Predictive Caching@Scale

A scalable ML caching at the Edge

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Experience the Edge

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The Akamai Platform

Distributed caching at the Edge

A Global Platform…

- Over 240,000 servers
- In over 2,400 locations
- In over 1,600 networks
- In over 650 cities
- In 138 countries

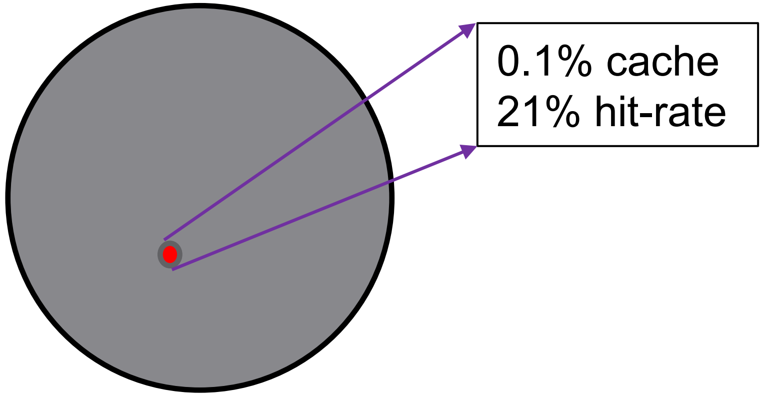
…With Enormous Scale

- 50+ trillion bits per second
- 60+ million hits per second
- 95+ Exabytes delivered per year
- 250M+ attacks defended per day

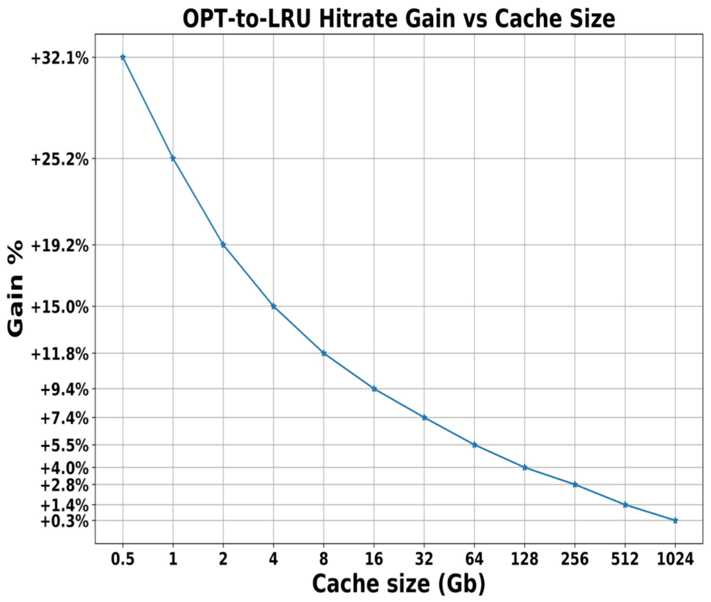
Caching Algorithms

Limitation of classical caching Algorithms

- Classical/Online caching algorithm
  - (LRU, LFU, S4LRU e.t.c.)
  - Are cheap and effective for web-traffic
  - Highly competitive in terms of cache effectiveness
  - Widely applicable and needs no meta information.



- Theoretically optimal Caching scheme, Bélády's
  - Uses future arrival time knowledge
  - Optimal only for single sized object cache
  - Can provide huge performance gains over online schemes.



- Variable object sized optimal can provide 190% mean and 133% median gains

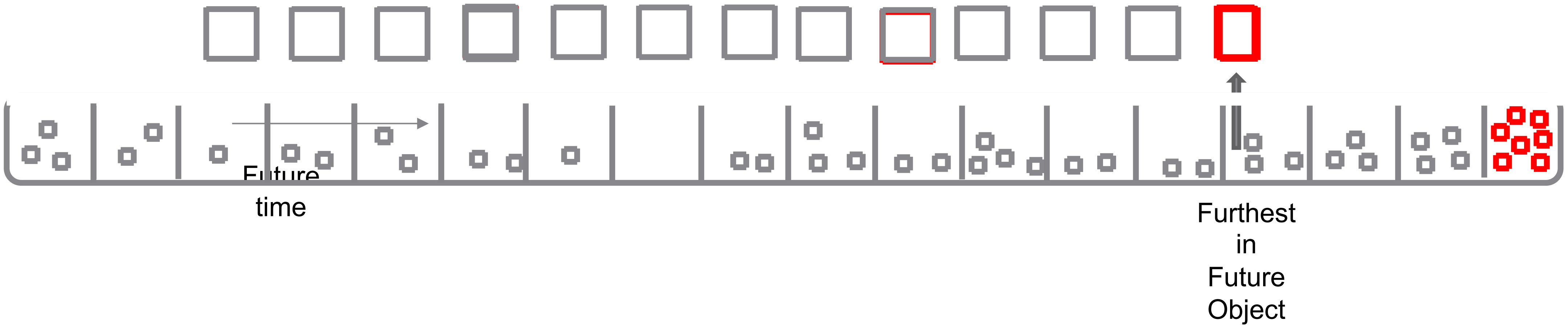
ML for Caching

How to use ML for caching

Previous methods of ML for caching
- Object Popularity prediction
- Using Reinforcement learning
- We developed a variant of **Bélády's** for our PredictiveCaching.

- Mimicking **Bélády's** we just need sequencing
- We don't have to predict actual arrival times but only quantized future arrival bins.
- Only need to predict if the object falls inside or outside of the eviction boundary.

How Bélády's OPT works **Quantized Bélády's**



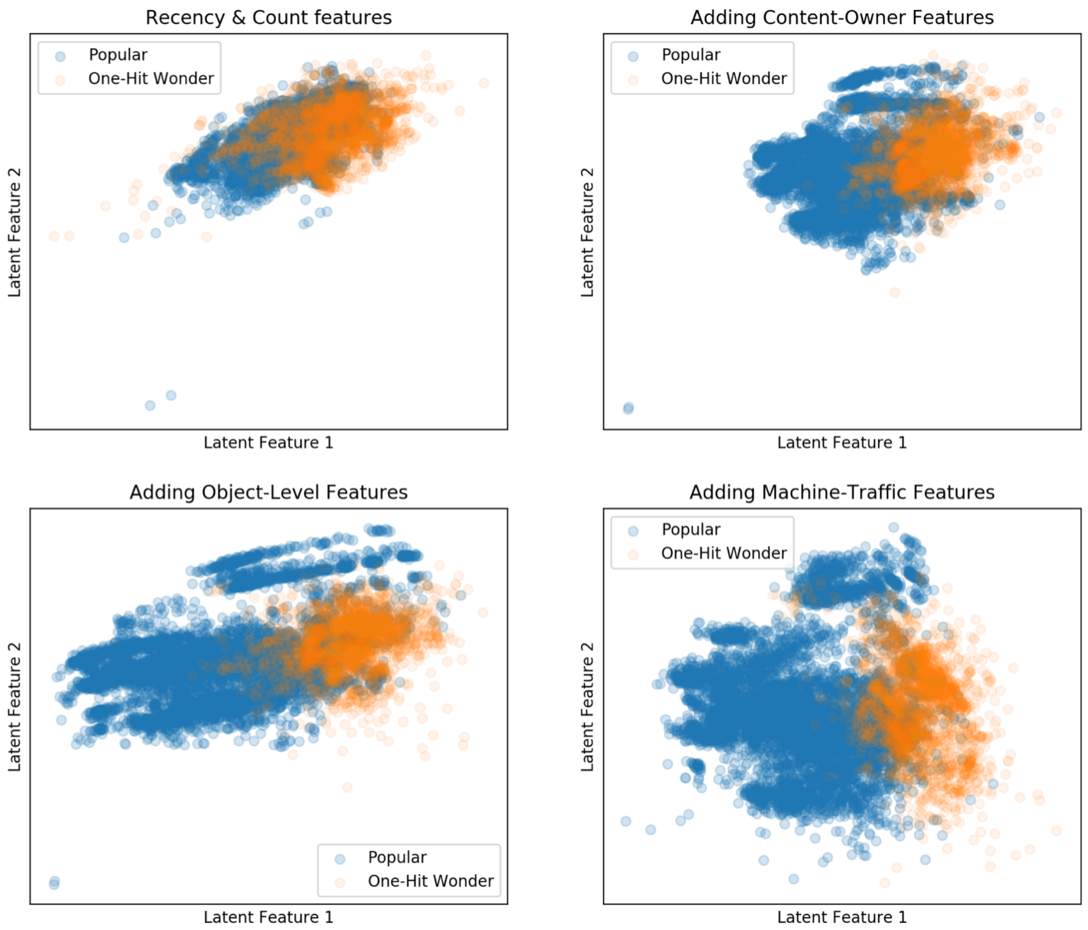
Traffic prediction

Challenges in Predicting Internet Traffic

- Multi-tenancy leads to competing traffic patterns overlapping at the Edge, making predictions challenging.

- We use several informative properties of content to differentiate these patterns:
  - Content level: Owner, size, type etc.
  - Machine level: Traffic throughput, traffic mix ratio, timeofday..
  - Network topology level: cache layer hierarchy, geo location, end-user patterns.

- Feature tuning helps to distinguish unique traffic patterns



Traffic Prediction

Simplifying the Predictions

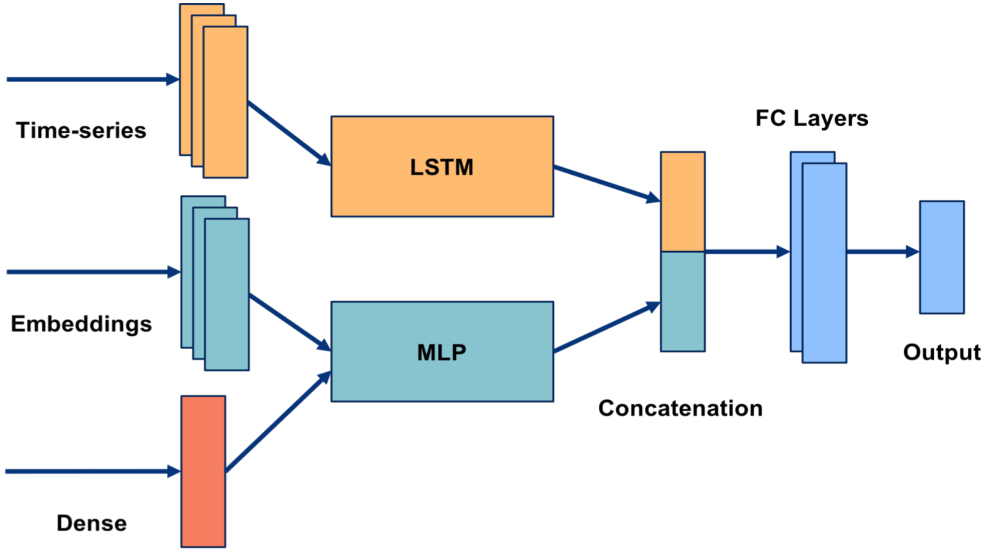
- Next arrival time Prediction → Regression problem
  - Output range [0.001 msec - 2*24*60*60 secs]: Difficult to reach optimal model parameters.
  - Difficult to relate Regression loss to downstream cache hit-rate losses.
- Approximation:
  - Regression → Ordinal Multi-class classification via quantization as sequencing is sufficient to mimic OPT.

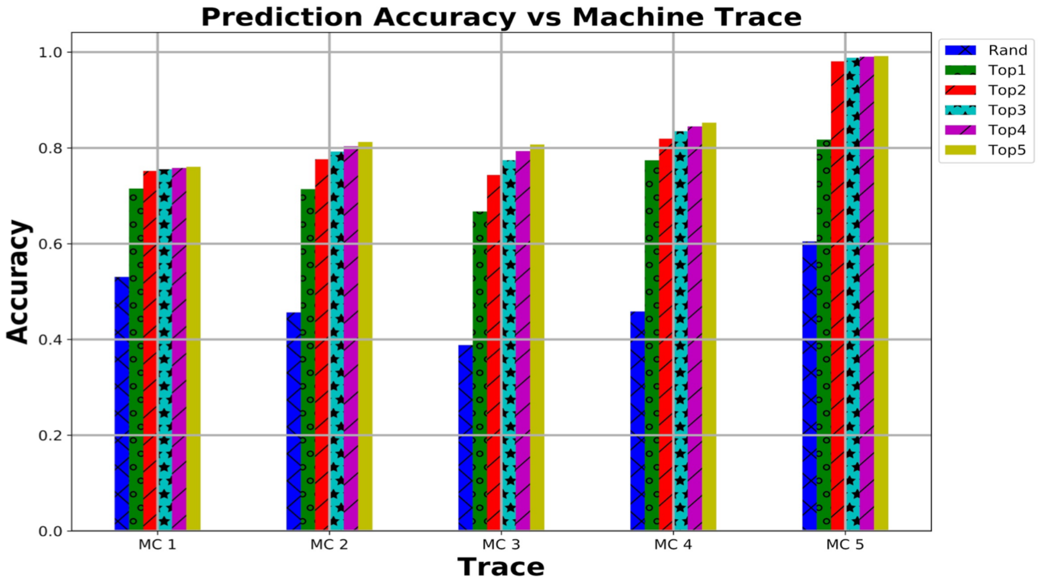
$$L(y,p) = \sum_{c=1}^{m} W_{ij} * y_i * log(p_j)$$

Where,
y: true label
p: predicted probability
m: output classes
i: true class
j: predicted class
W_{ij}: weight of loss for the pair (i,j)

(Order enforcing loss)
|i-j| ↑ ⇒ W_ij ↑

  - Easier to relate mis-classification rate to cache hit-rate performance.
  - Can leverage TopK predictions in caching policy.

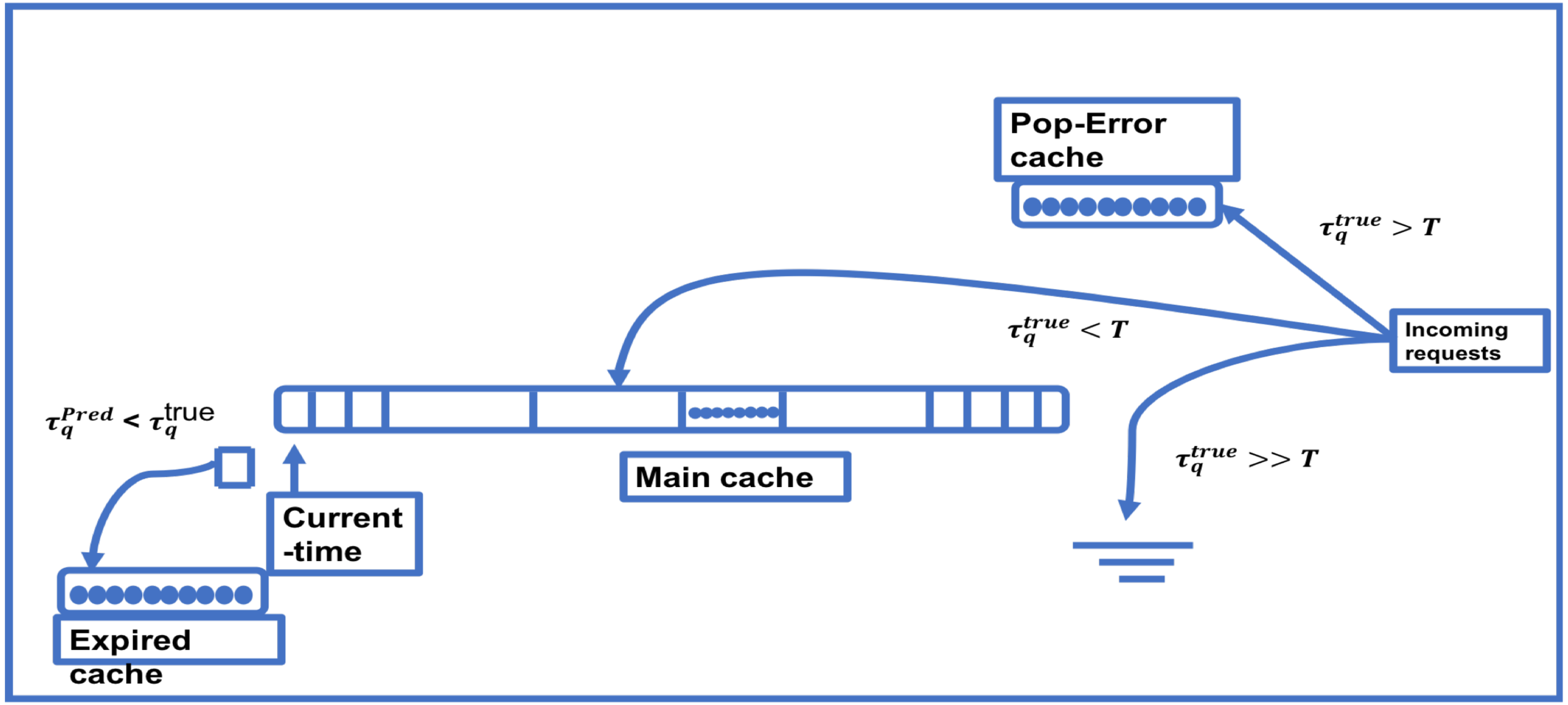




Prediction-Error Segmented Cache (PeSC)

A caching to recover from Prediction errors

- Requirements:
  - Outperform LRU-based policy in an online situation.
  - Robust enough to use unreliable predictions with varying confidence.
- Strategy:
  - Isolate the prediction errors into separate segments of controlled size.
  - Use next most likely predictions from topK predictions to make eviction decisions.



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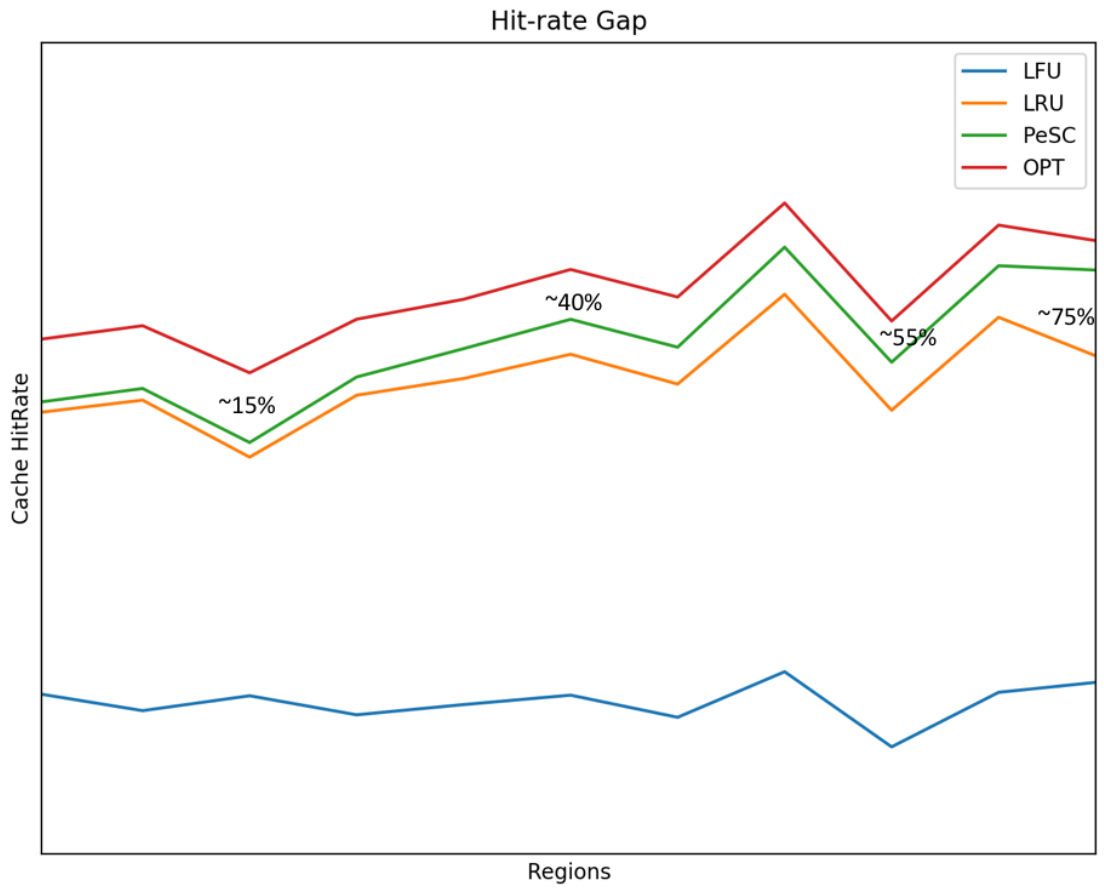
Performance of PeSC

Predictive Caching closing the gap on LRU

- We compare the performance of PeSC we trace the cache hit gap between OPT, LRU and LFU. And the of % cache hit gap recovered by PeSC.
- We turn on the PeSC on several regions and plot the Cache hitrate for 4 schemes.
- 10%-60% of the gap recovered by PeSC depending on the traffic/Region.



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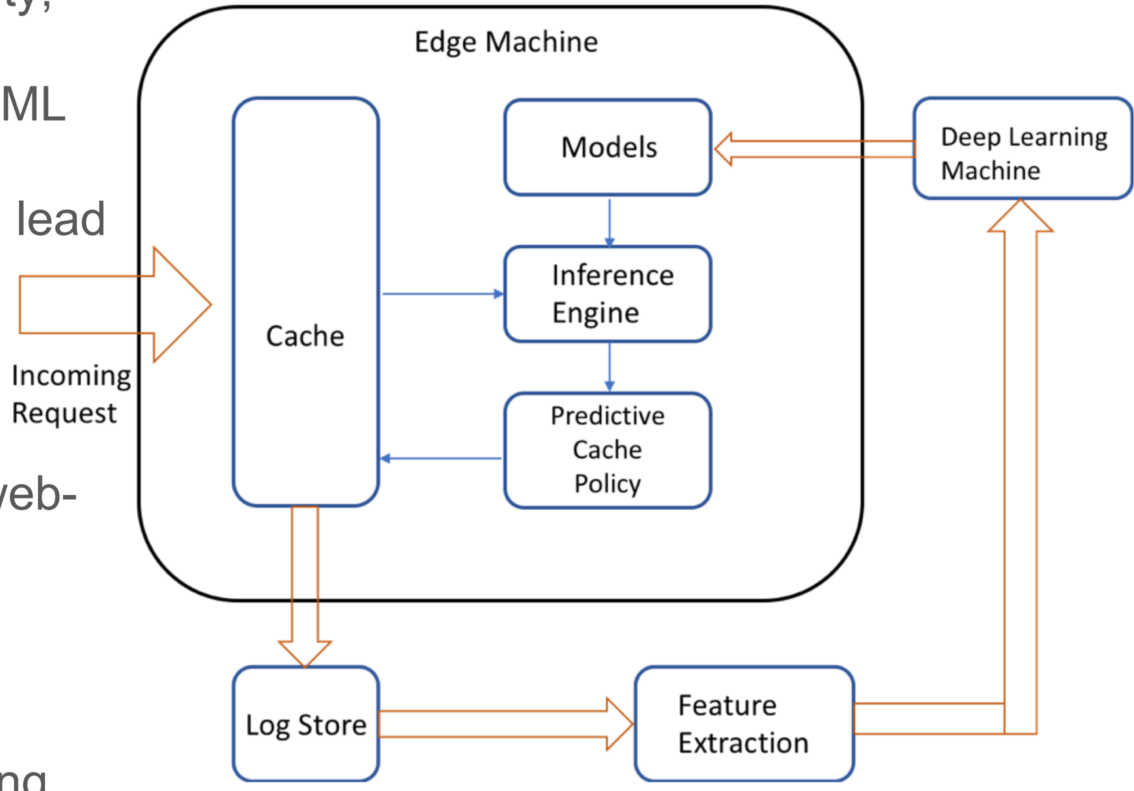
PeSC System Design – Data Pipeline

Building a low overhead data pipeline at the Edge

- Challenges:
  - Proxy servers were not designed to connect cacheability, load-balancing and user-attributes for ML training.
  - Edge machines don't have spare capacity to generate ML training sets.
  - Multi-tenancy leads to missing/corrupt/default data can lead to silent failures in the ML pipeline.

- Solutions:
  - Re-write application modules to connect storage and web-application tiers.
  - Infer and log load-balancing attributes.
  - Feature extraction and transformation modules were changed to work under constrained resources.
  - Deploy data validator: Range check on features, tracking changing distribution of features, monitoring default value imputations, etc.



PeSC System Design – Automation and Training

Building a robust model for the Edge

- Challenges:
  - Training robust models for the multi-tenant Edge workload.
  - Model should be adaptable for changing traffic and concept shift.
  - On-the-fly model hyperparameter selection, capturing dataset silent failures, etc.
  - The large volume of training data and the frequence of re-training the model.
- Solutions:
  - Selecting less sensitive hyperparameters/model design, lr-scheduling, cv-selection over multiple epochs.
  - Continuous learning via partial retraining models on new available data.
  - Targeting most critical PoPs in the network.
  - Pre-training models and loading weights from older models.
  - Down-sampling datasets to reduce the size.
  - Multiplexing GPU machine to handle multiple edge servers.
  - Exploring FP16 training for faster training.

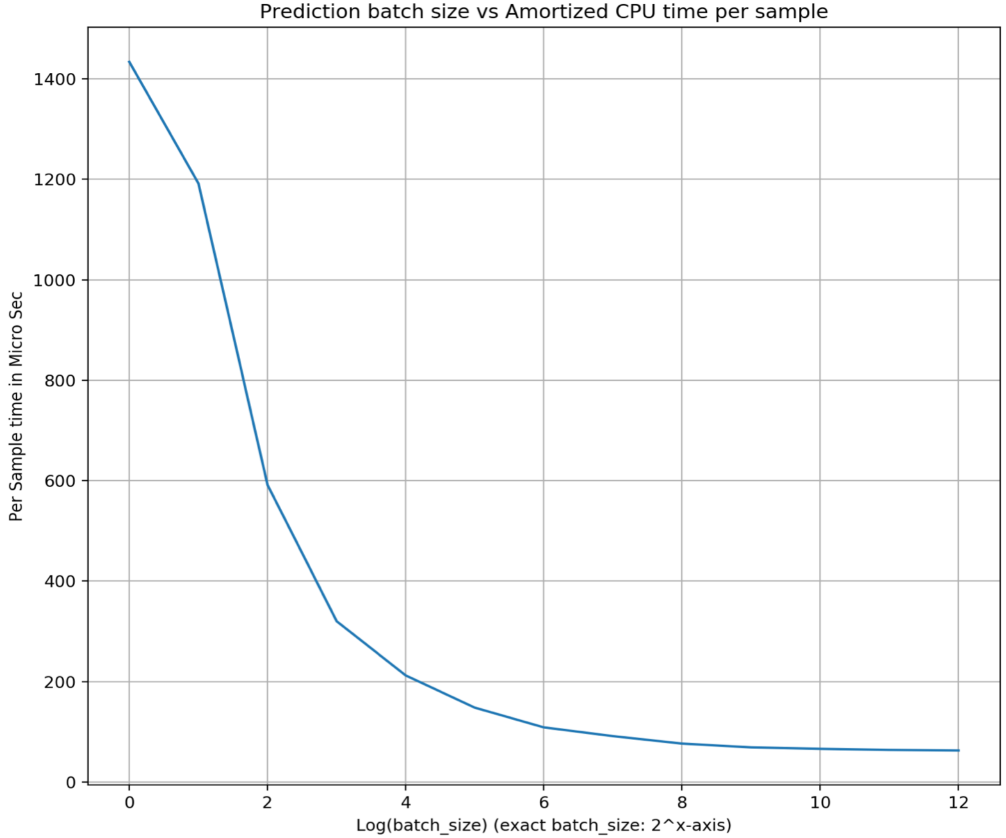
- > 2mil req/hour per Edge
- Retraining ever few hours with 3-7 day of data.

PeSC System Design – Inference

A low-overhead inference at the Edge

- Challenges:
  - Cost of Inference is extremely critical on performance sensitive Edge servers.
  - Inference cost should be comparable to sys-call cost.
  - No hardware accelerators are available at the Edge. Traditional x86 machines.
  - Missing features can lead to silent inference failures.
- Solutions:
  - Lazy-Batched Inference: Decouple content serving and eviction policy logic.
  - Do lazy inference on a batch of requests rather then for each request which reduces amortized cost.
  - Re-writing server application logic to collect and scale features at inference time, which use to be only available at the time of logging.
  - Inference cost of batch size 256 is ~ 100 micro sec.

Inference time per request



Conclusions and Future work

- Demonstrates there is a lot of value in re-thinking limitations of classical algorithms
- We can safely build and use ML, deep inside a high performing web-server or similar real-time applications
- Future work:
    - Building a more general model that works across traffic patterns
    - Reduce the cost of training
    - Building predictive caching for variable object sizes

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