CS 744: BAGPIPE

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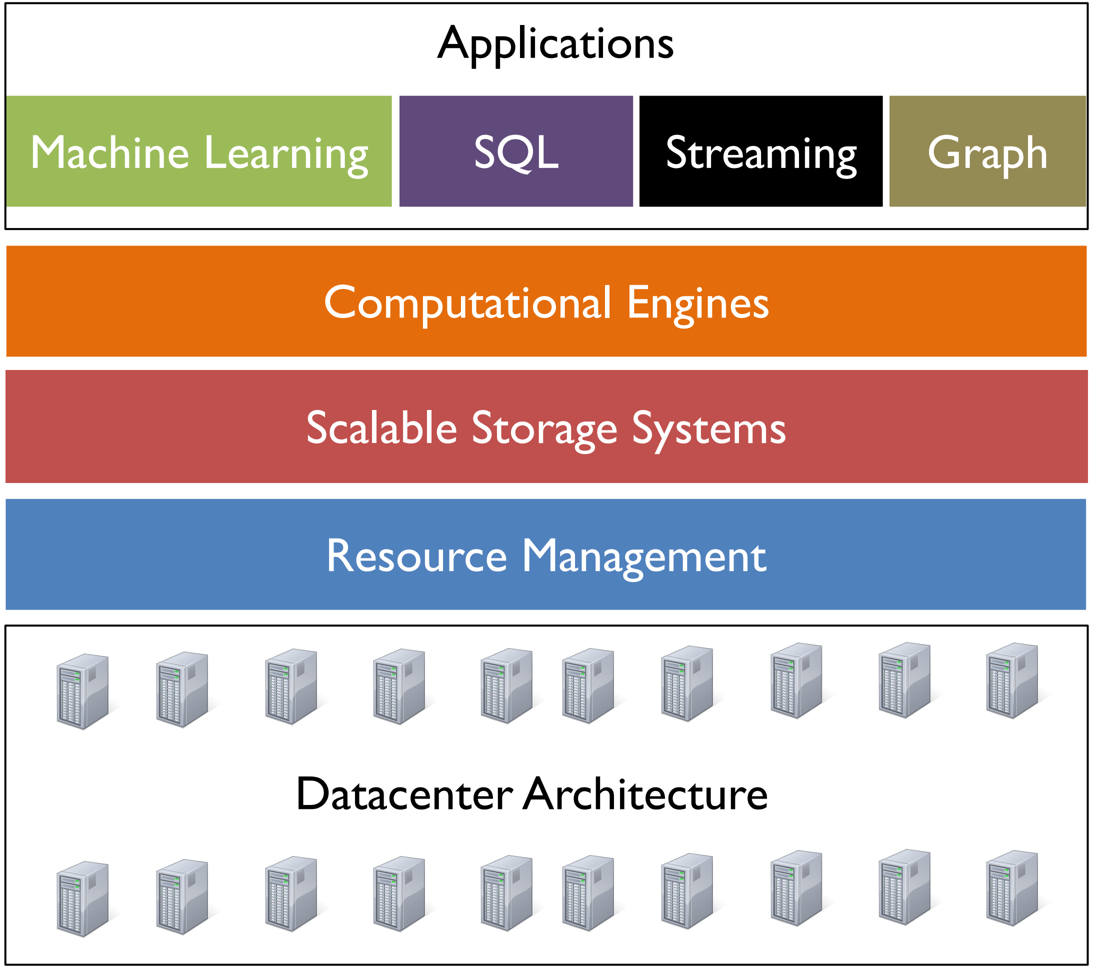
Spring 2024

ADMINISTRIVIA

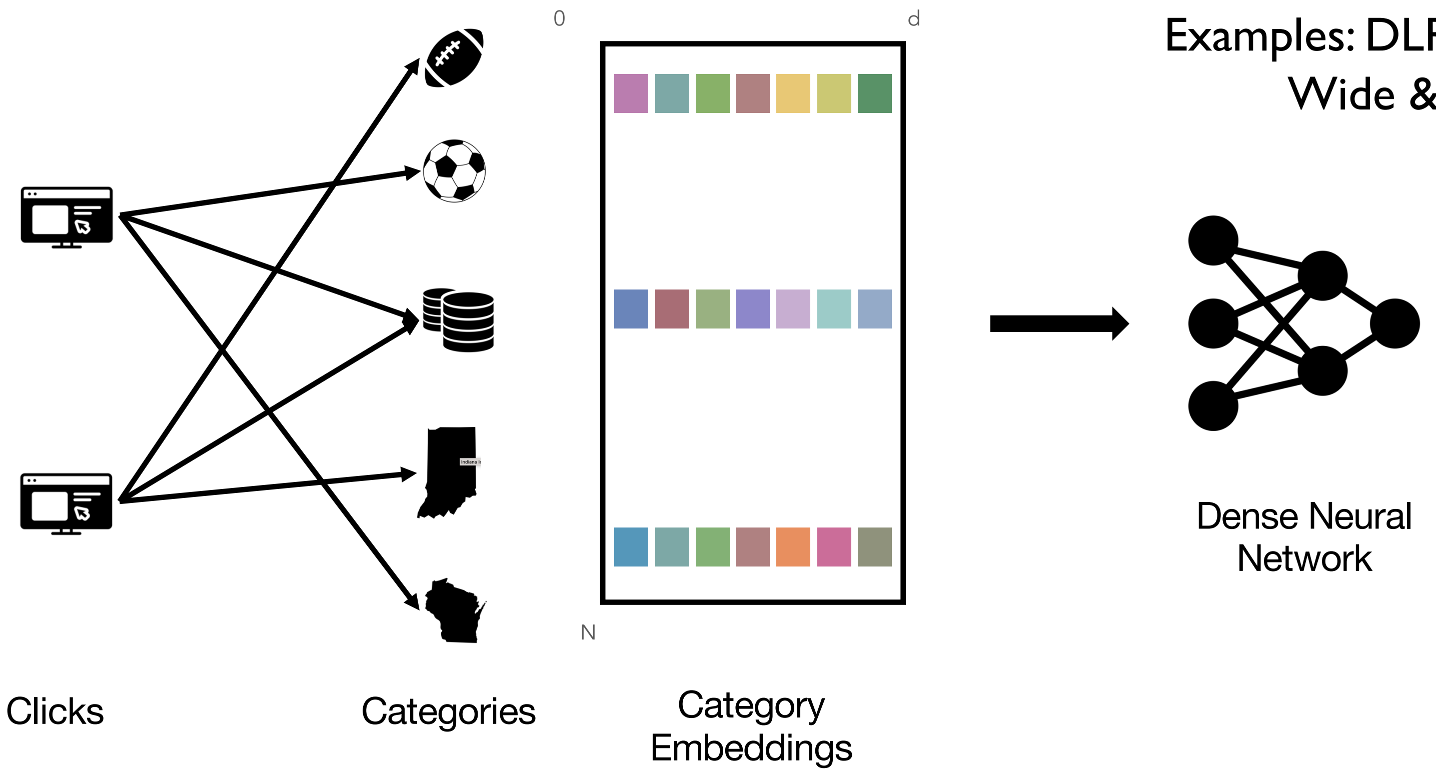
- Midterm grades on Gradescope!
    - Submit regrade requests through Gradescope

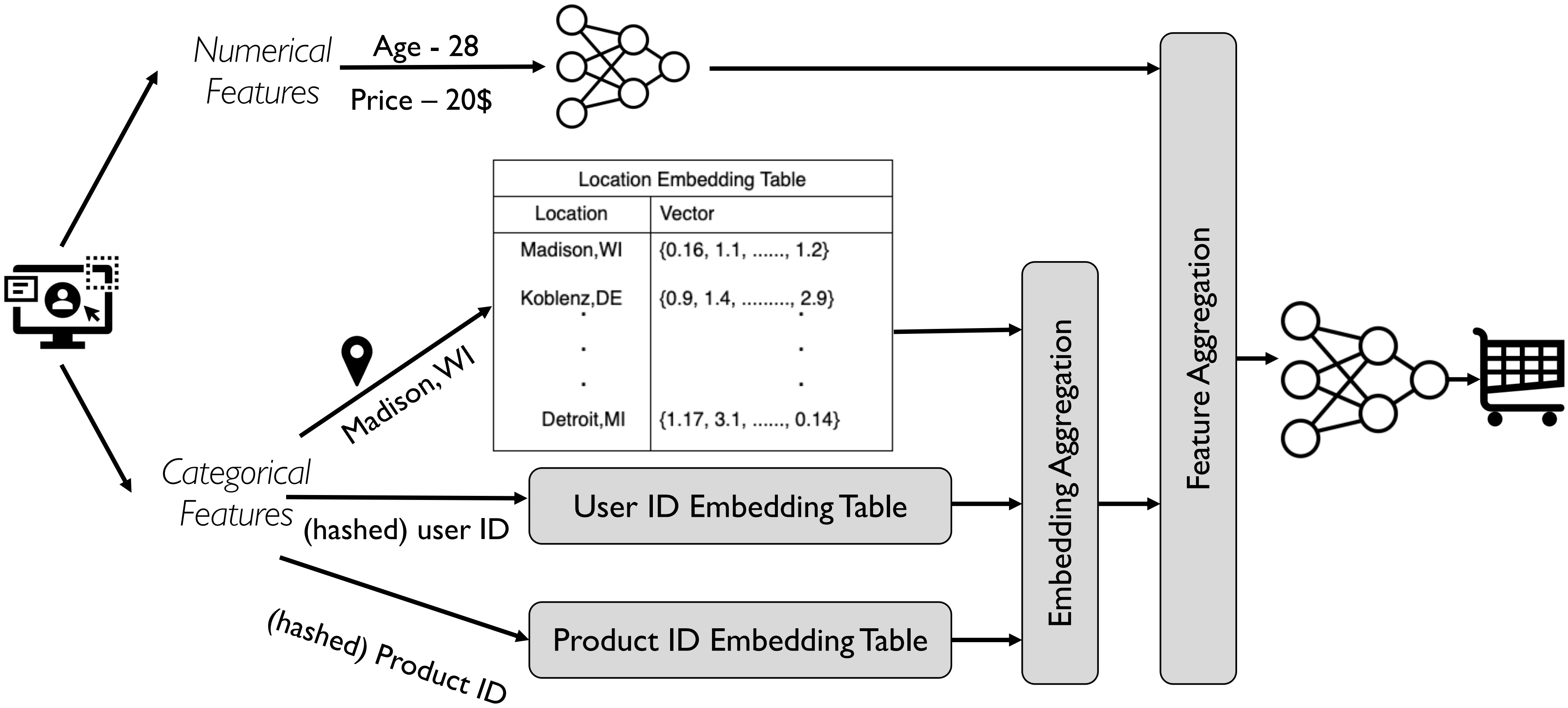
- Course Project: Check in by April 16th


Applications
Machine Learning
SQL
Streaming
Graph
Computational Engines
Scalable Storage Systems
Resource Management
Datacenter Architecture

RECOMMENDATION MODELS

Examples: DLRM, DeepFM, Wide & Deep




Numerical Features
Age - 28
Price – 20$
Location Embedding Table
Location
Vector
Madison,WI
{0.16, 1.1, ..., 1.2}
Koblenz,DE
{0.9, 1.4, ..., 2.9}
Detroit,MI
{1.17, 3.1, ..., 0.14}
Madison,WI
Categorical Features
(hashed) user ID
User ID Embedding Table
(hashed) Product ID
Product ID Embedding Table
Embedding Aggregation
Feature Aggregation

EMBEDDING TABLES

Convert categorical features to numerical features

Example: Geographic Location to a vector

Extremely memory intensive, could be up to TBs

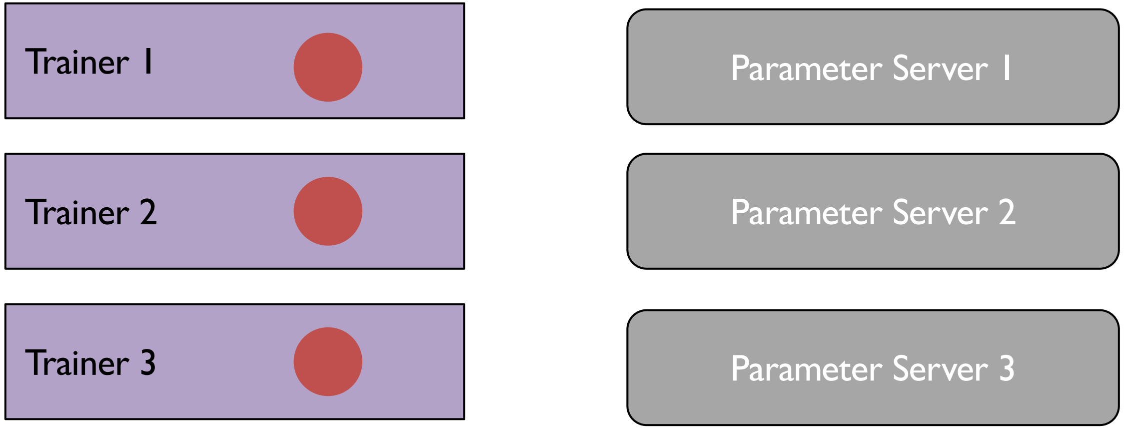
Have sparse access pattern

Geographical Location Embedding Table

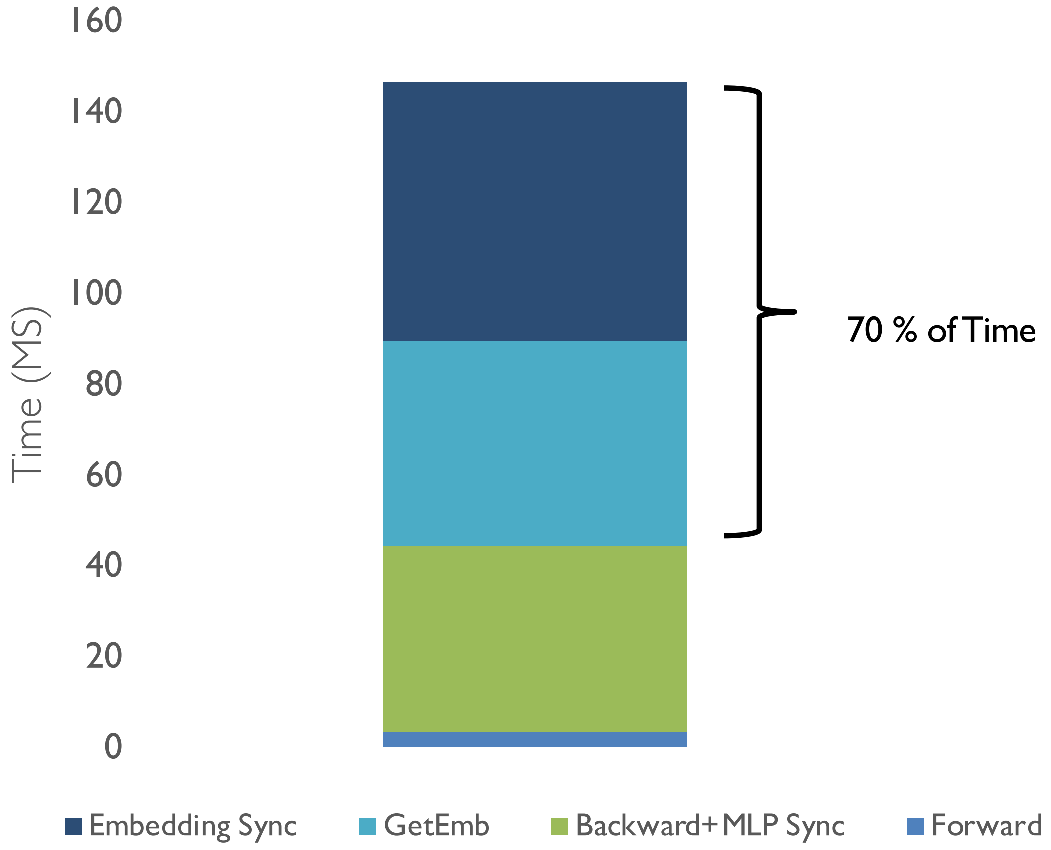
UserID Embedding Table

Product ID Embedding Table

DISTRIBUTED TRAINING ITERATION



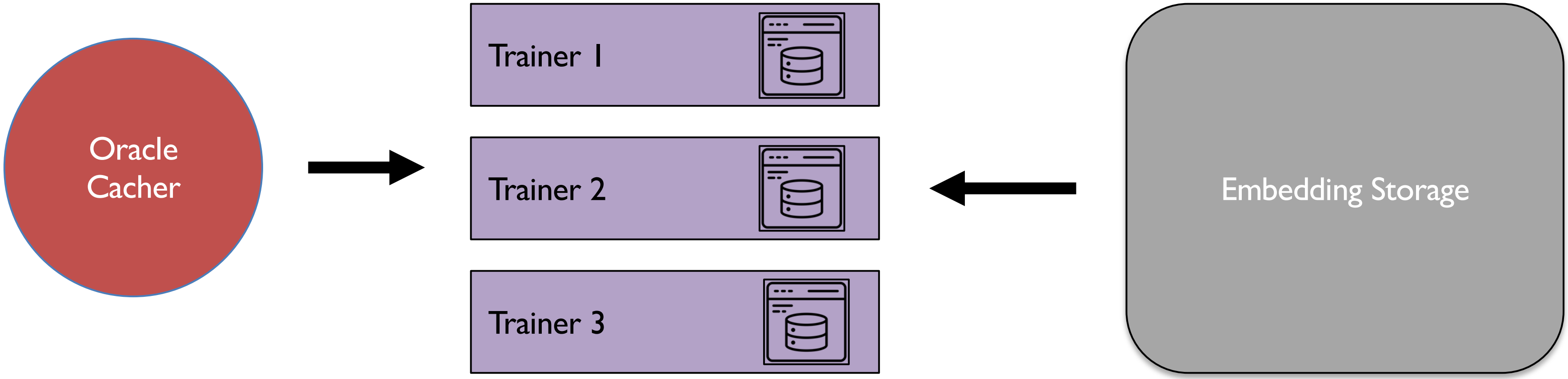
EMBEDDING ACCESS OVERHEADS



Setup:

- DLRM model
- *8 trainers (p3.2xlarge* EC2 instances 1 V100 each node).
- Batch 2048 per machine.
- Criteo Terabyte Dataset

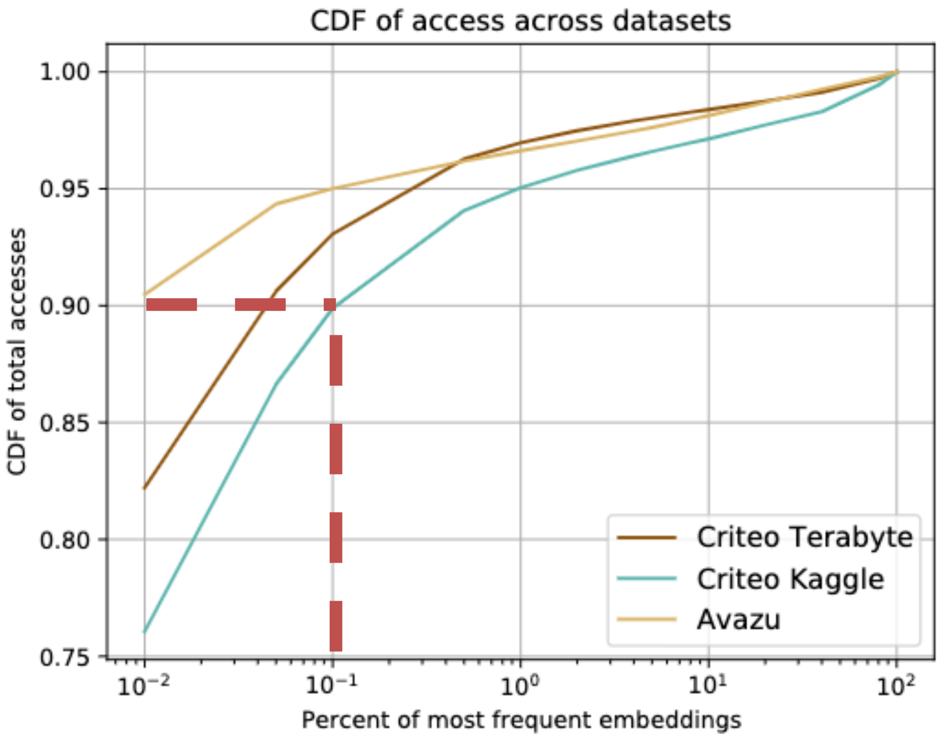
BAGPIPE DESIGN



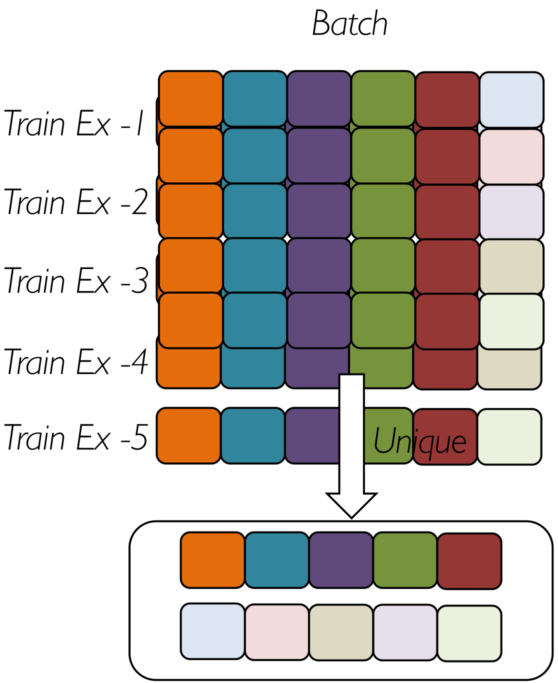
Lookahead; determine what to prefetch, cache

Prefetch embeddings and store in local cache

EMBEDDING ACCESS PATTERNS



LONG TAIL ACCESSES



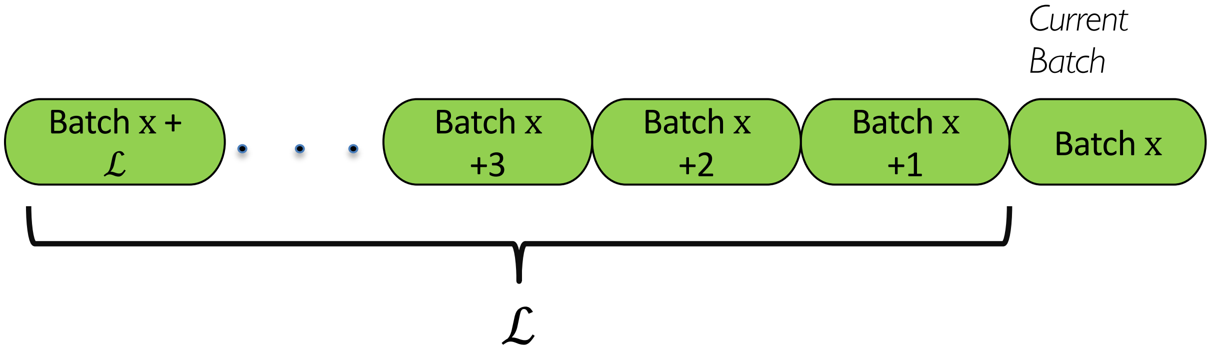
Models are trained with a batch of examples.

- *For a batch only fetch unique embeddings*

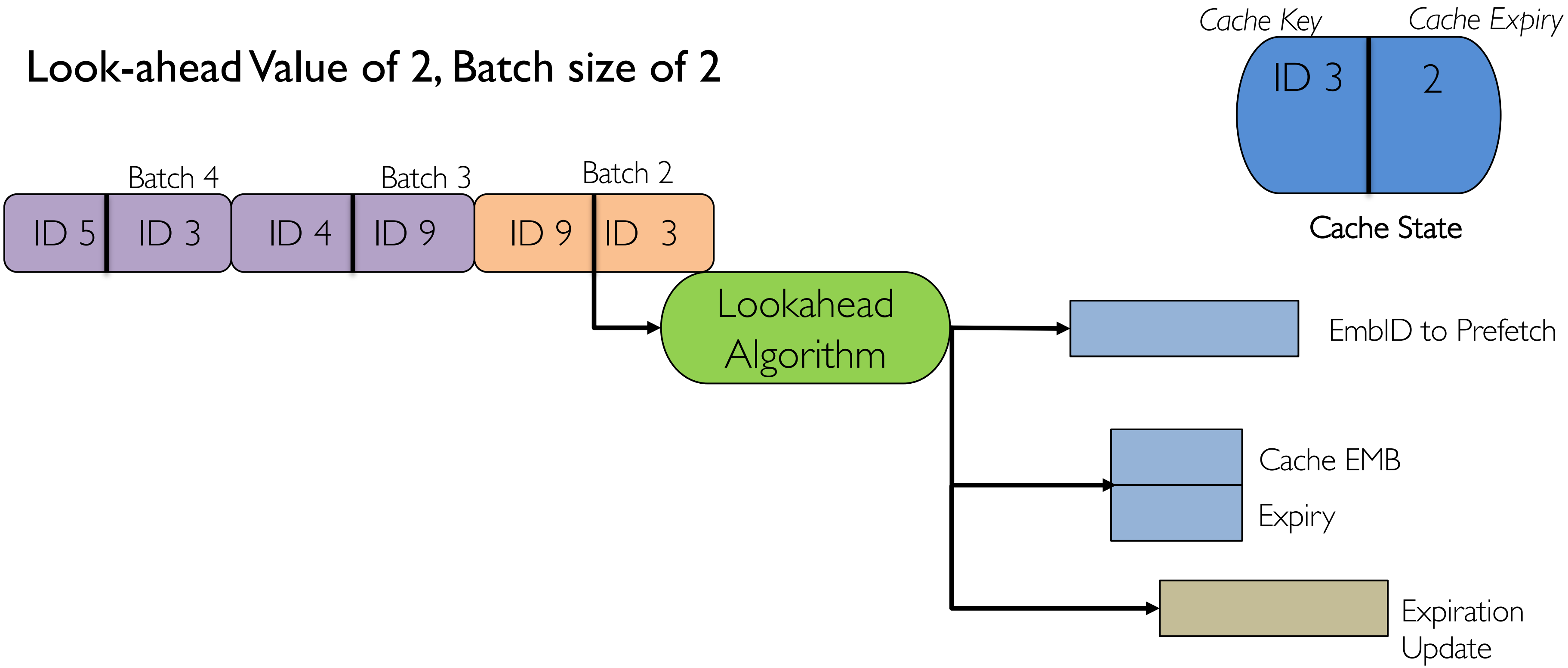
- *Since hot embeddings are replicated, unique embeddings are comprised of long-tail accesses.*

LOOKAHEAD ALGORITHM

Look at "$\mathcal{L}$" next batches ahead of current batch to extract access pattern of embeddings by future batches



Look-ahead Value of 2, Batch size of 2



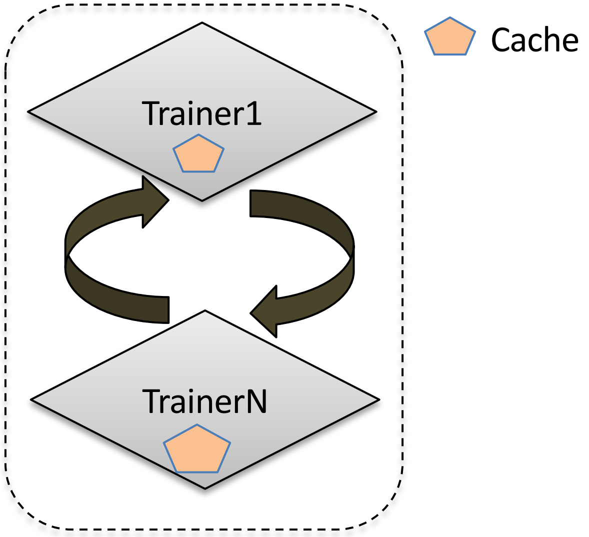
LOOKAHEAD GUARANTEES

An embedding used by batch x, will either be available in cache, or no preceding batch in range [x- $\mathcal{L}$, x) has accessed it.

Consequently, we can prefetch embeddings used by batch x, once embeddings for batch x- $\mathcal{L}$ have been updated

CACHE SYNCHRONIZATION

At the end of each iteration, each trainer synchronizes caches



SUMMARY

Recommendation models: Embeddings access overheads

BagPipe: Efficient distributed training

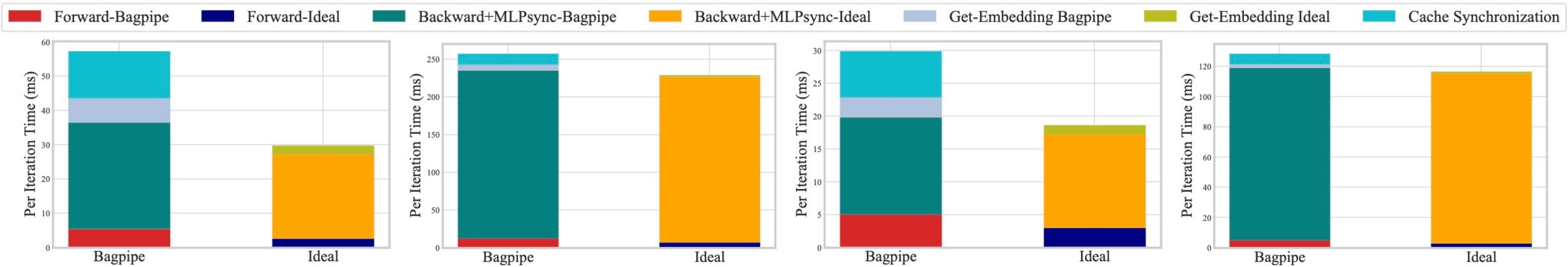
Lookahead to pre-fetch and cache embeddings

Cache synchronization across trainers

DISCUSSION

https://forms.gle/xfTAHiQ5bNENZk7m9

Consider a recommendation model trained on a graph where we use 2-hop neighbors. What are some challenges in using BagPipe-style ideas for such a workload?



(a) DLRM: p3.2xlarge **(b)** DeepFM: p3.2xlarge **(c)** DLRM: g5.8xlarge **(d)** DeepFM: g5.8xlarge

NEXT STEPS

Next class: Serverless computing

Project check-ins next week