Good morning!

CS 744: BAGPIPE

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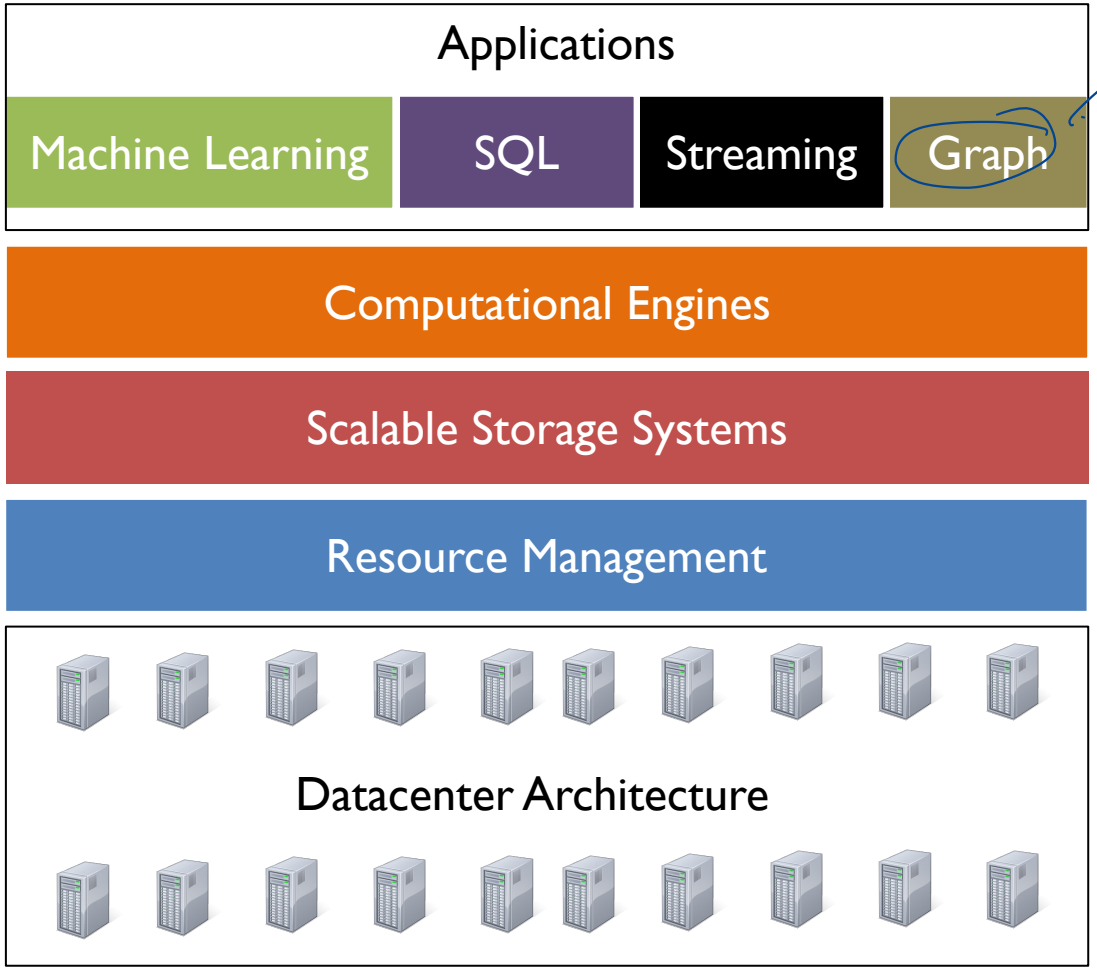
Spring 2024

ADMINISTRIVIA

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

~ 21.2 average

- Course Project: Check in by April 16th



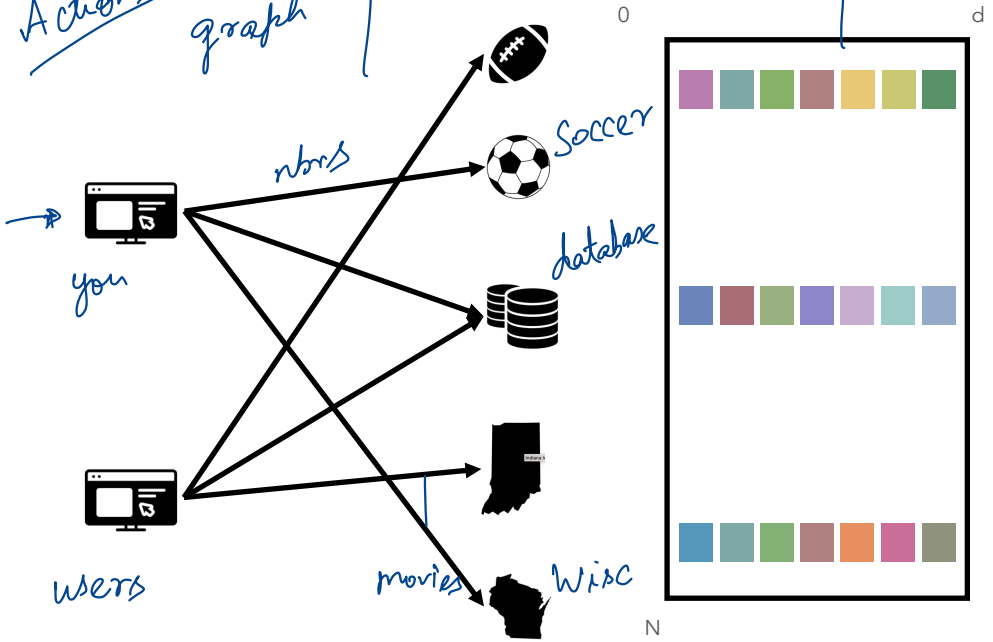
Powergraph
↳ PageRank
↳ Single mc
Distributed
↳ ML on graphs
↳ Single GPU
Marius

ML × Distributed

RECOMMENDATION MODELS = DLRM

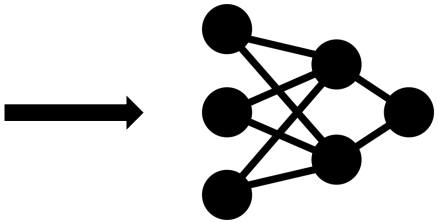
Bipartite graph
large num of nbrs
Sparse / Structured

Actions graph → Bipartite graph → embeddings



Clicks | Categories | Category Embeddings

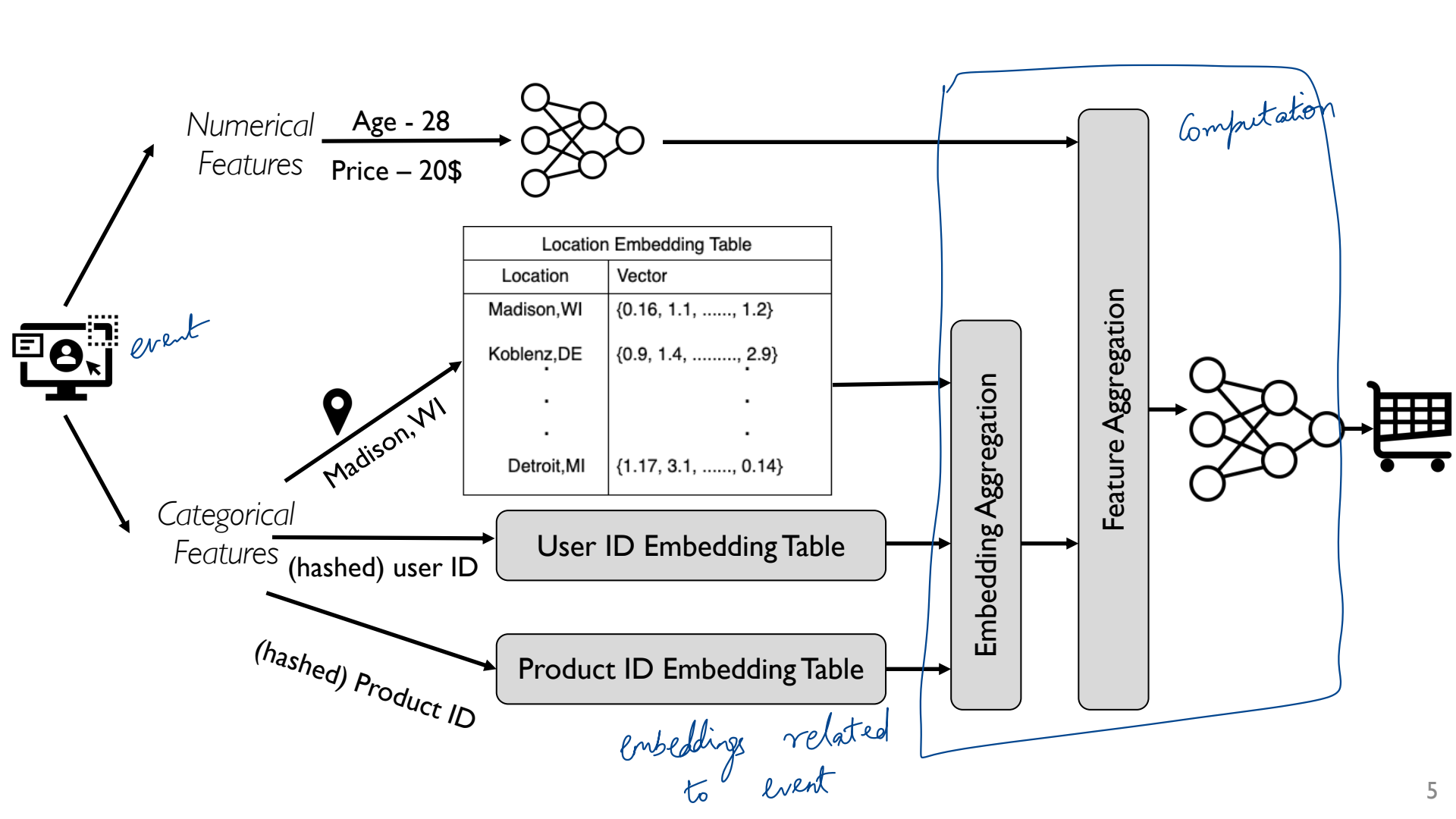
Examples: DLRM, DeepFM, Wide & Deep



Dense Neural Network

Arch
→ layers
→ kind of layers

events → batch of event . For every event
↳ Fetch Nbrs
→ Fwd / Bwd

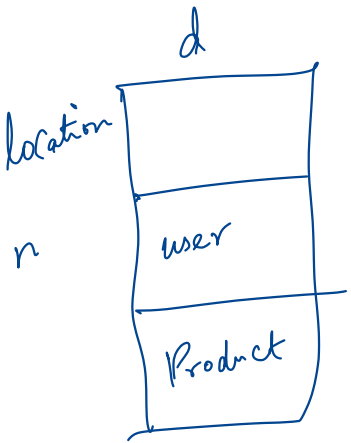

Numerical Features
Age - 28
Price – 20$
Location Embedding Table
Location
Vector
Madison,WI
{0.16, 1.1, ..., 1.2}
Koblenz,DE
{0.9, 1.4, ..., 2.9}
Detroit,MI
{1.17, 3.1, ..., 0.14}
event
Madison, WI
Categorical Features
(hashed) user ID
(hashed) Product ID
User ID Embedding Table
Product ID Embedding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

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

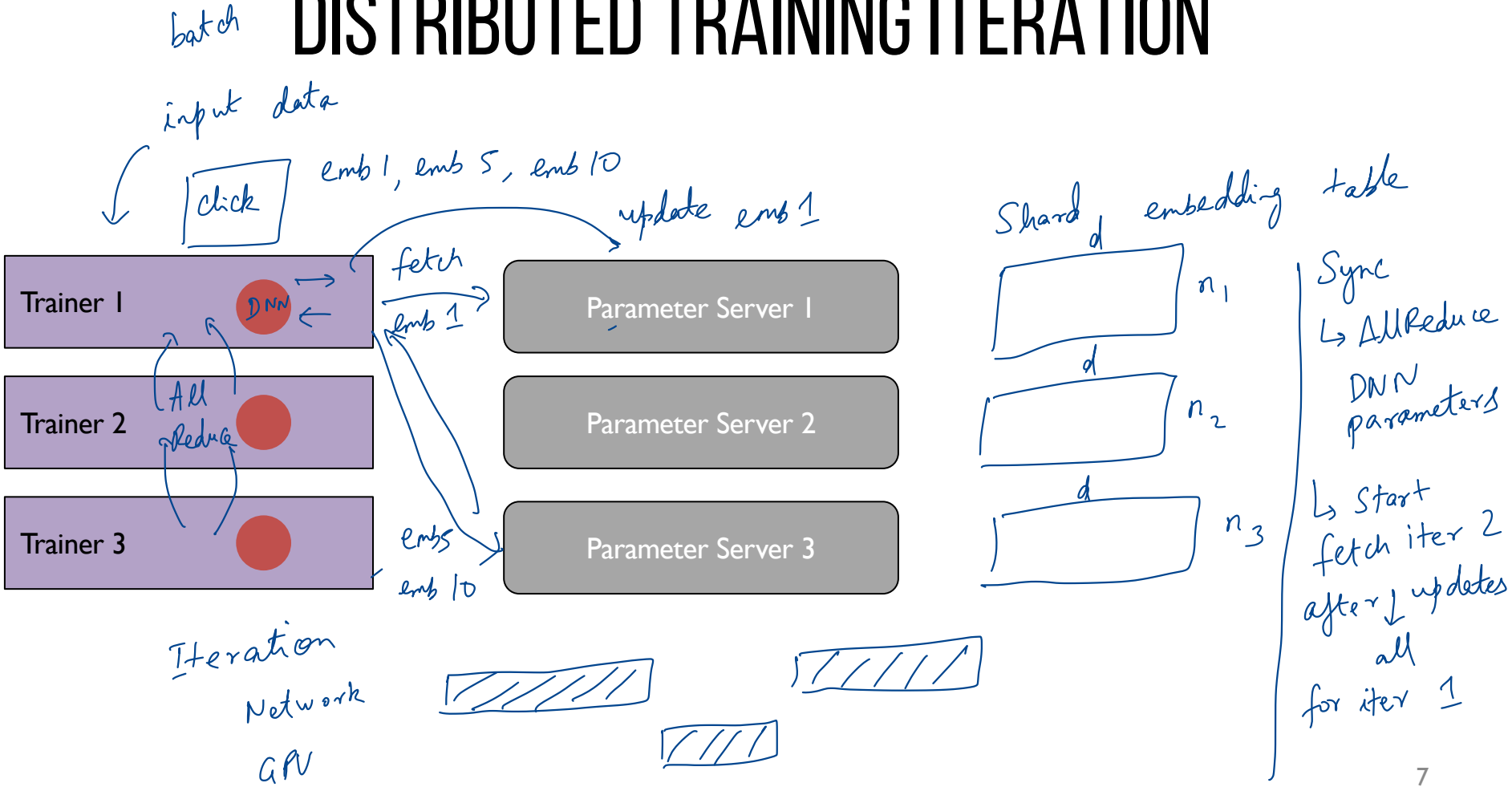


Geographical Location Embedding Table

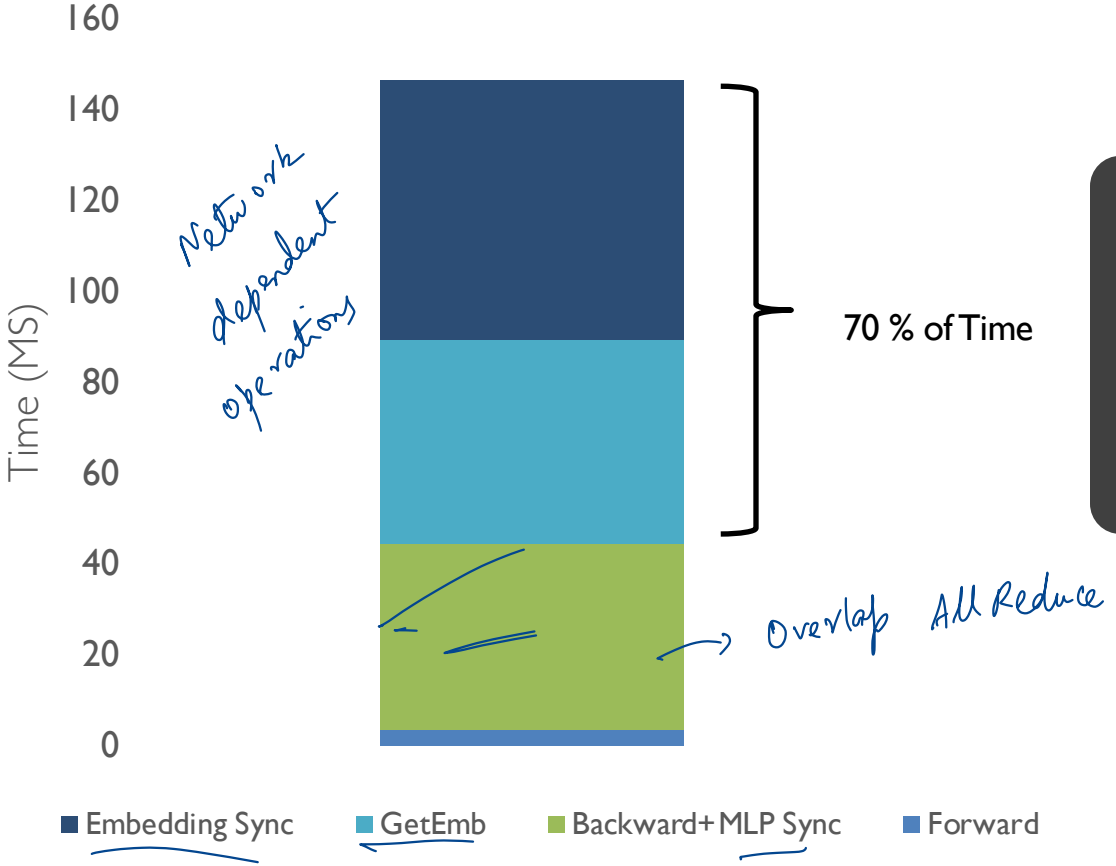
UserID Embedding Table

Product ID Embedding Table

DISTRIBUTED TRAINING ITERATION



EMBEDDING ACCESS OVERHEADS



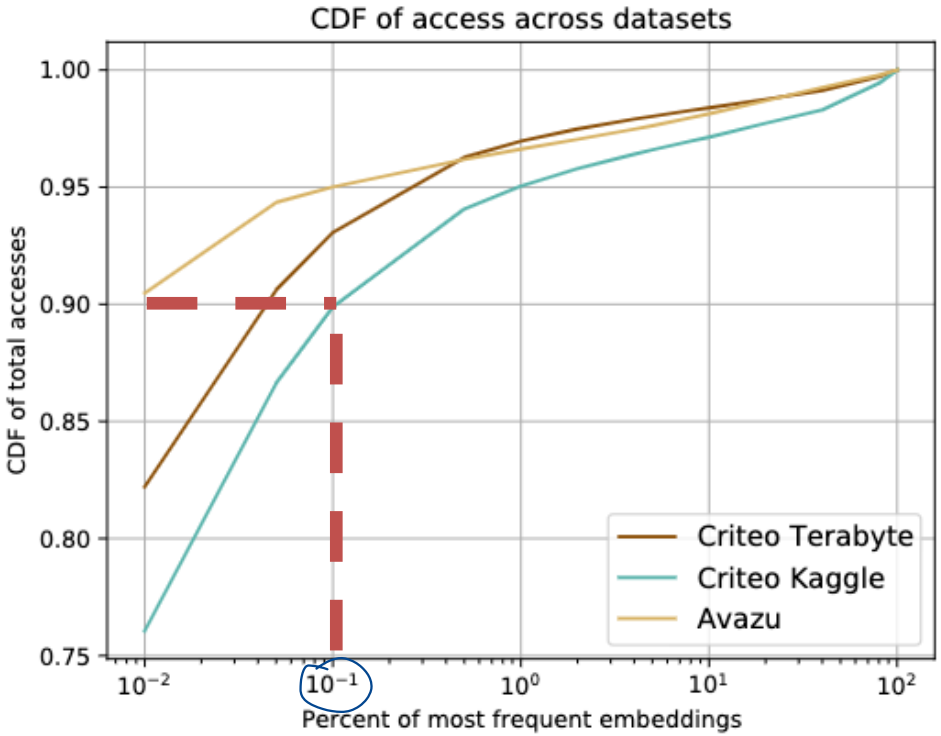
Setup:

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

BAGPIPE DESIGN

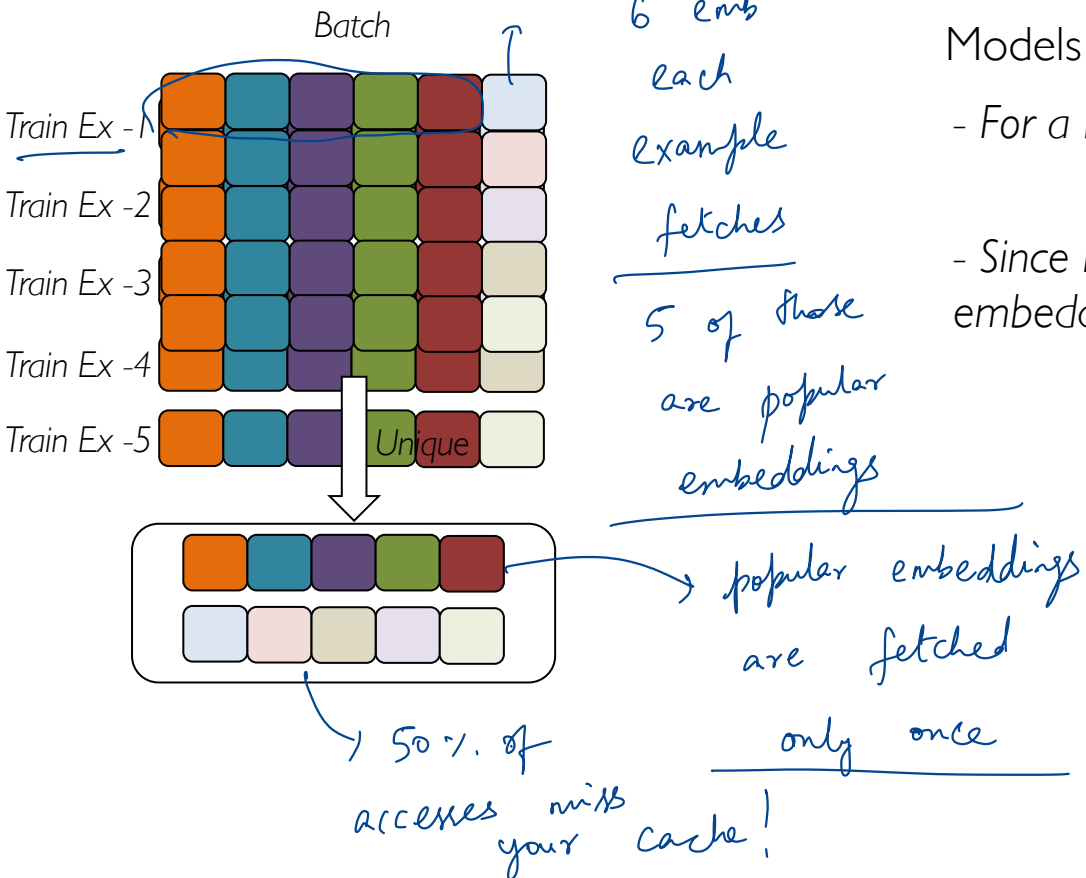
EMBEDDING ACCESS PATTERNS

Power-law in terms of emb. popularity



0.1% of embeddings account for 90% of access

LONG TAIL ACCESSES



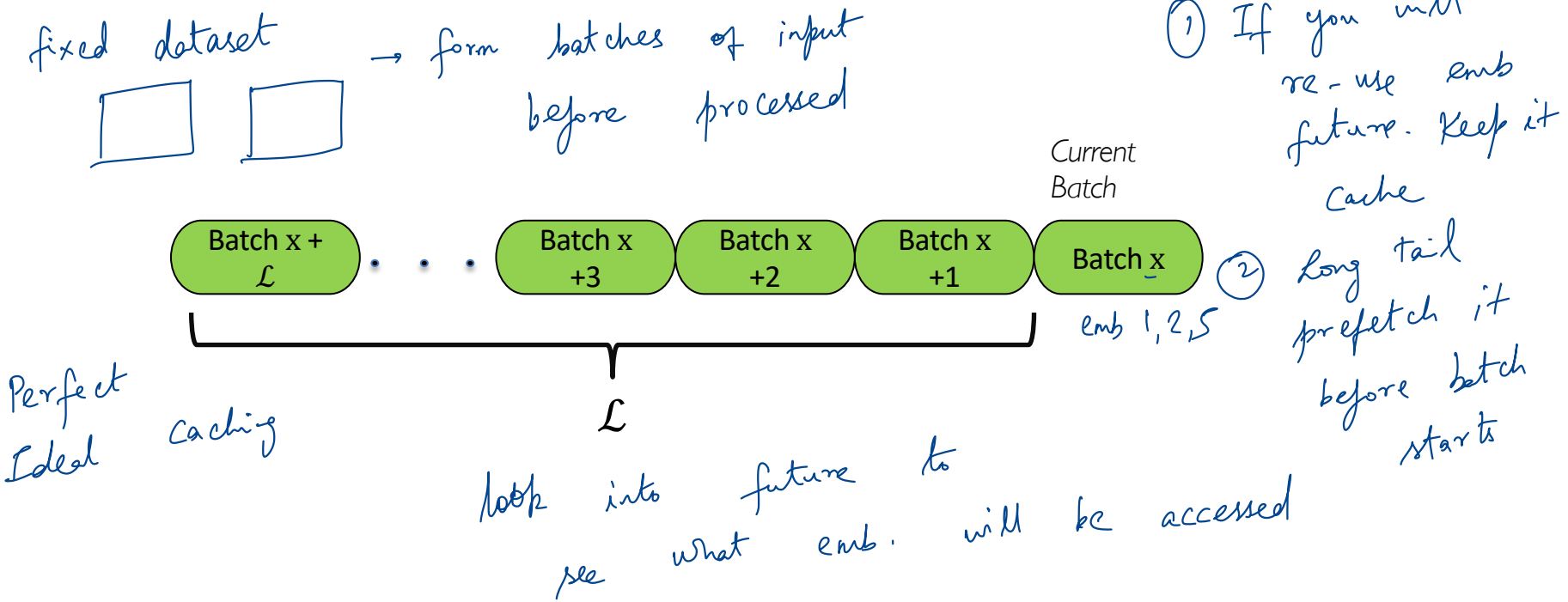
Models are trained with a batch of examples.

- *For a batch only fetch unique embeddings*

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

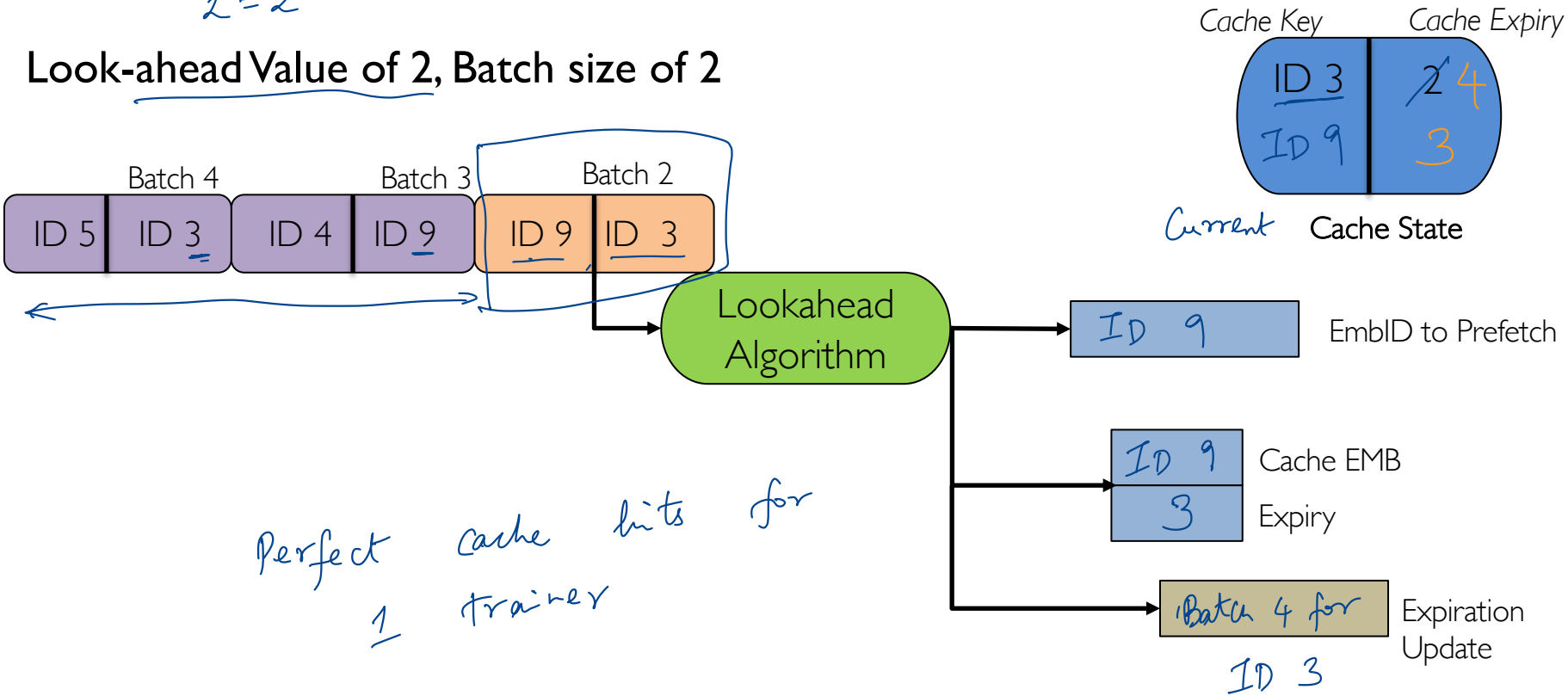
LOOKAHEAD ALGORITHM

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



$\mathcal{L} = 2$

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.

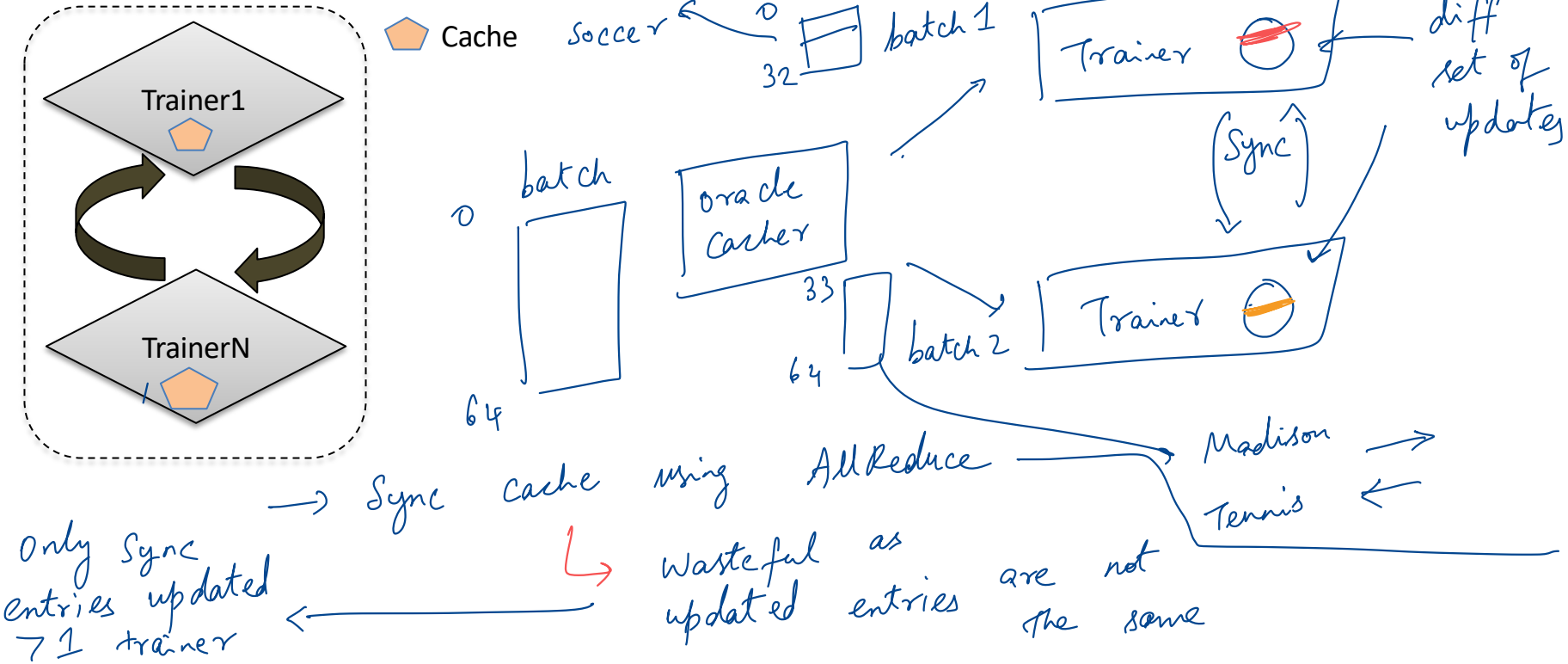
Consequently, we can prefetch embeddings used by batch x, once embeddings for batch $x-\mathcal{L}$ have been updated

When can I prefetch a embedding 10, $\mathcal{L} = 5$

- batch 10. I wait till batch 5 is flushed and after that its safe to prefetch

CACHE SYNCHRONIZATION

At the end of each iteration, each trainer synchronizes caches



SUMMARY

Recommendation models: Embeddings access overheads

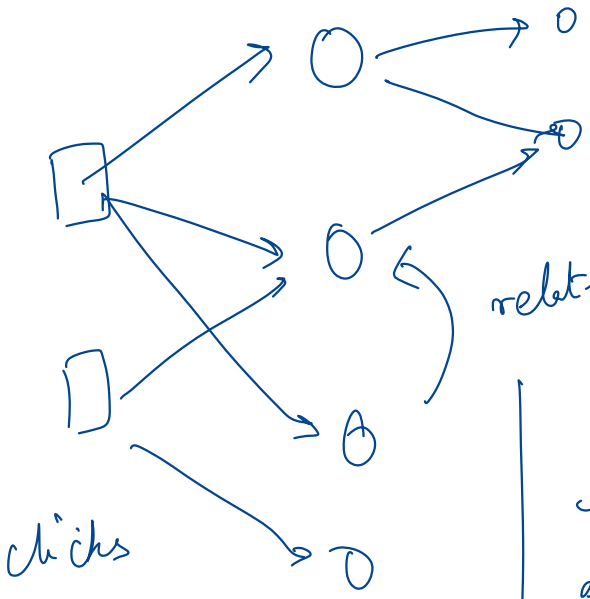
BagPipe: Efficient distributed training

- 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?



Skewed degrees

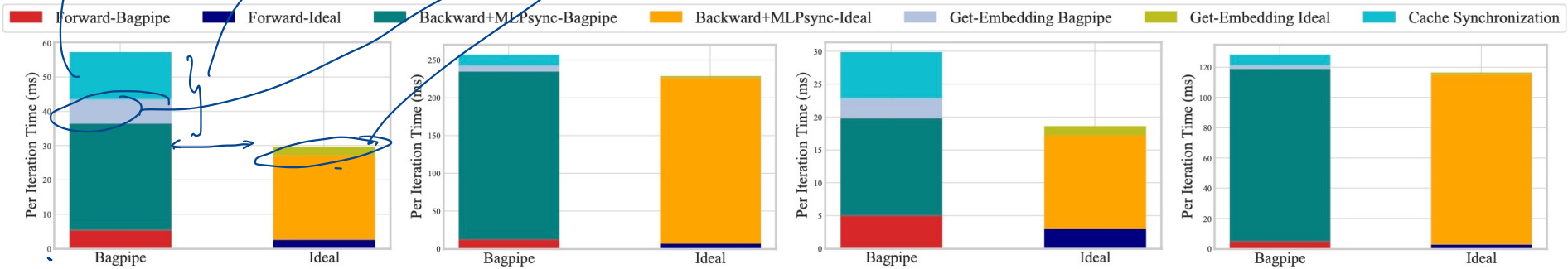
Lookahead is expensive

↳ k nbrs

↳ k^2 2-hop nbrs

↳ finite cache size
lower hit rate

→ Cache Sync ↑



(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