ELECTRICITY PRICES PREDICTION

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Problem Definition:

The problem is to develop a predictive model that uses historical electricity prices and relevant factors to forecast future electricity prices. The objective is to create a tool that assists both energy providers and consumers in making informed decisions regarding consumption and investment by predicting future electricity prices. This project involves data preprocessing, feature engineering, model selection, training, and evaluation.

Abstract:

The objective of this project is to develop a predictive model for forecasting future electricity prices by leveraging historical price data and relevant influencing factors. The proposed tool aims to empower both energy providers and consumers with actionable insights to make informed decisions regarding consumption and investment in the dynamic energy market. The project encompasses a comprehensive workflow, including data preprocessing, feature engineering, model selection, training, and evaluation. The predictive model's deployment will facilitate real-time decision-making, while ongoing monitoring and feedback loops ensure its accuracy and relevance in an ever-changing energy landscape. This project not only addresses the complexities of electricity price forecasting but also underscores the potential for data-driven solutions to drive efficiency and informed choices within the energy sector.

Design Thinking:

Data Source:

To develop a predictive model for forecasting electricity prices, relevant data sources play a pivotal role. These sources encompass official energy market databases, utility companies, and government agencies, which offer historical electricity price data. Independent market operators, open data portals, and APIs are also valuable resources for accessing real-time or historical market information. Weather data providers and economic indicators contribute insights into factors influencing electricity prices. Fuel price data and historical event records can further enrich the dataset. Commercial data providers specialising in energy market data may provide comprehensive datasets and APIs for research and analysis. Careful consideration of data quality, reliability, and adherence to data usage terms is essential when selecting and combining data from these sources to enable the development of an accurate predictive model for electricity price forecasting.

Data Preprocessing:

In the context of forecasting electricity prices, data preprocessing involves several crucial steps to ensure data quality and model readiness. This includes handling missing values, removing duplicates, converting timestamps into datetime objects, encoding categorical variables, detecting and addressing outliers, and engineering relevant features. Scaling and normalisation may be necessary to put numerical features on a consistent scale, while splitting the data into training, validation, and test sets, and resampling when required for temporal data. Data visualisation aids in confirming the success of preprocessing steps, and thorough documentation ensures transparency and reproducibility. These preprocessing efforts are essential for building an accurate and robust predictive model for electricity price forecasting.

Feature Engineering:

In the context of forecasting electricity prices, feature engineering involves crafting informative attributes from the raw data to enhance the predictive model's accuracy. Key techniques include extracting time-based components like day of the week, generating lag features to capture historical patterns, calculating rolling statistics and moving averages to discern short-term trends, and incorporating seasonal indicators and weather-related data. Economic indicators, fuel prices, and event-based features offer insights into external factors impacting electricity prices. Moreover, cross-correlations with relevant time series data and domain-specific features contribute to a more comprehensive feature set. Effective feature engineering is instrumental in ensuring that the model can capture the intricate dynamics of electricity price fluctuations accurately.

Model Selection:

In selecting the most suitable model for forecasting electricity prices, several options tailored to the specific dataset and problem should be considered. Time series models like ARIMA and SARIMA are adept at capturing temporal dependencies and seasonality. Machine learning models such as Random Forest and Gradient Boosting excel in capturing complex relationships and feature importance. Recurrent neural networks like LSTM and GRU can effectively model sequential data, while hybrid models like Prophet combined with regression features leverage external factors. Ensemble models and stacking techniques can also be explored to combine the strengths of multiple models. The model choice should be informed by the dataset's characteristics, the presence of seasonality, and the availability of relevant external factors, with performance evaluation and hyperparameter tuning guiding the final selection for accurate electricity price forecasting.

Model Training:

Model training for electricity price forecasting begins by preparing historical data and optimising hyperparameters if necessary. The model is trained on the training dataset, and its performance is assessed on a validation set using appropriate metrics. Iterative adjustments and hyperparameter tuning follow based on validation results. Optionally, ensemble techniques can be employed, and once the model's performance on the validation data meets expectations, it is tested on a hold-out test dataset for a final evaluation. Serialised models are documented and may be deployed for real-time predictions. Monitoring and maintenance plans are established to ensure continued accuracy in a dynamic energy market.

Evaluation:

Evaluating a predictive model for electricity price forecasting entails assessing its accuracy and practicality. This involves choosing appropriate metrics like Mean Absolute Error (MAE) or Mean Squared Error (MSE) and validating the model's performance on separate test data. Visualisations, residual analysis, and backtesting can offer insights into its ability to capture patterns and trends. Additionally, benchmarking against simpler models aids in gauging the model's value. Business impact assessment, out-of-sample testing, and a feedback loop for continuous improvement are integral parts of the evaluation process. Comprehensive documentation and clear reporting ensure transparency in model performance, enabling informed decision-making in the dynamic energy market.