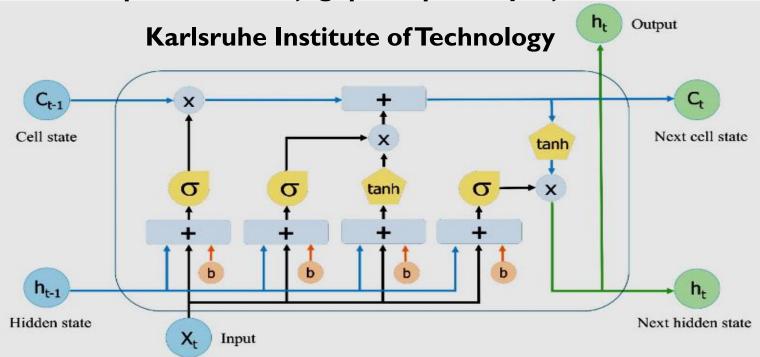


Music Generation with LSTM Networks Date: 06 May, 2025

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Outline



1 Motivation

3 Music Generation with LSTM

5 Tools and Timeline









2 Introduction to LSTM



4 Project Workflow

Why Music Generation with LSTM Networks?



- Traditional music composition methods are labor-intensive and limited by human creativity.
- Machine Learning offers the ability to explore and generate diverse, novel musical ideas.
- RNNs can model sequential data effectively but struggle with long-term dependencies.
- LSTMs address this issue, allowing networks to remember and utilize important information from earlier in the sequence.

Introduction to LSTM



What is LSTM?

- Long Short-Term Memory (LSTM) is a special kind of RNN architecture.
- Capable of learning long-range dependencies in sequence prediction tasks.
- Consists of gates (input, forget, output) which control the flow of information, enhancing the memory capacity over traditional RNNs.

Introduction to Music Generation



What is Music Generation?

- Automated creation of musical pieces using computational models.
- Utilizes computational algorithms to emulate the creative processes of human composers.
- Generates original musical sequences or extensions of existing pieces.

Why use Machine Learning?

- Enables analysis of large datasets to recognize complex patterns within musical data.
- Facilitates automated learning and creativity without explicitly programming rules.
- Allows the generation of novel and diverse musical compositions that maintain coherent structure and musicality.
- Offers scalability and continuous improvement as more data becomes available.

Basics to Know



- Machine Learning Fundamentals:
 - Supervised vs. Unsupervised learning
 - Sequence modeling and prediction
- Deep Learning Basics:
 - Neural Networks
 - Recurrent Neural Networks (RNN)

What is LSTM?



- It is a special type of RNN, capable of learning long-term dependencies.
- Long Short Term Memory (LSTM) is a type of deep learning model that is mostly used for analysis of sequential data (time series data prediction).
- There are different application areas that are used:
 - Language model,
 - Neural machine translation,
 - Music generation,
 - Time series prediction,
 - Financial prediction,
 - Robot control,
 - Time series prediction,
 - Speech recognition,
 - Rhythm learning, Music composition, Grammar learning, Handwriting recognition etc.

Essential Concepts of LSTM



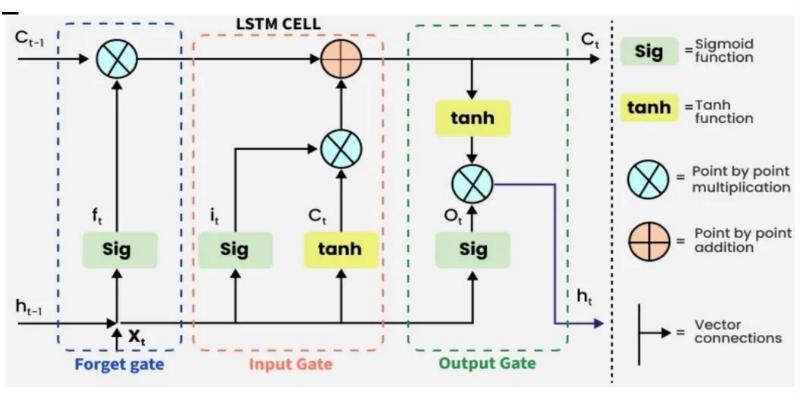
- Gates in LSTM:
 - Input gate: Controls what information is added to the memory cell.
 - Forget gate: Determines what information is removed from the memory cell.
 - Output gate: Controls what information is output from the memory cell.
- Role of gates: Manage information flow and memory in sequential data



 LSTM architecture has a chain structure that contains four neural networks and different memory blocks called cells.

Information is retained by the cells and the memory manipulations are done by the

gates. There are three gates –



https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/

Forget Gate

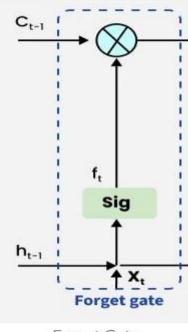


- The information that is no longer useful in the cell state is removed with the forget gate.
- Two inputs x_t (input at the particular time) and h_{t-1} (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias.
- The resultant is passed through an activation function which gives a binary output. If for a particular cell state the output is 0, the piece of information is forgotten and for output 1, the information is retained for future use.
- The equation for the forget gate is:

$$f_t = \sigma(W_f \cdot [h_t - 1, x_t] + b_f)$$

where:

- W_f represents the weight matrix associated with the forget gate.
- \blacksquare [h_{t-1}, x_t] denotes concatenation of the current input & previous hidden state.
- lacktriangle b_f is the bias with the forget gate., σ is the sigmoid activation function.



Forget Gate

Input gate



- The addition of useful information to the cell state is done by the input gate.
- First, the information is regulated using the sigmoid function and filter the values to be remembered similar to the forget gate using inputs h_{t-1} and x_t .
- Then, a vector is created using tanh function that gives an output from -1 to +1, which contains all the possible values from h_{t-1} and x_t .
- At last, values of the vector and the regulated values are multiplied to obtain the useful information. The equation for the input gate is:

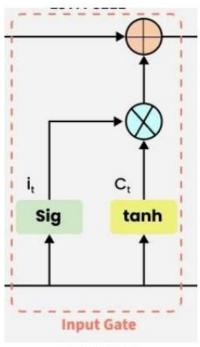
$$i_t = \sigma(W_i \cdot [h_t - 1, x_t] + b_i)$$

$$C_t = \tanh(W_c \cdot [h_t - 1, x_t] + b_c)$$

We multiply the previous state by f_t, disregarding the information we had previously chosen to ignore. Next, we include i_t*C_t. This represents the update candidate values, adjusted that we chose to update each state value.

$$C_t = f_t \odot C_{t-1} + i_t \odot C^{\wedge}_t$$

where ⊙ denotes element-wise multiplication, tanh is tanh activation function

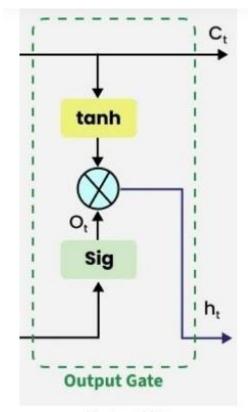


Input Gate



Output gate

- The task of extracting useful information from the current cell state to be presented as output is done by the output gate.
- First, a vector is generated by applying tanh function on the cell.
- Then, the information is regulated using the sigmoid function and filter by the values to be remembered using inputs h_{t-1} and x_t .
- At last, the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell.
- The equation for the output gate is:



Output Gate

File Types and Data Preparation



MIDI Files:

- Primary format for music generation
- Contains information on notes, duration, tempo, instruments

Data Preprocessing Steps:

- Conversion of MIDI files into sequences understandable by the neural network
- Tokenization and encoding of musical data

Project Workflow



- **Data Collection:** Gather MIDI files from diverse sources.
- **Preprocessing:** Convert MIDI files into suitable numerical sequences.
- **Model Training:** Utilize LSTM to learn sequential patterns.
- **Generation:** Produce new musical sequences based on learned patterns.
- **Evaluation:** Assess generated music qualitatively (listening) and quantitatively (pattern similarity).

Tools and Technologies



- Programming Language: Python
 - Libraries and Frameworks: TensorFlow/Keras for neural network implementation
 - Music21 or pretty_midi for MIDI file handling
- IDE and Tools
 - Jupyter Notebooks
 - GitHub for version control

References:

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

https://github.com/Kulbear/deep-learning-coursera/tree/master/Sequence%20Models

https://www.kaggle.com/code/pablocastilla/predict-stock-prices-with-lstm/notebook

Project Organization Suggestions



- GitHub Repository Structure:
 - /data: Raw and processed MIDI files
 - /src: Python scripts for preprocessing, training, generation
 - /models: Saved trained LSTM models
 - /outputs: Generated music files (MIDI/WAV)
 - README.md: Clearly document steps for project setup and execution

Milestones & Timeline



- Week 1-2: Basic concepts and tools familiarization
- Week 3-4: Data collection and preprocessing
- Week 5-7: Initial model training
- Week 7-9: Music generation tests
- Week 10-12: Project refinement and documentation and presentation (by September 15)

Thank you for your attention!

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