Recommendation Engine For Data Eviction Policy Selection

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Problem Description

- Ability to Advice clients:
  - “If we migrated[evicted] this extent our client will experience fall in IO latency by x% points”
  - “If we added one more VM, to the Controller, the IO latency for existing client will reduce by x% points”
  - “If we promoted this extent our IO latency for 80% of customers will improve by y%”
IO Controller Outline / Framework

Generic Socket Thread

Admit Thread

Read Thread

Framework Thread

Wait/Latency

Read IO/s

MB/s

Latency
Framework and Metrics

- Threads for admitting, processing and communicating responses for Requests.
- Requests Split to Operations
- Operations (Ops) may get Queued
- Ops contend Locks, experience Wait times
- Ops’s Responses communicated to clients.
- Request Latency, Wait times, Request Rates etc
Exploring The Problem Space

- Is it a N-class Classification Problem?
- Is it a Regression Problem?
- Is it a Queue Modelling Problem?
- Can we model it as a Poisson Process?
- Is it All of the Above?
Approaches

- Linear Regression
- Naïve Bayes Classification
- Multi-Resource Queue Modelling
- ARIMA (Time Based Forecasting)
- Predictive State Modelling
- Neural Networks
- Neural Networks with Internal States
Basic Statistics

- Are the variables dependent?
- Cost function response to delta changes in dependent variables?
- Is it linear, non-linear, parametric or not?
- Does the response vary from time A to time B?
- Bootstrapping, Markov Chain Monte-Carlo, Layers and Features learning
Mbps Plot Vs Normalized IOPS

Inernal/AvgThgput

readMBps

DiskThrgput

AsyncReadMBps

avgThrgPutNormIOPS

QoS_cpuFrac

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Inference / Observations

- Projections are continuous in low dimensional space and similar histories get clustered
- Parameter sharing among similar histories
- K-State Markov Model (HMM, Memory less model)
- Predictive State Representative Models
- Time Varying Models
- StateFul Neural Networks Models (RNN ?)
Context Sensitive Models
Time Sensitive Models

- ARIMA
- NN
- RNNs
- RNNs with LSTM (Vanilla LSTM)
- RNN Bidirectional LSTM
- RNN ESN LSTM
ARIMA

Pros
- Dependent on relationship with past observations
- Uses differences of Raw Observations

Cons
- Lag or the size of the Moving Average window be known
- The number of times, the Raw Observations, are differenced
- The number of Raw Observations
Neural Networks

- **Pros**
  - Works slightly better when it comes to Classification Problems
  - Can be deployed to predict almost any thing

- **Cons**
  - No insights for the reason why it did or did not work
  - Treats samples as just observations
  - Has no mechanism to predict for Time series data
Context Sensitive Time Variant Models
RNN

- **Pros**
  - Works better when data has time variations
  - Memorizes sequences well
  - Has dynamic state with context-dependent computation (Vs HMM)

- **Cons**
  - Are not necessarily Inductive
  - Problem of Vanishing and Exploding gradients
  - Results vary abruptly based on Models/Layers chosen
RNNs with LSTM

- **Pros**
  - Embeds integrators for memory storage in network
  - Remembers sequence to predict the outcomes

- **Cons**
  - Internal States must be selected to use memory, not abuse.
  - Works very bad when all the data is correlated
  - Poor results when times series responses are chaotic
RNN Stacked LSTMs

- **Pros**
  - Create new representations at high levels of abstractions
  - Increasing depths trade off with fewer neurons that trains faster

- **Cons**
  - Involve huge computational resources
  - Not a silver bullet
Results

![Graph showing loss over epochs for different types of LSTMs: Simple LSTMs, Variational LSTMs, Stacked LSTMs.](image)
Futures and Scope

- RNN ESN LSTMs

Pros
- Work well for chaotic time series
- Reservoirs show non-linearity w.r.t inputs
- Outputs show linear regression

Cons
- Training is a challenge
Scope and Futures

- CSPs can use this Recommendation Engine to make decisions regarding Eviction Policy to improve SLAs.
- Traditional methods of modelling unable to catch up with the complexities of the system
- RNN, LSTMs, Stack LSTM, ESN provide us with huge scope to tune the model
- Models Vs Complex or Stacked Models share similar relationship as series and Fourier series
Queue Analysis

- Dispatching Discipline
  - Priority Based, FCFS
- Distribution of Arrivals
  - Poisson
- Distribution of Service Times
  - Depends on Request Size
  - Rate of Requests
  - The state of the system.
Queue Analysis

Arrivals

\( \lambda = \text{arrival rate} \)

Waiting line (queue)

Dispatching discipline

Server

Departures

\( w = \text{items waiting} \)

\( T_w = \text{waiting time} \)

\( T_s = \text{service time} \)

\( \rho = \text{utilization} \)

\( r = \text{items resident in queuing system} \)

\( T_r = \text{residence time} \)
Law’s At Play

- \( L = \lambda \ast \dot{W} \) Little’s Law

- Service Time/Response Time = 1 – Utilization
  - \( (R_T - S_T)/R_T = Utilization \)

- \( W(t + 1) = W(t) + \sum_{z=0}^{T} s(t - z - 1)e_h(t - z)^T \)

- Central Limit Theorem
Bibliography and Credits

- Reservoir Computing Approaches to Recurrent Neural Network Training
- Credits for Graphs and Data Cleaning – Rahul Tripathi
- https://drive.google.com/open?id=1l98SeI_LV4FOkY10P EfV_YLwQV-5WDgf
Q&A

- “Introduction of Numbers as Co-ordinates is an Act of Violence”
  - Hermann Weyl

- “All models are wrong some are more useful”