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Understanding Household Energy Consumption: A Deep Learning Approach

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Agenda

1) Problem Description - Why does it matter?
2) Deep Learning Technique
3) Update on Tutorial

Significance of Accurate Energy Consumption Forecasting

- **Why?**: Rising global energy demand and the need for sustainable energy management
- **Past Limitations**: Struggles with complexity and non-linearity of energy data; limited in handling multivariate data inputs
- **LSTMs**: Multivariate forecasting with LSTMs allows for considering multiple influencing factors simultaneously
- **Policy Relevance**: More accurate energy consumption data to inform policy decisions
- **Dataset**: Individual Household Electric Power Consumption

Relevance to Public Policy and Government

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- Predicting household energy consumption patterns
  - Development of more efficient and effective energy use policies
- Informs energy infrastructure development
- Crucial for the development of smart grid systems
- Enable dynamic pricing models and load balancing
- Informs government decisions on energy subsidies, tariffs

Individual Household Electric Power Consumption: Dataset Overview

- A comprehensive dataset capturing electric power consumption in one household over a four-year period
- Dataset sourced from the UCI Machine Learning Repository
- Data collected from December 2006 to November 2020 at one-minute intervals
- Multivariate time series with ~2 million measurements across 9 attributes
- Some attributes include:
  - Date, time
  - Global active power & Global reactive power
  - Voltage and current
  - Energy consumption for kitchen, laundry, and heating/cooling

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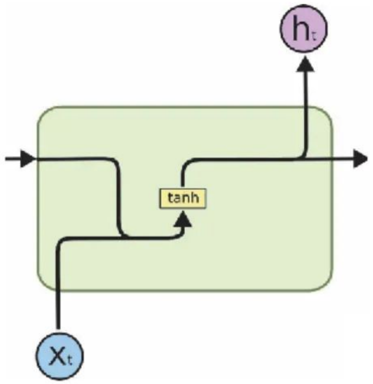
Deep Learning Techniques

What will you learn?

- **Tools you will be using**: Python, TensorFlow, Keras, Jupyter Notebooks, and all your neurons.
- **Deep learning models**: Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM).
- **From Theory to Practice**: Data Preprocessing, model building, training, evaluation.

Understanding Recurrent Neural Networks (RNNs) and LSTM - pt1

- **RNNs**: are a type of neural network designed for processing sequential data.
- Each neuron in an RNN has a 'memory' of previous inputs, allowing it to capture information about the sequence as a whole.



Basic Architecture of RNN Cell, referenced from: Towards Data Science

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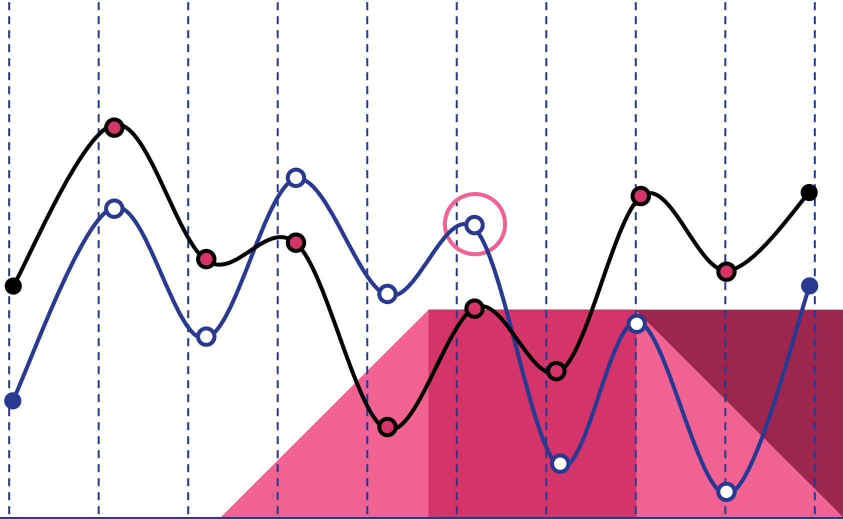
Why is it suitable for sequenced Data?

- **Temporal Dependencies:** recognize patterns across time.
- **Variable-Length Inputs:** handle input sequences of varying lengths.
- **Feature Learning**: Automatically learn and extract features from sequence data.



Understanding Recurrent Neural Networks (RNNs) and LSTM - pt2

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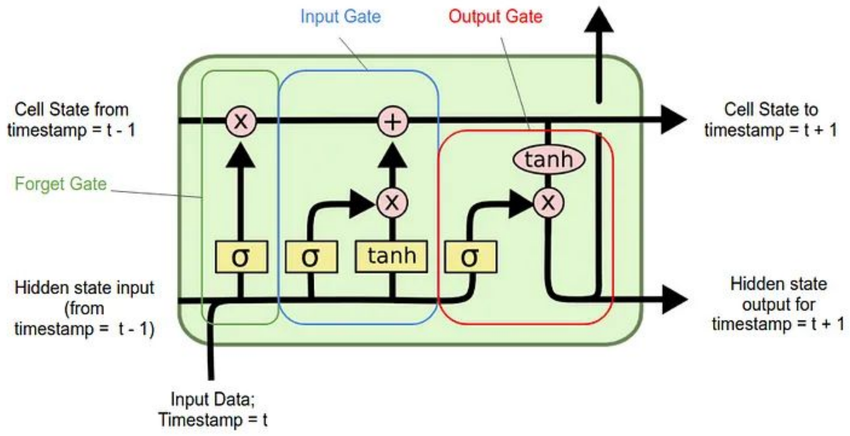
LSTM: advanced type of Recurrent Neural Networks (RNNs) specially crafted to overcome the vanishing gradient problem, a limitation in standard RNNs where they fail to capture long-range dependencies in data.

Key Features

Memory Cells: store information over extended periods, enabling them to remember and utilize past data effectively for more accurate predictions.

Gates: Forget, Input, and Output gates. Work together to regulate the flow of information, deciding what to retain or discard from the cell state, enhancing the model's learning and decision-making capabilities.



Single LSTM Cell, referenced from: [Medium]

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Tutorial content

From the beginning to the end

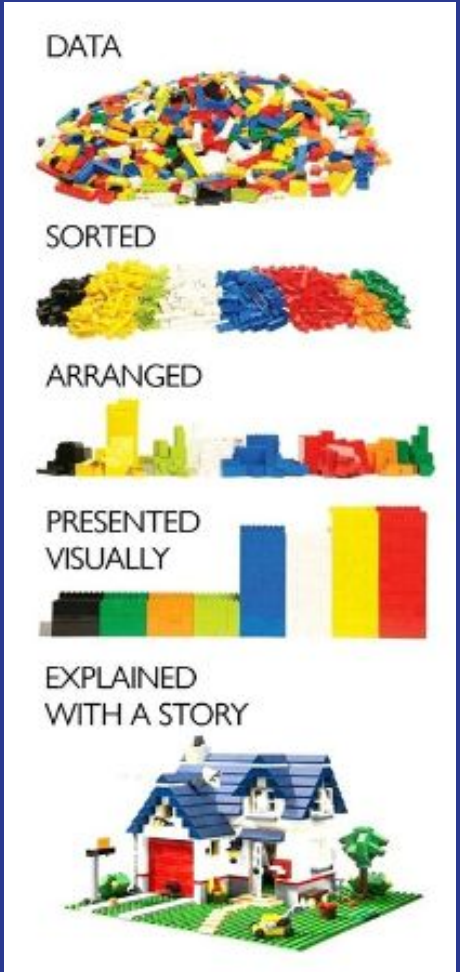

Image: https://www.effectivedatastorytelling.com/post/a-deeper-dive-into-lego-bricks-and-data-stories

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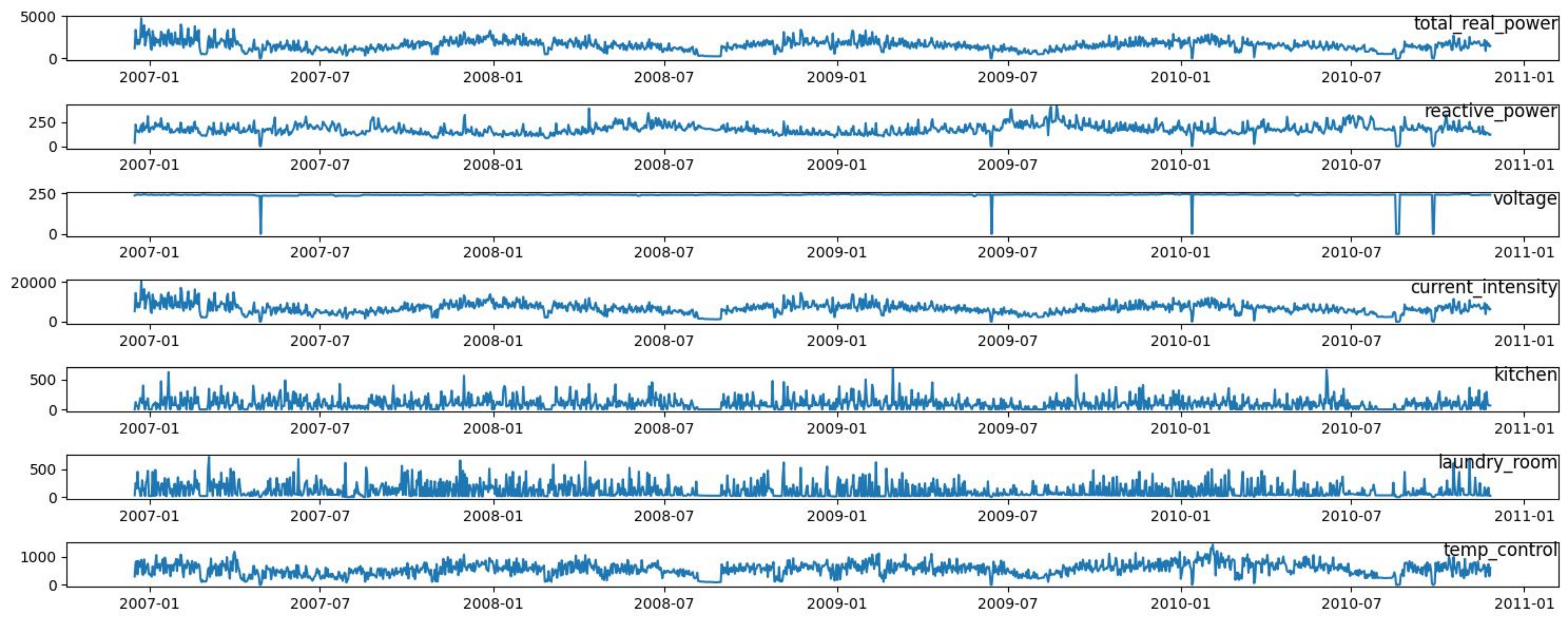
Main goal of this tutorial:
predict the total power to be consumed based on previous records



LSTM model for multivariate time series forecasting

- **Data cleaning:**
  - Adjust variable names, check NAs,
  - Create a date and time index,
  - Convert some variables to the same order of magnitude.
- **Data Preparation:**
  - Raw data: 1 observation/minute -> 1 hourly/daily record.
  - Frame the dataset as a supervised learning
  - Normalize the input variables
- **Model tuning:**
  - Training/test sets? How many neurons? Batch size?
  - Predict based on the last day/week/month? Which variables do we need to predict?
  - Loss function - Mean Absolute Error (MAE).
- **Evaluate model:**
  - Invert the scale and calculate the Root Mean Squared Error (RMSE).
  - Compare with other benchmarks.

Thank you!

Any questions?