Using Deep Learning Methods to Analyze User Behavior in CNGrid

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Introduction

- User behavior is complex and variable
- There are many users in a supercomputing environment
  - Each user behavior has its own characteristics
- User behavior includes user operational characteristics
- It needs to be analyzed using some automated detection methods

- An unsupervised learning algorithm based on deep learning is introduced to analyze user behavior in network environment
  - Data preprocessing
  - Use of LSTM language models
  - Attention mechanism is used to improve accuracy
- Use Case
  - The user behavior map can be obtained by using this model
  - This model can be used for single-user exception detection

Background

- The early stage of the work
  - Thinking based on log analysis anomaly detection model
  - Preprocessing of log data modeling
  - Heuristics for log type operation lists

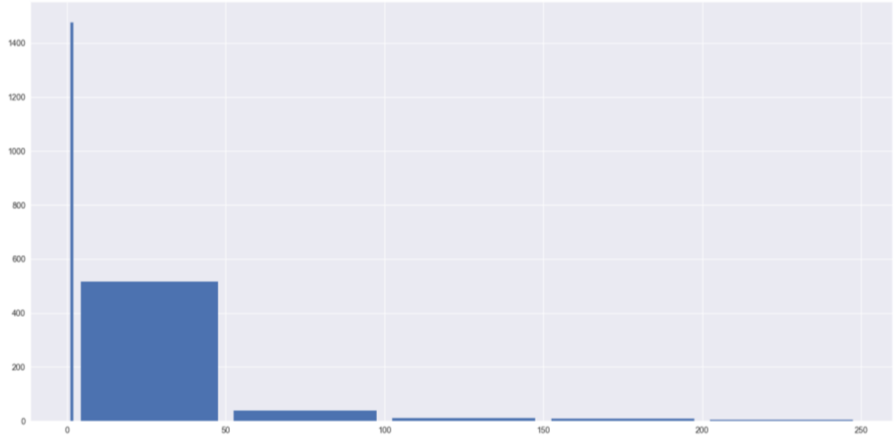
- Definition1： For user operation Op_i $(i \in 1,2,\ldots,n)$， Which n express The operation number of user . $UserBehavior = \{Op_{i1}, Op_{i2}, \ldots, Op_{im}\}$ Represents a user action.

Operation type	Operation Type interpretation	Operation type number
end	The end tag	0
SCE_CMD_MREMOTE	FS命令执行	1
SCE_BJOBS_ENC	Job list	2
SCE_JOB_LISTRES_ENC	List resources	3
SCE_JOB_SUBMIT	Submit job	4
SCE_CMD_REMOTE	FS Command execution	5
Start	The start tag	6

An ordered connection between different types of user operations represents a session operation

Preprocessing Module

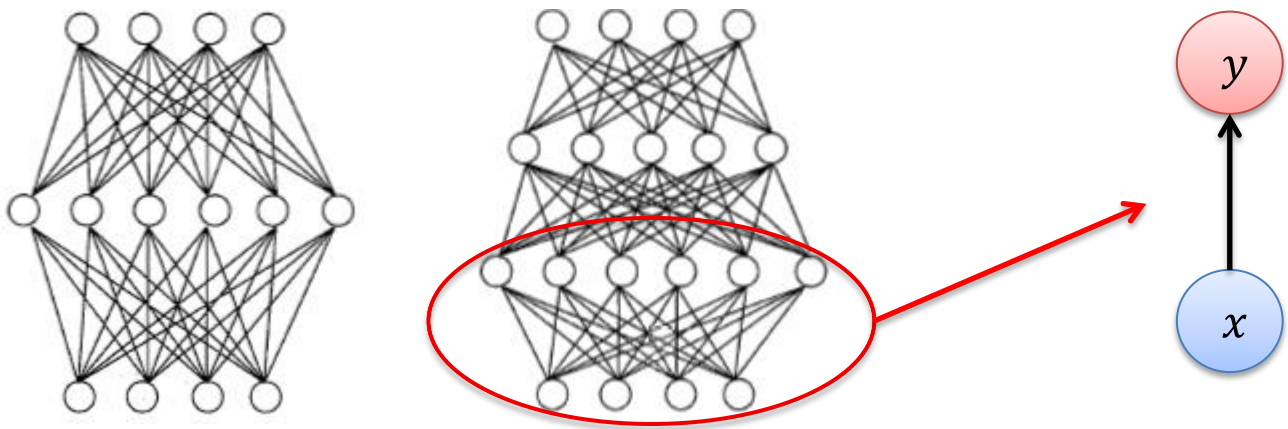
- A trapezoid diagram of the number of operations under different sessions



- Filter small number of operations reason
  - The number of one operation sessions is large
  - A single action does not make much sense for an ordered list analysis of user actions
- Filter large number of operations reason
  - Sessions larger than 100 appear very infrequently

LSTM Language Model

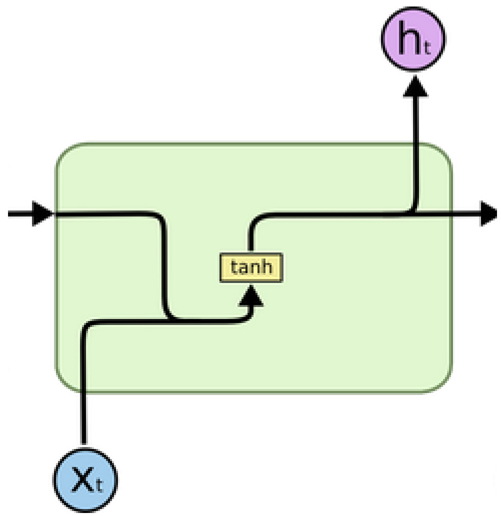
- RNN basic structure



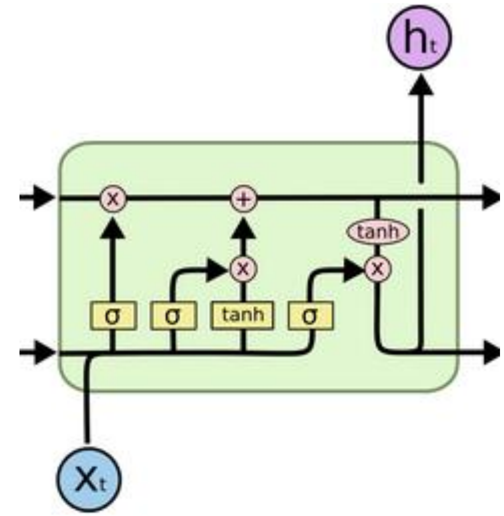
$y = f(Wx + b)$

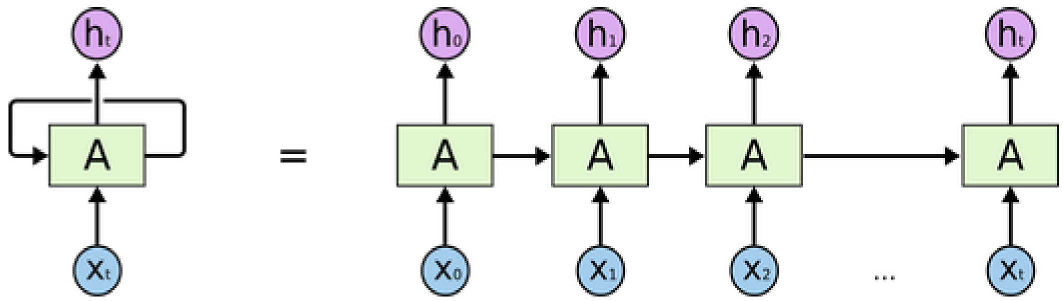
- Sequential data model
  - Natural language problems, x_1 for the first word, x_2 for the second word, and so on
  - Time series, take the daily stock price
  - User behavior analysis, the type of each user action

LSTM Language Model



RNN to LSTM

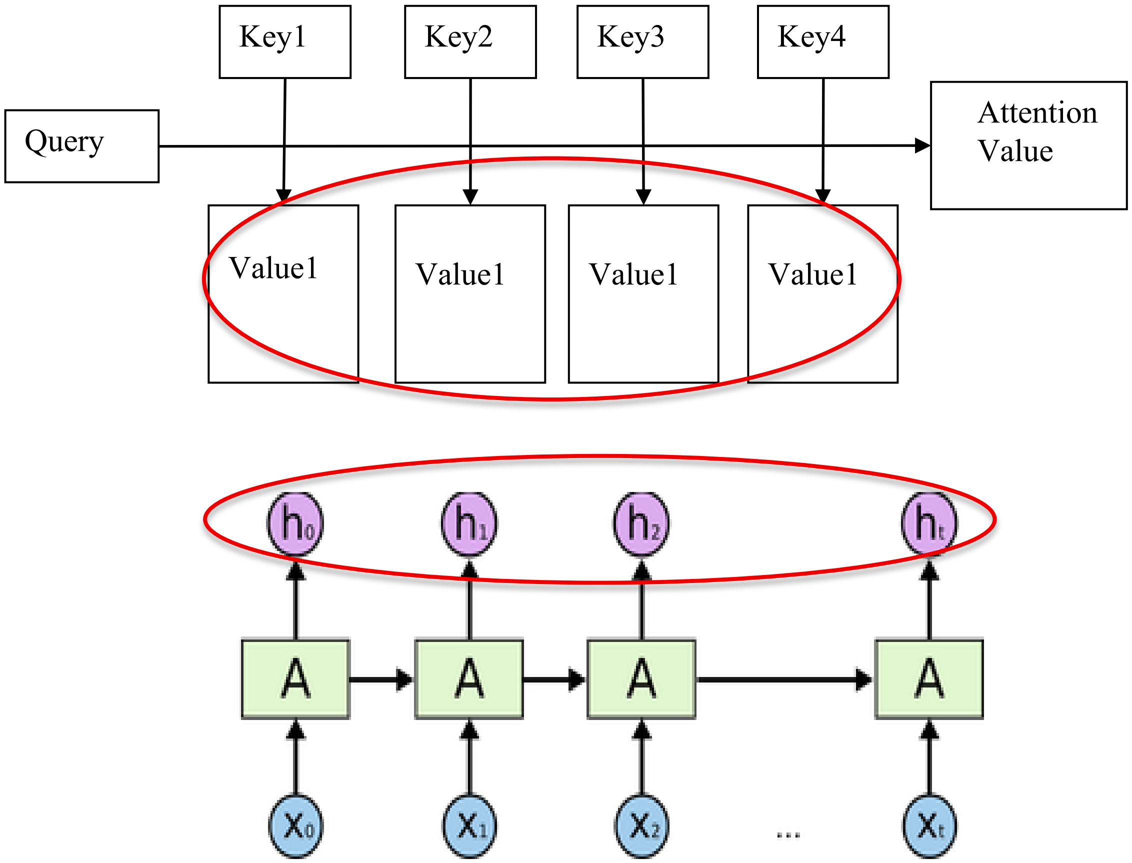




Source of the above picture： http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Attention Mechanism

- The nature of the Attention function can be described as a mapping from a query to a set of key-value pairs



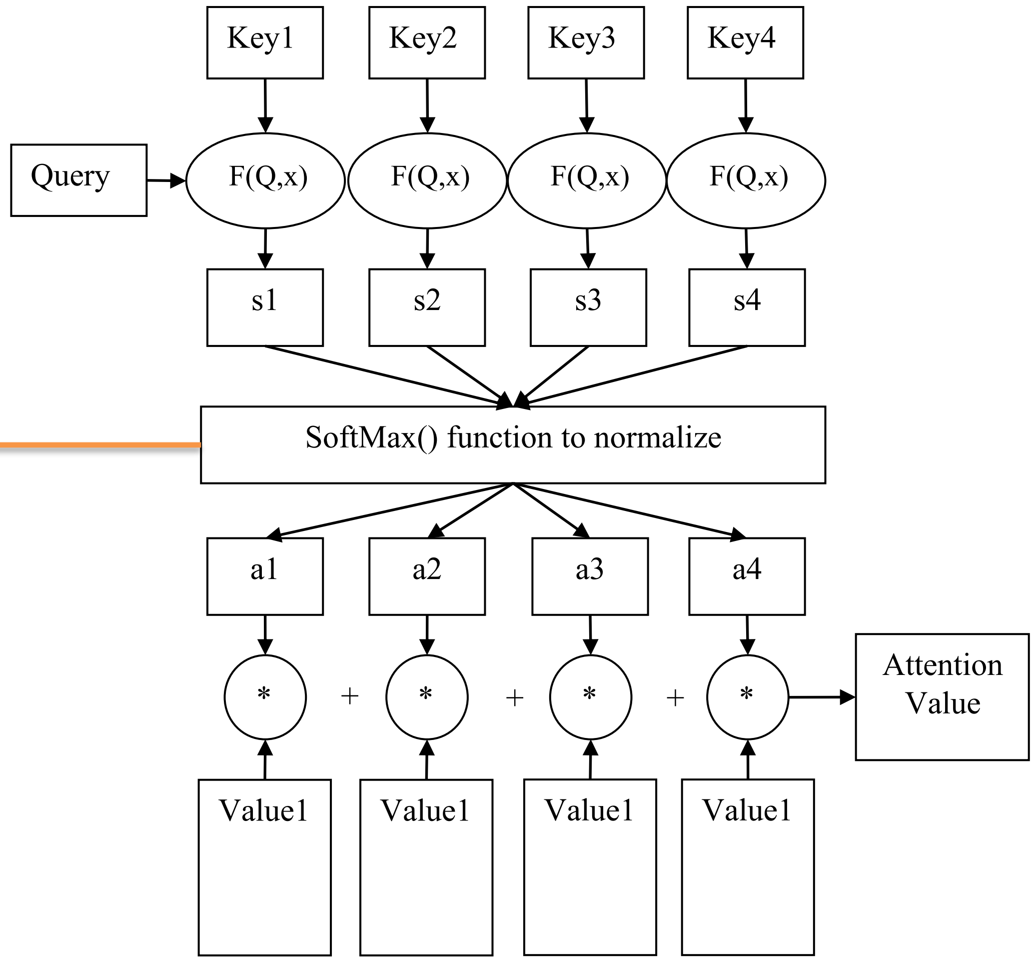
Attention Mechanism

- Dot product, splicing, perceptron

$$f(Q,k) = Q^T K$$
$$f(Q,k) = W_a[Q;K]$$
$$f(Q,k) = V tanh(WQ + UK)$$

$$a = softmax(f(Q,K))$$

$$Attention = \sum aV$$



Attention Mechanism

- The value matrix

$$V_{(t)} = \begin{bmatrix} h_1 \\ \vdots \\ h_t \end{bmatrix} \in R^{t \times L_h}$$

- h_i : hidden state
- t : time steps
- L_h : output dimension at this time of hidden
- The key matrix

$$K_{(t)} = \tanh\left(V_{(t)} \times W^{a}\right) \in R^{t \times L_a}$$

- The weight coefficient:

$$d_{(t)} = softmax\left(\left[K_{(t)} \otimes q_{(t)}\right]^{T}\right) \in R^{t \times t}$$

$\otimes$ will be described at next page.

Attention Mechanism

- Attention result:

$$\mathrm{a}_{(\mathrm{t})} = d_{(t)} V_{(t)}$$

- The notation $\otimes$ is calculated as follows:

$$K_{(t)} \otimes q_{(t)} = K_{(t)} \times W^{q} \cdot M_{triu}$$

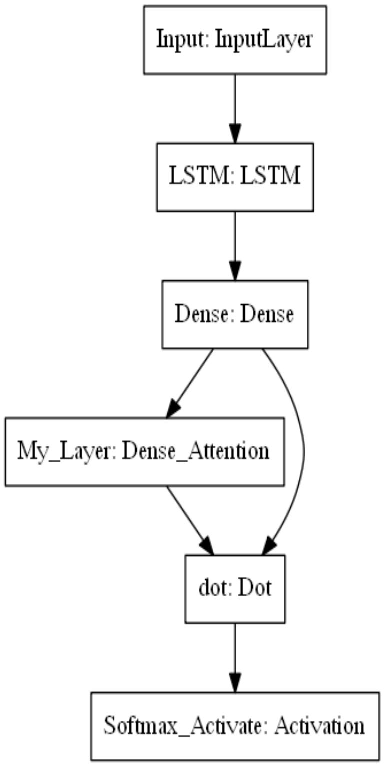
- M_{triu}: a non-zero value of 1 all upper triangular matrix

Thus ensure the $K_{(t)} \otimes q_{(t)}$ is an upper triangular matrix. After transposing, the time step is transposed to the last dimension and the time step dimension is normalized by the activation function softmax().

Attention Mechanism

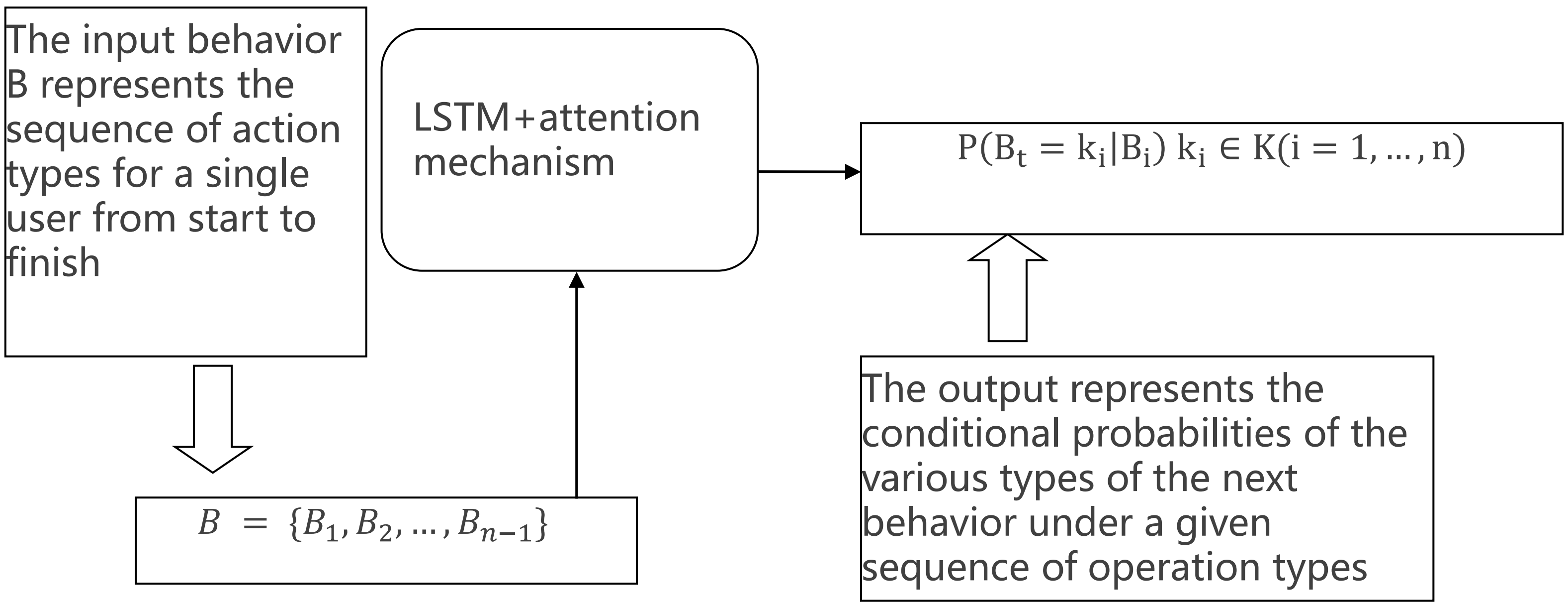
- Final overall structure

Layer Structure	Output the shape of the dimension	Number of parameters (Single LSTM)
InputLayer	(None, 100, 14)	0
LSTM	(None, 100, 128)	73216
Dense	(None, 100, 14)	1806
My_Layer (Dense_Attention)	(None, 100, 100)	7296
dot (Dot)	(None, 100, 14)	0
Softmax_Activate	(None, 100, 14)	0



User Behavior Mapping

- Establishment of prediction model
  - The probability of each type of user behavior occurring the next time is determined by the type sequence



- The user behavior map can be mapped into a multi-fork tree structure
- Each node represents an operation type
- The father-child connection represents the probability of transitioning to the next action

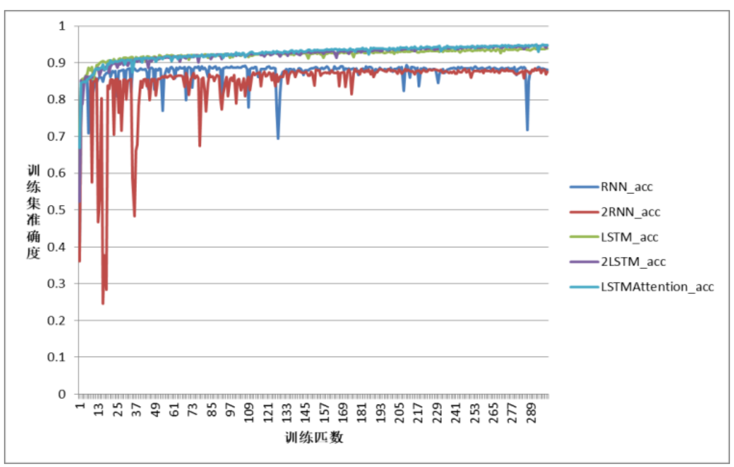
Anomaly Detection of Single User

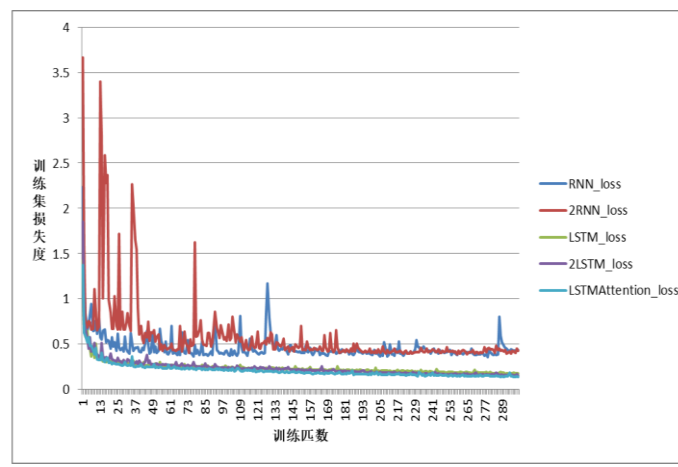
- Mode for single user
  - Determine the selected model (single-layer LSTM+attention mechanism)
  - A sequence of action types for each session of a single user is obtained from historical data
  - Input the model and adjust the model parameters
  - Each user is monitored in real time separately according to the adjusted model

- The maximum probability method is used for anomaly detection
  - The probability of various types of the next action is predicted based on all the previous actions of the user and the model
  - If the first n operation types of the prediction probability of the operation do not match the actual user's operation type, the operation is considered as abnormal behavior

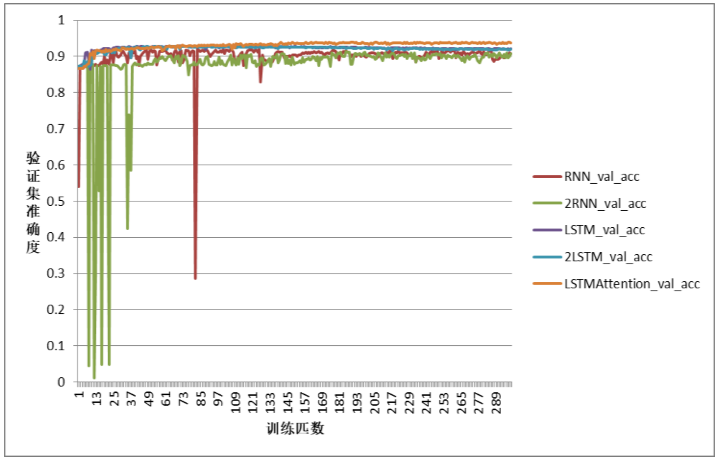
The Experiment and Analysis

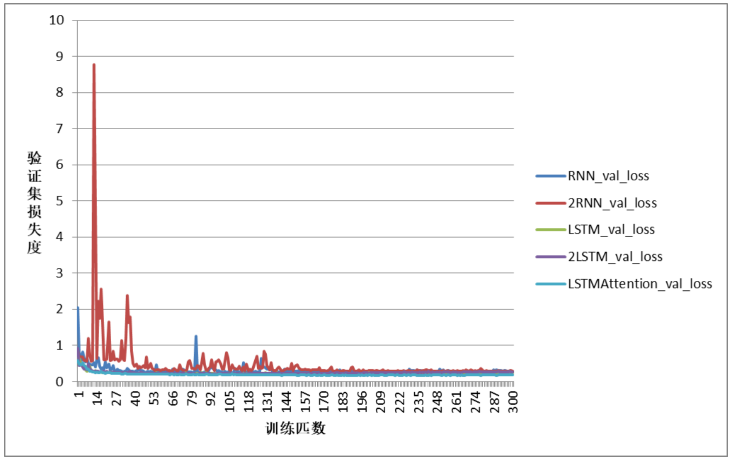
- Data preparation
  - User operation dataset was obtained from CNGrid in the period of 2018/5/9 to 2018/6/12
  - 80% data was used as training set, and 20% data was used as verification set for training and verification
  - Use 100 - dimensional time step input
  - Each type of dimension corresponds to a unique heat encoding of a 14-dimensional vector
  - Single-layer, double-layer RNN, LSTM and LSTM+attention mechanisms were used for training and prediction





The Experiment and Analysis



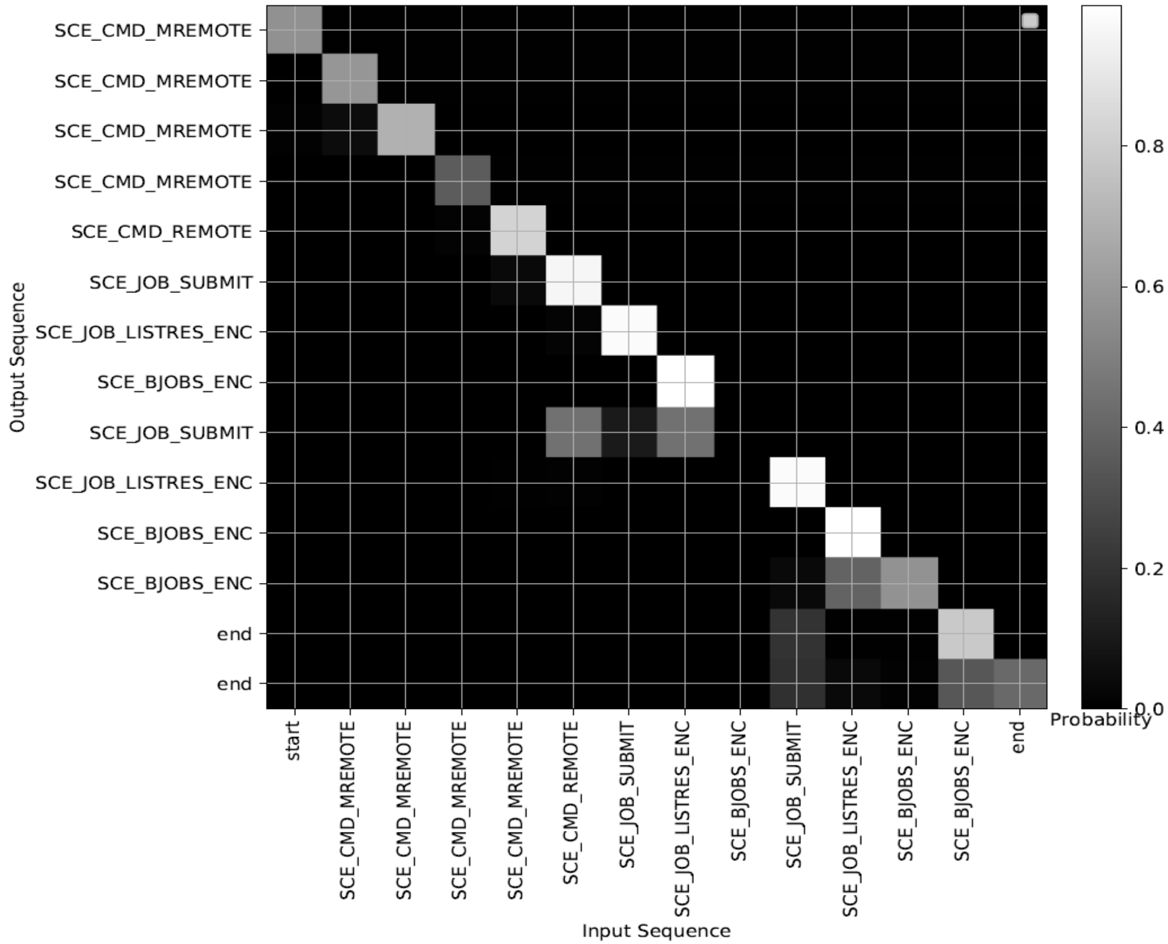


Network type	Highest verification set accuracy	Corresponding batch
Single RNN	92.02%	105
Double RNN	91.29%	185
Single LSTM	92.87%	70
Double LSTM	92.81%	73
Single LSTM + dot attention mechanism	**94.03%**	192

- According to the table above
  - LSTM network is superior to ordinary RNN circulation neural network
  - There is no significant difference in the use of single and double layers between the same networks
  - Attention mechanism can improve the accuracy of deep learning

The Experiment and Analysis

- Attention mechanism figure



The figure shows the weight of time step obtained by deep learning according to training, and increases the interpretability

The Experiment and Analysis

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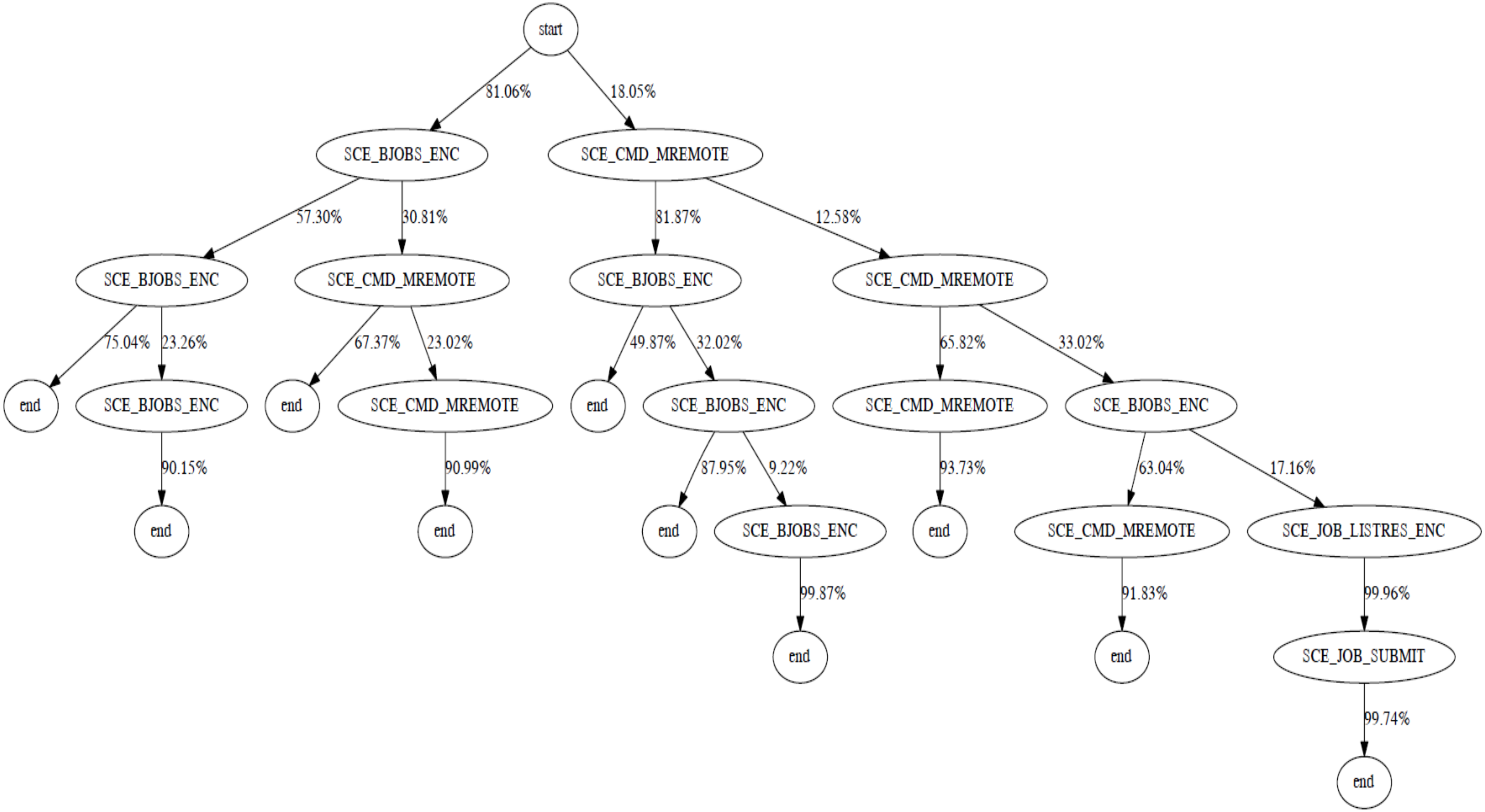
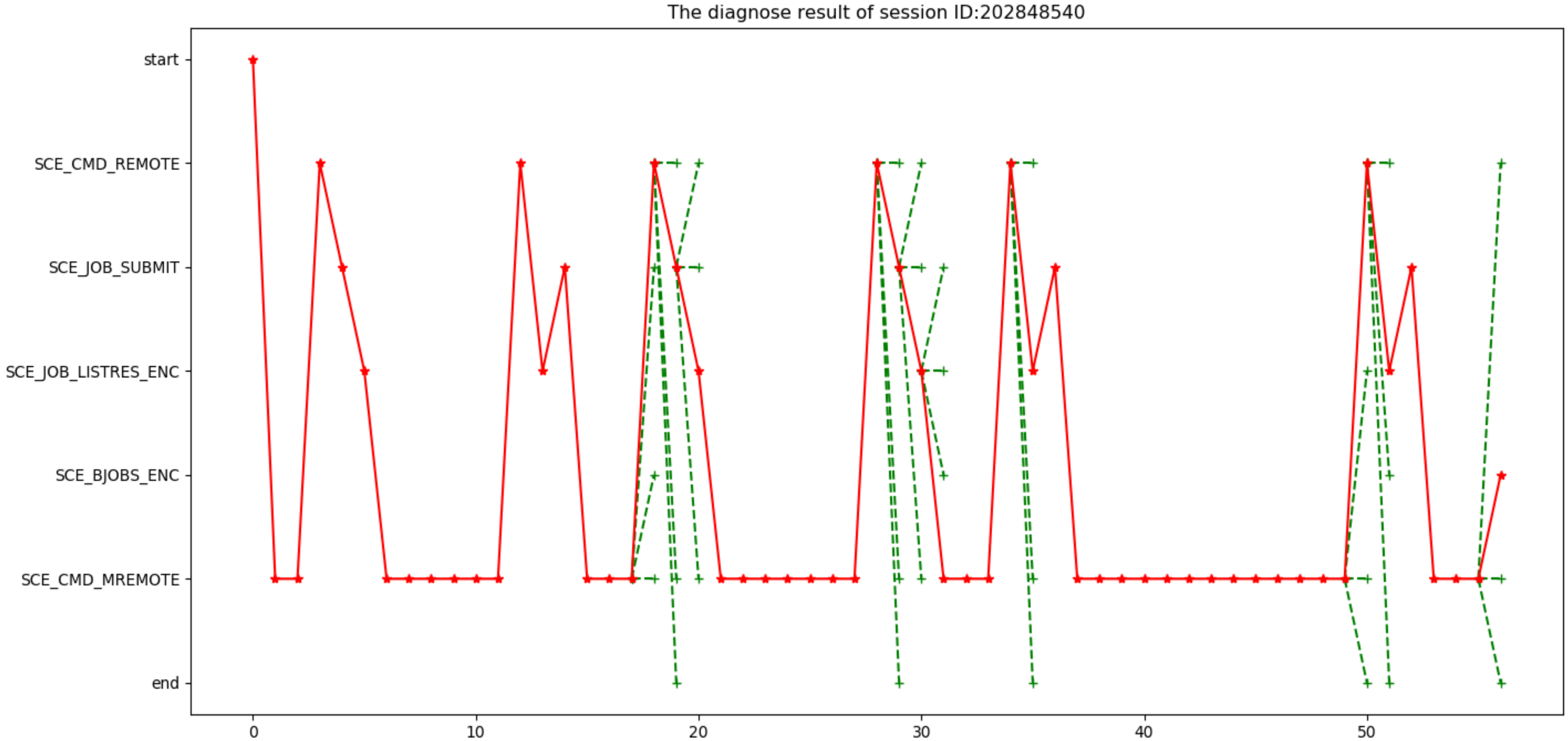
- A case study of single-user behavior mapping
  (User_Example_18/5/9_2018/7/9)



The Experiment and Analysis

- If set n=3, the user (User_Example_18/5/9_2018/7/9) has the following figure of abnormal operation under a session



Conclusion

- Conclusion
  - The user behavior in high performance computing environment is modeled by deep learning cyclic neural network model
  - By comparing the results of different network structure and attention mechanism, the optimal method of constructing user behavior model is obtained
  - The model is used to generate the user behavior map
  - The model is used to detect and analyze user behavior anomalies and provide feedback

- Future Work
  - More refined classification of user operations
  - More kinds of user data from CNGrid

Thank you!

Welcome to visit CNGrid!

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Reference

- Reference Articles：
  - Recurrent Neural Network Language Models for Open Vocabulary Event-Level Cyber Anomaly Detection
  - Recurrent Neural Network Attention Mechanisms for Interpretable System Log Anomaly Detection
  - DeepLog: Anomaly Detection and Diagnosis from System Logs through Deep Learning
  - Attention Is All You Need
- Reference Books：
  - http://www.deeplearningbook.org/
- Reference Codes：
  - https://github.com/philipperemy/keras-attention-mechanism
  - https://github.com/datalogue/keras-attention
  - https://github.com/philipperemy/keras-visualize-activations
- Reference Blogs：
  - http://colah.github.io/posts/2015-08-Understanding-LSTMs/