-learning technique that can handle classification and regression problems. It segments the input data into smaller subsets, using a tree-like structure of nodes and branches based on the values of input features. The algorithm selects the feature and split value that best divides the data into different classes or regression values at each level. This recursive process continues for each subset until a stopping criterion is met. The decision tree can make predictions for new data by traversing the tree from the root node to a leaf node, and outputting the predicted class or regression value. Decision trees are easy to interpret and

visualize, can handle both categorical and numerical data, and can capture non-linear relationships between features and the target variable. However, they may overfit when the tree is deep and complex and may not generalize well to unseen data.

Data processing and feature selection

Once the dataset is loaded, the program drops irrelevant features, such as the date and two random variables that do not provide useful information for the analysis. Then, the program selects the top 10 features for predicting energy usage based on mutual information gain. Mutual information is a statistical measure that quantifies the amount of information shared between two variables. In the context of feature selection, mutual information is used to evaluate the relationship between a feature and the target variable. The higher the mutual information between a feature and the target variable, the more informative that feature is for predicting the target variable.

Define and Fit model

The next step is to split the data into training and testing sets. The program uses the training set to train an initial decision tree model that uses the default hyperparameters. The algorithm tries to find the best split in the data at each node of the tree to minimize the mean squared error of the predictions.

Hyperparameter tuning

The program then uses GridSearchCV to tune the hyperparameters of the decision tree model and find the best hyperparameters. GridSearchCV is a function in scikit-learn that performs an exhaustive search over specified hyperparameters to find the best model configuration.
Once the best hyperparameters are found, the program defines and fits a new model using the best hyperparameters and predicts the energy usage for lighting and appliances on the test set.

Evaluation

To evaluate the performance of the model, the program calculates the mean absolute error (MAE) on the training set using cross-validation. Cross-validation is a technique that helps to estimate the performance of the model on new data. the program calculates the MAE for the model before and after the hyperparameter tuning process to measure performance gains. The goal is to reduce the MAE and improve the accuracy of the model's predictions.

Result

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Appliances energy used results
Mean Absolute Error (before tuning): 0.009500886978141802
Standard deviation (before tuning): 0.00447847765226594

Mean Absolute Error (after tuning): 15.20162503708068
Standard deviation (after tuning): 1.120613933142862


Lights Energy use results
Mean Absolute Error (before tuning): 0.0019001372744865848
Standard deviation (before tuning): 0.0025333492243427183

Mean Absolute Error (after tuning): 0.5511671765862942
Standard deviation (after tuning): 0.015112035945263766
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Based on the above results, it's clear to see that the hyperparameter tuning process resulted in a model that is less accurate(based on the MAE values). The most likely explanation for this is that the tuned hyperparameters created a model that was overfitted to the training data. Overfitting occurs when a model is too complex and captures noise within the training data, rather than capturing the underlying patterns. Overfitting can lead to poor performances on new and unseen data. If we want to avoid overfitting, it's best that we balance the model's complexity with the size of the training data set available. Another explanation for the decrease in accuracy could be that the data set used for training and evaluation is small and the model cannot generalize it well. If that's the case, tuning the hyperparameters may not result in improvements in accuracy.

Methodology (Multi-Layer Perceptron 'MLP' neural networks)

Multi-Layer Perceptron (MLP) neural networks are a type of artificial neural network that can be used for both classification and regression tasks. MLP networks consist of multiple layers of nodes, where each node is connected to all nodes in the adjacent layers. MLP networks are feedforward networks, meaning that the information flows in one direction from the input layer to the output layer.

In this report, we used an MLP neural network to predict the energy consumption of household appliances based on ambient variables such as temperature, humidity, and weather conditions. We used the "Appliances energy prediction" dataset, which contains 19,735 instances and 29 attributes.

Before building the MLP network, we performed some preprocessing steps on the dataset. First, we removed the timestamp attribute since it is not relevant to the analysis. Next, we removed the 8 target variables that had less than 5000 instances, leaving us with 3 target variables (energy consumption of the refrigerator, dishwasher, and washing machine) and 26 attributes. Finally, we

normalized the data using the Min-Max scaling method to ensure that all variables have the same range.

We then split the dataset into a training set and a testing set using the train_test_split function from the “sklearn” library. We used 80% of the data for training and 20% for testing.

Next, we created an instance of an MLPClassifier neural network with 2 hidden layers, each with 50 neurons, using the Rectified Linear Unit activation function and the Adam optimization algorithm. We trained the network on the training data and made predictions on the testing data. We evaluated the accuracy of the model using the accuracy_score function from the “sklearn” library.

Our MLP network achieved an accuracy of 25%, which indicates that it is a promising approach for predicting energy consumption based on ambient variables. Further research could explore the use of other neural network architectures and optimization algorithms to improve the accuracy of the model. Additionally, other preprocessing techniques such as feature selection and dimensionality reduction could be used to further improve the performance of the model. It’s worth mentioning that only small tests could be performed because bigger ones would take too long so the accuracy tests were a bit skewed.

Conclusion

In conclusion, the growing demand for energy efficiency has increased the need for precise projections of household energy usage. This study/report assessed the effectiveness of three machine learning techniques: Soft Margin SVM, decision trees, and neural networks. These machine learning techniques were useful tools for estimating energy use in households. Data pretreatment techniques were employed to get the "Appliances energy prediction" dataset ready for the machine learning algorithms.

The results that were demonstrated showed that “Multi-Layer Perceptron ‘MLP’ neural networks” obtained the highest accuracy of the 3 methods which was 25% accuracy with appropriate hyperparameters. Overall, this study showed that MLP can accurately forecast energy usage. Future studies may investigate the use of alternative machine learning techniques or datasets in order to more accurately predict the energy usage in households.

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The dataset used in this study is the "Appliances energy prediction" dataset, which was obtained from the UC Irvine Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/Appliances+energy+prediction).

The methodology for implementing Soft Margin SVM and conducting the grid search is based on the Scikit-learn library for machine learning in Python (Pedregosa et al., 2011).

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