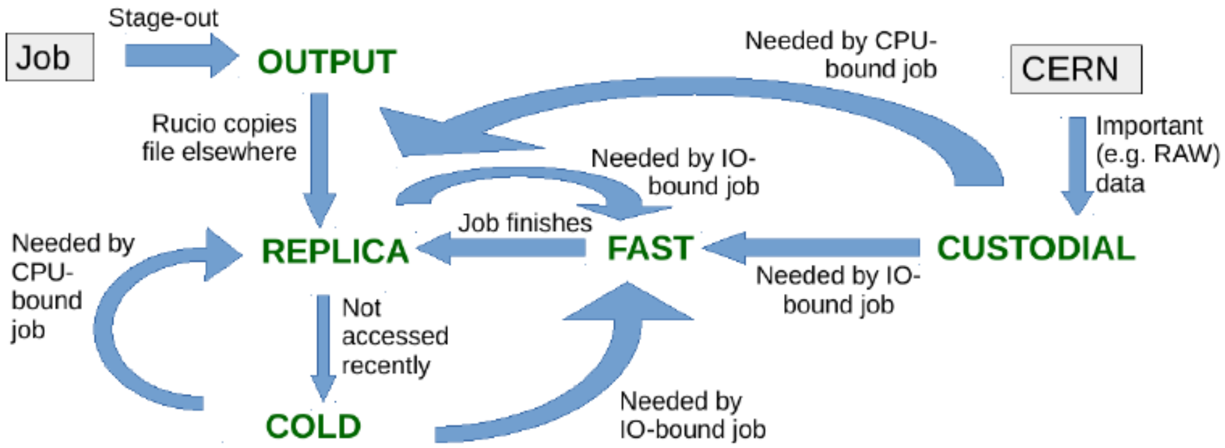
Motivation:

- Large scale high energy physics experiments will generate hundreds of PB data
  - LSST, LHC, JUNI, LHAASO, CEPC…
- Not all the data requires same Quality of Service(QoS)
  - Data popularity is not constant in the data life cycle
- Tiered storage may provide a cost-effective and high-performance solution
  - SSD, HDD, Tape, Public Cloud, Remote Site, …
- Data migration strategy is the essence of a tiered storage system!



Source: Oliver Keeble, WLCG Workshop 2019: QoS Session

Machine Learning Based Data Migration Strategy for Tiered Storage Systems

Challenge:

- EOS cluster operators don’t understand the meaning of user data
  - We only know users’ file history access statistics - by analyzing EOS FST logs

Available solutions:

- LRU based on history data access frequency
  - LRU: least recently used files migrated to lower tier (SSD->HDD)
  - mainly used in cache replacement policy
  - LRU claims probability of file revisiting will increased if the number of the visits is larger

Existing issues:

(1) Traditional solutions support just the fundamental locality principle

(2) low prediction accuracy

(3) complexity growing rapidly and performance descend for massive files

Machine Learning Based Data Migration Strategy for Tiered Storage Systems

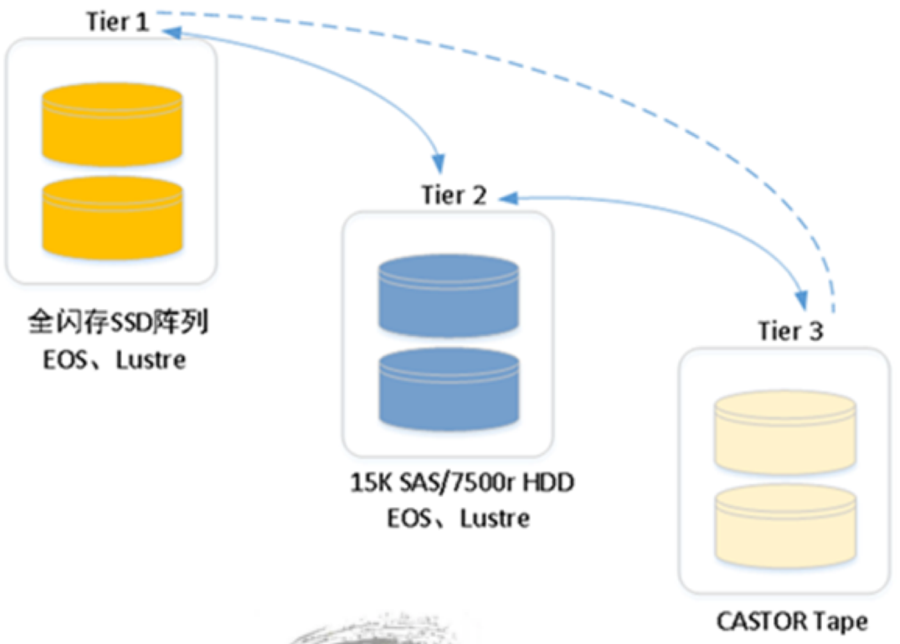
Built a migration engine based on Deep Learning techniques

(1) Define File Heat

- "hot data"
  - small amount of files and datasets that many users are interested in
  - ✓ migrate to faster storage like SSD and SAS
- " cold data",
  - mass files and datasets used by a single user for limited processing times,
  - ✓ migrate to lower but high-capacity storage like HDD

(2) Divide HEP files into different categories using the prediction model

(3) migrate files according to predefined rules by time

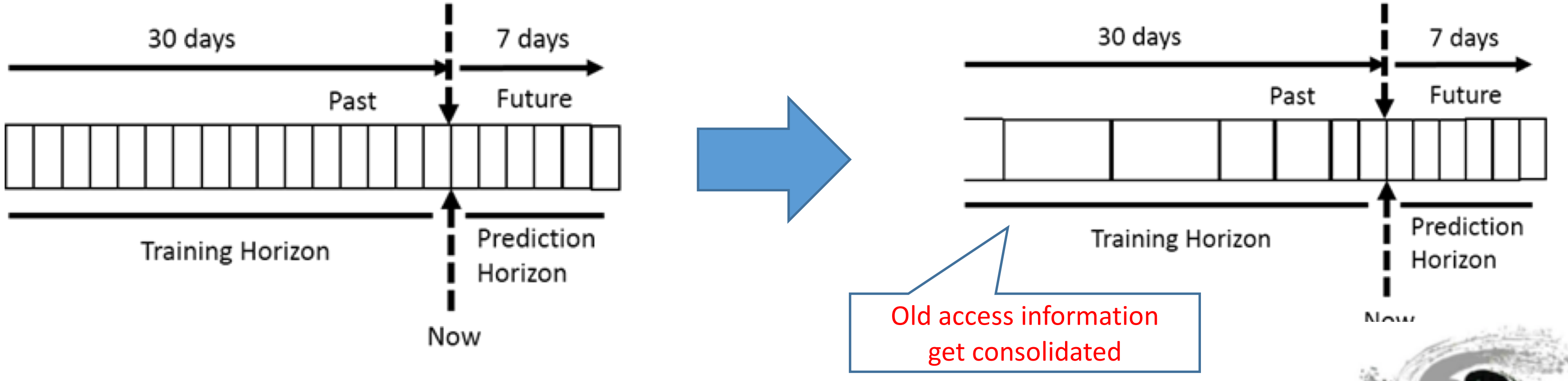


Prediction model:

- Based on LSTM(Long short-term memory network)
  - an improved RNN which is capable of learning the long-term dependencies
- Model Input features comes from EOS log
  - historical counters of read/write ratio, Re-read, Re-write, Random read, Random write
  - Build file access vectors

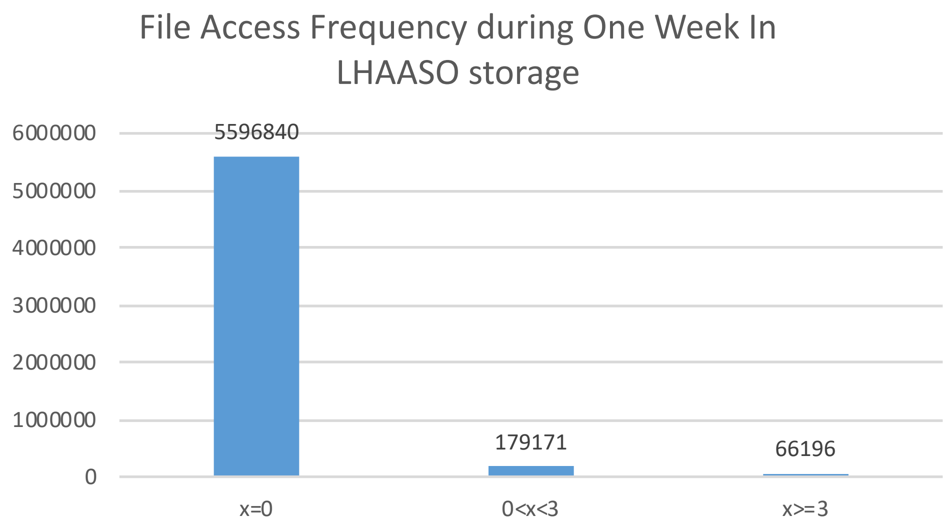
<timestamp, filename, filesize, read/write ratio, read/write bytes sequence/random read >

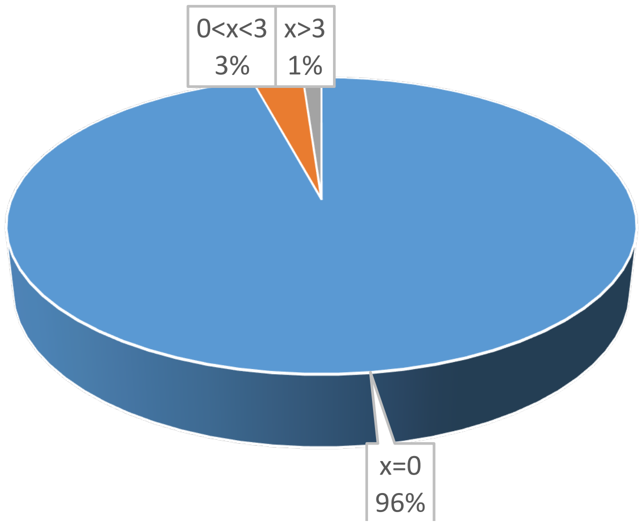
- Use access features in the past to predict future file heat
  - dynamical training time window



Preliminary Tests:

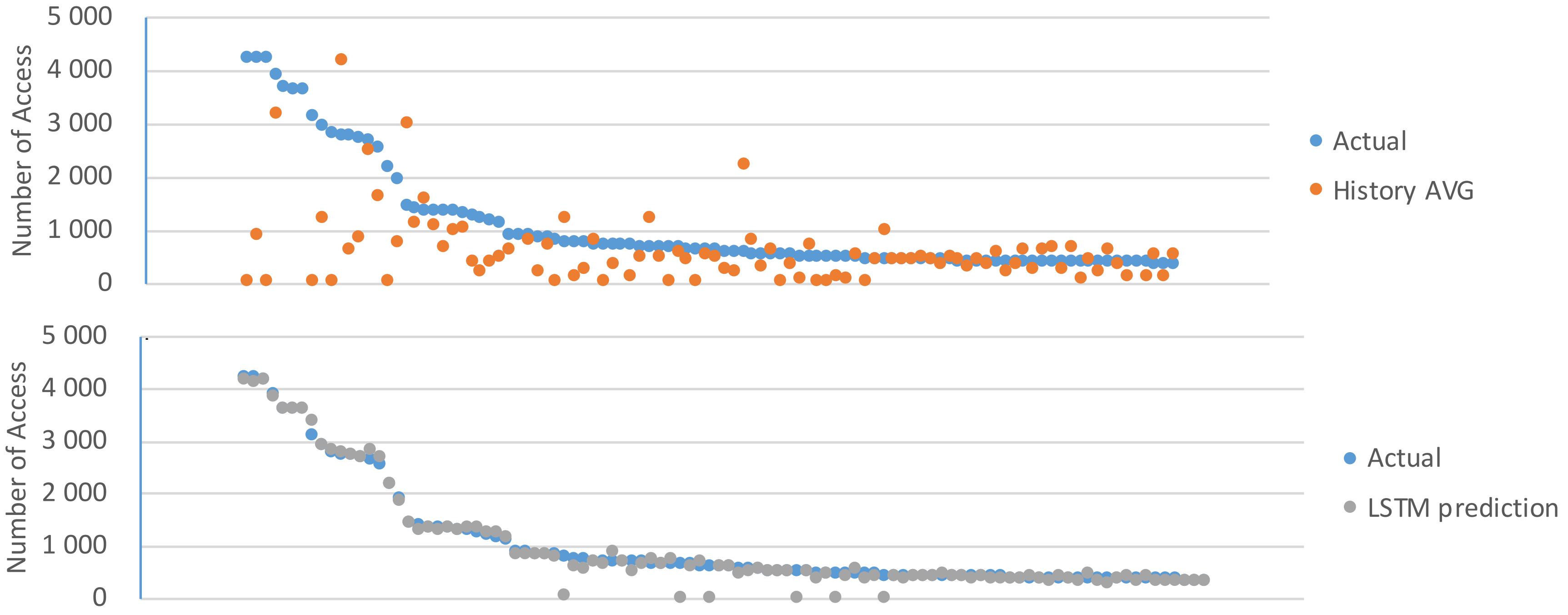
- We have trained a prediction model for LHAASO's EOS storage
  - so far, USED CAPACITY 1.362PB statfs_files 3.19Mil
  - 5,842,207 files access records (2018.4.1-2018.5.1)
  - divided into three groups, training data set(80%), verification data set(10%), test data set(10%)





Test(1) : LSTM prediction vs LRU

- select 100 very hot files and order them by actual file access frequency
- use LSTM and history average value to predict frequency in the next week



Test(2): predict which category would fall in?(hot file or cold file)

- classification accuracy
  - Hot file prediction accuracy: 87.52%
  - Cold file prediction accuracy: 92.89%
  - Overall classification accuracy : 91.78%

- Other metrics
  - classification report on two classes, good precision and recall for the LSTM model

	Precision	**Recall**	**f1-score**
Avg	0.8716	0.8944	0.8829

precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F1-score = 2*precision*recall/(precision + recall)

Conclusion and outlook:

- Hierarchical storage is the trend for HEP storage. Deep learning helps make data migration strategy
  - ✓ We implemented a binary classification model for the prediction of file heat: cold or hot
  - ✓ In the future, multiple classification for more complex hierarchy will be implemented.
- We have not considered impact brought by data migration to the storage performance
  - In the future, we will introduce the concept of migration cost, and consider data migration impact on storage performance