Carnegie Mellon University
Software Engineering Institute

RESEARCH
REVIEW
2020

Topics in Advanced Computing: Promise and Challenges of Recommendation Systems for the DoD

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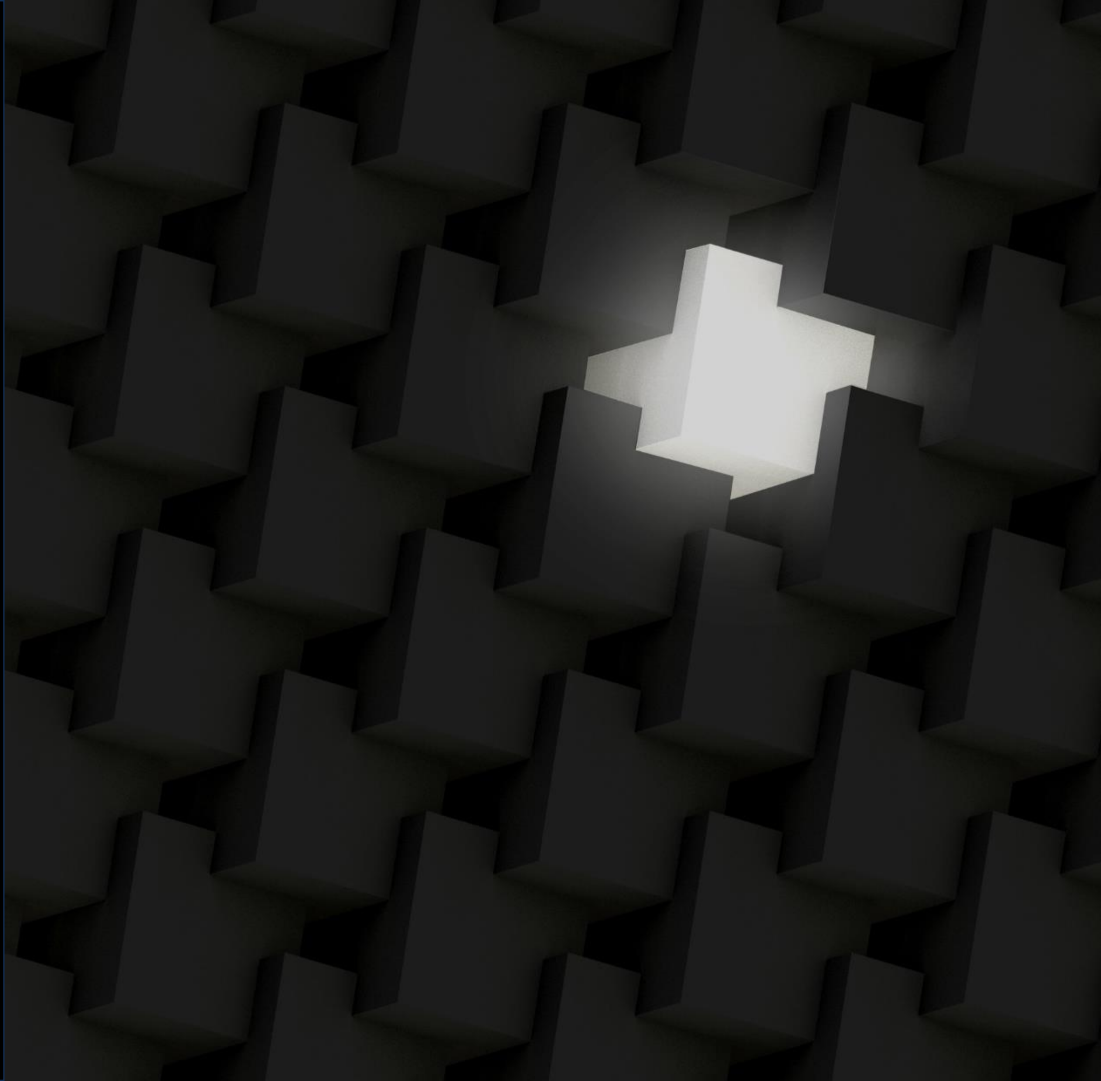

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Recommendation Systems Overview

- Concepts and foundations
- Applications to DoD and IC
- Facebook DLRM and MLPerf
- Advanced computing in the ETC
- CMU SEI advances in DLRM
- Impact

What is a Recommendation System?

Given your profile and the things you've liked in the past, what is the probability that you will "click through" on a recommendation?

- Netflix
- Amazon
- YouTube
- Spotify
- Facebook
- Twitter

"DNN-based personalized recommendation models comprise up to 79% of AI inference cycles in a production-scale data center."

Gupta, Udit, et al. "The architectural implications of Facebook's DNN-based personalized recommendation." 2020 IEEE International Symposium on High Performance Computer Architecture (HPCA). IEEE, 2020.

The Idea Behind Recommendation Systems

Given a “user” and an “item” that the user has not interacted with, what is the probability that the user will click on the item?

User-item pairs with the highest predicted click-through rate are prioritized

The data is “sparse,” i.e., any given user has interacted with very few items

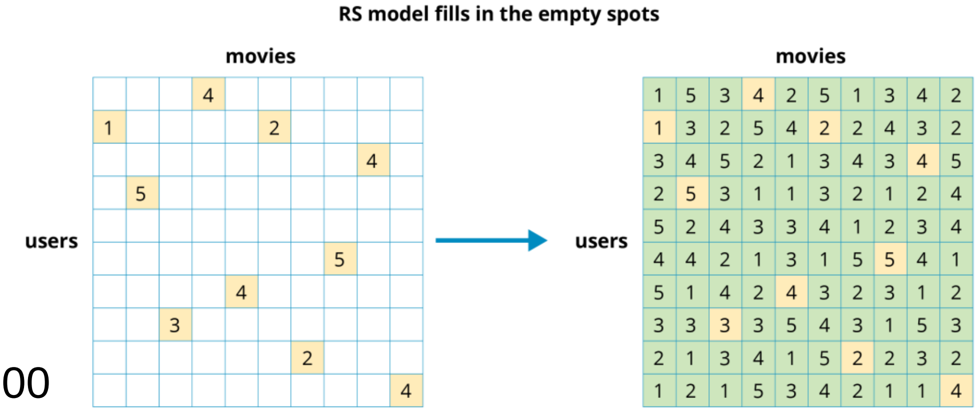
Sparsity example: Netflix Prize Dataset

- 17,770 movies
- 480,189 users

Ratings on scale of 1 – 5.

~100,000,000 total ratings

- ~20,000 x ~500,000 = ~10,000,000,000
- Sparsity: 100,000,000 / 10,000,000,000 ~ 1%



RS model fills in the empty spots

movies

users

			4						
1					2				
								4	
	5								
							5		
				4					
		3							
						2			
									4

movies

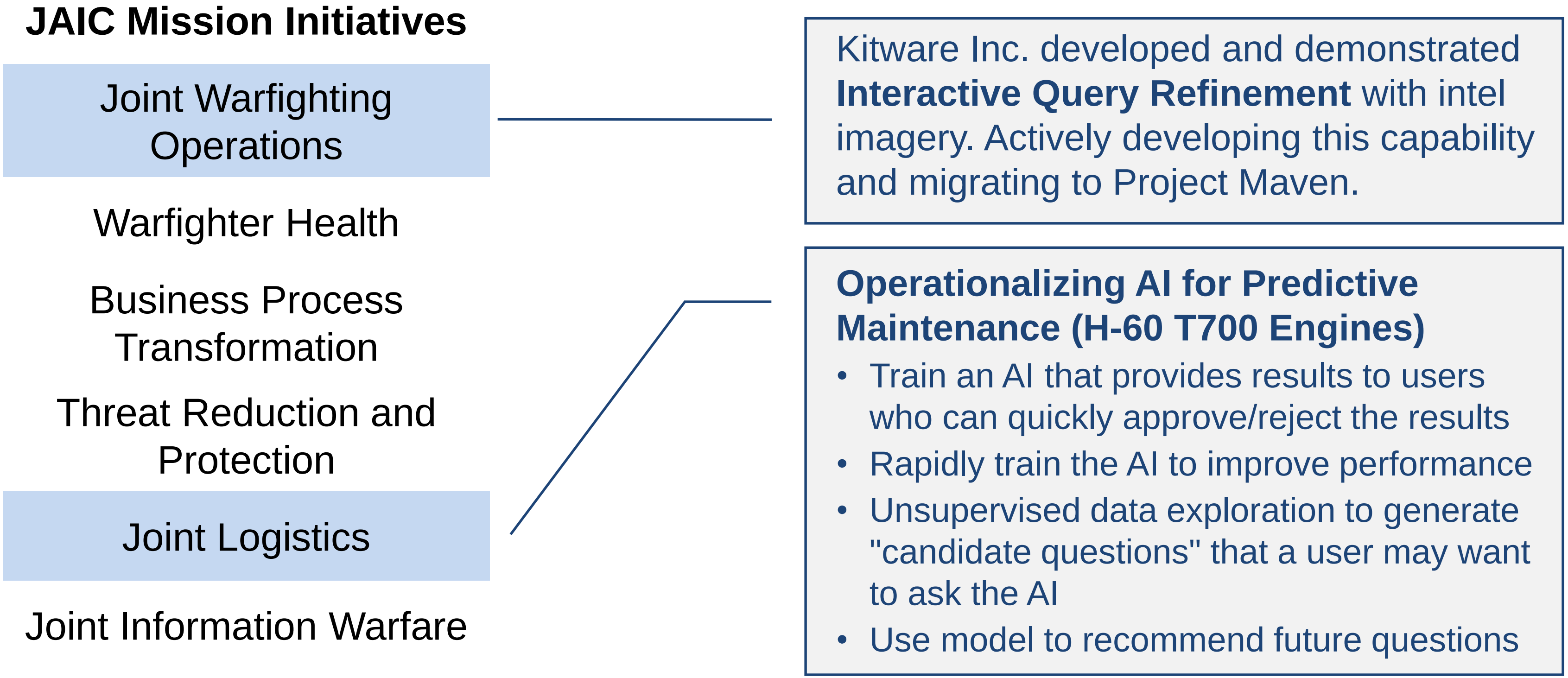
users

1	5	3	4	2	5	1	3	4	2
1	3	2	5	4	2	2	4	3	2
3	4	5	2	1	3	4	3	4	5
2	5	3	1	1	3	2	1	2	4
5	2	4	3	3	4	1	2	3	4
4	4	2	1	3	1	5	5	4	1
5	1	4	2	4	3	2	3	1	2
3	3	3	3	5	4	3	1	5	3
2	1	3	4	1	5	2	2	3	2
1	2	1	5	3	4	2	1	1	4

Recommendation Systems in the DoD and IC

Intelligence Analysis	Cybersecurity Analysis	Social Network Analysis
• Prioritizing documents when number of documents much greater than number of analysts • Guiding novice analyst searches using search paths of more experienced analysts	• Generating prioritized lists for defense actions • Detecting insider threats • Monitoring network security • Predicting cyber attacks • As an attack vector • Software vulnerability severity assessments	• Discovering fake news • Identifying malicious conversations

Recommendation Systems are Appearing in the JAIC



JAIC Mission Initiatives

- Joint Warfighting Operations
- Warfighter Health
- Business Process Transformation
- Threat Reduction and Protection
- Joint Logistics
- Joint Information Warfare

Kitware Inc. developed and demonstrated **Interactive Query Refinement** with intel imagery. Actively developing this capability and migrating to Project Maven.

Operationalizing AI for Predictive Maintenance (H-60 T700 Engines)

- Train an AI that provides results to users who can quickly approve/reject the results
- Rapidly train the AI to improve performance
- Unsupervised data exploration to generate "candidate questions" that a user may want to ask the AI
- Use model to recommend future questions

Contact: Dr. Juan Vasquez, AFRL ACT3 Product Development Director

MLPerf

Community-wide effort to develop benchmarks for evaluating vendor hardware that represent real-world problems

- 70+ companies including:

AMD
Google
NetApp
Lenovo
Facebook
Dell
Baidu
Cisco
NetApp
IBM
Microsoft
Intel
VMWare
Qualcomm

- 10 universities and research institutes including:

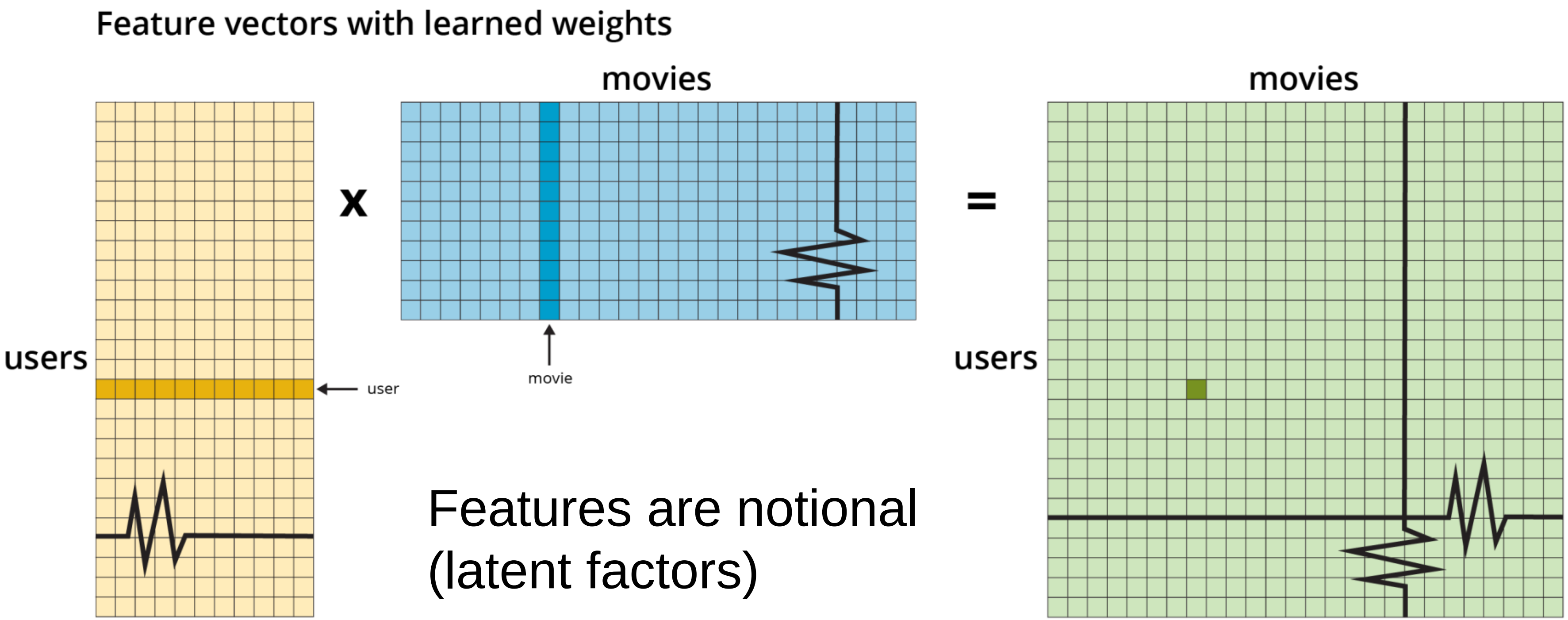
Harvard University
Stanford University
University of Minnesota
University of Toronto
University of Illinois, Urbana Champaign
University of Texas, Austin
University of California, Santa Cruz
University of California, Berkeley

DoD-relevant benchmarks:

- Image classification and object detection
- Natural language processing
- Recommendation systems

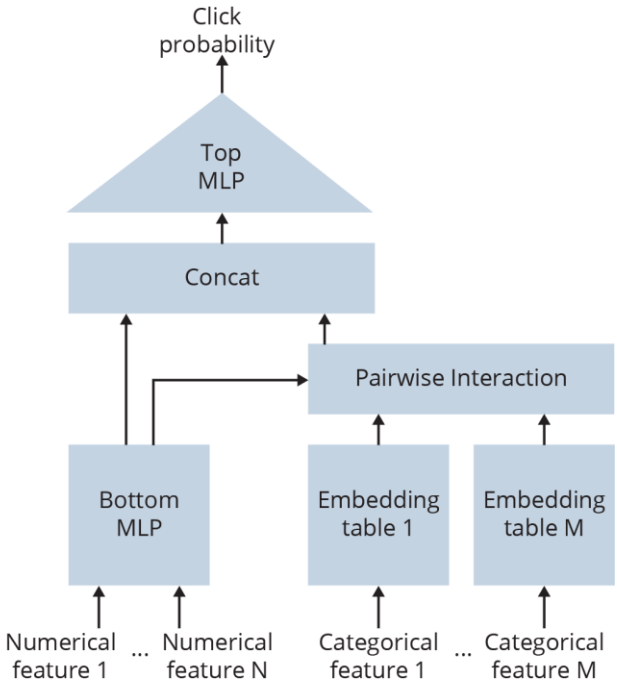
Facebook's Deep Learning Recommendation Model recently added

Feature vectors and latent factors



Features are notional
(latent factors)

Will a User Click on an Ad?

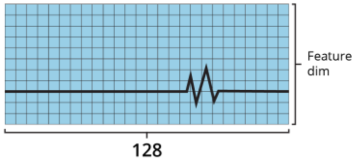


MLP = multilayer percepteron (neural network)

Click-through rate prediction

Users and products represented by **continuous** and **categorical** features

- User represented by a latent factor vector
- Categorical features described by an embedding matrix
  - Different numbers of categories:
    - new, used, in original box
    - sports, music, theater, movies, news, cuisine, …
    - “category” for each individual website
  - 26 Categorical features



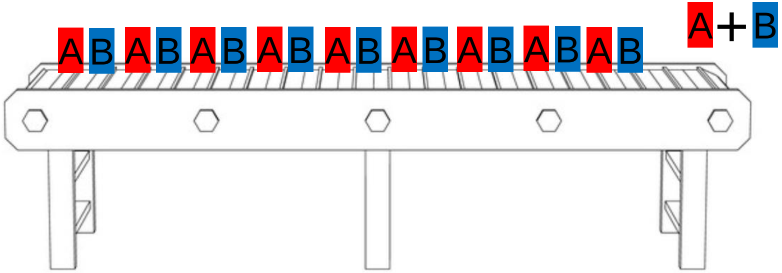
Facebook released Deep Learning Recommendation Model (DLRM) May 31, 2019 https://arxiv.org/abs/1906.00091

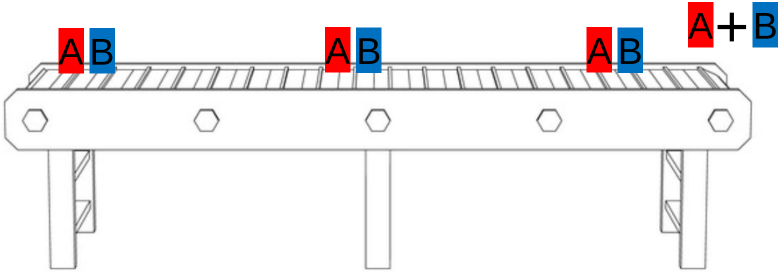
Advanced Computing and DLRM: Relevant ETC Projects

Research Areas in Advanced Computing	Big Learning Benchmarks	Spiral AI/ML	Quantum Computing	DARPA SDH
Parallelism				
Data-level Parallelism	✓	✓	✓	✓
Model-level Parallelism	✓	✓	✓	✓
Interlayer Parallelism	✓	✓	✓	
Intralayer Parallelism	✓	✓	✓	
SIMD/SIMT Parallelism	✓	✓	✓	✓
Specialized Processing Units				
Vector Cores	✓	✓	✓	✓
Tensor Cores	✓	✓	✓	✓
Application-Specific Integrated Circuits			✓	✓
Data Motion	✓	✓	✓	✓

What is Data Motion?

- The most expensive part of any calculation
  - “expense” – time and energy
- Values moved between memory spaces
- Types of memory boundedness
  - **Bandwidth bound** – data pipe is full
    - Can process data much faster than it is delivered
    - Dense, structured workloads (computer vision)
  - **Latency bound** – data pipe is not full
    - Spends time waiting for data to arrive
    - Workloads with random access to data
- Math is ***fast***, data motion is **slow**

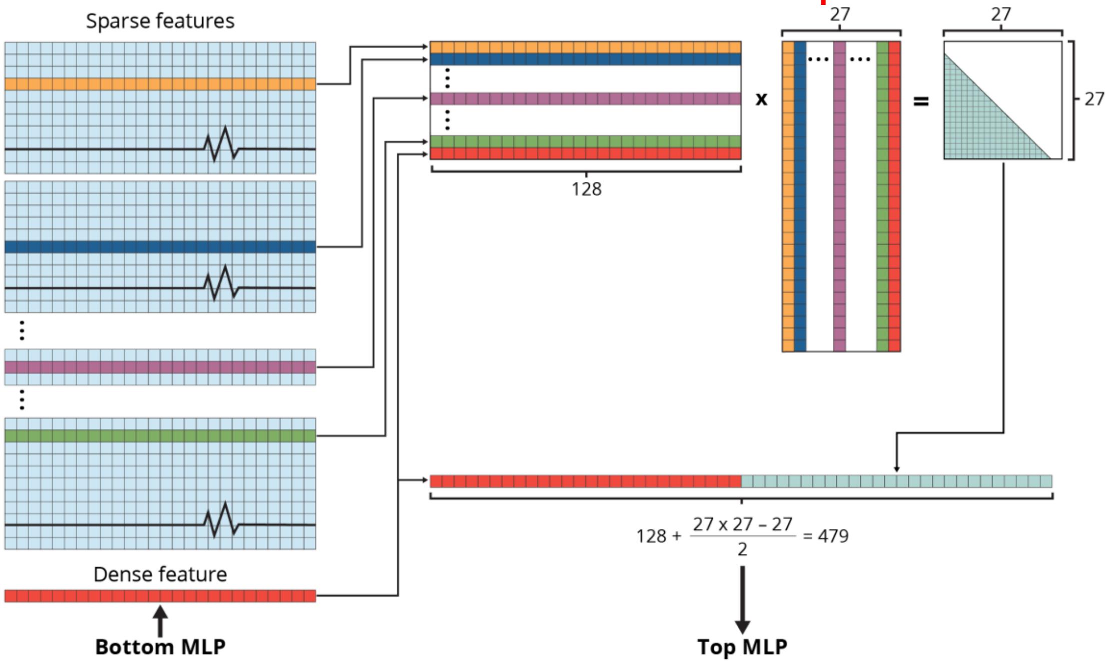




DLRM Piece Parts – Data Motion

slow – Transpose

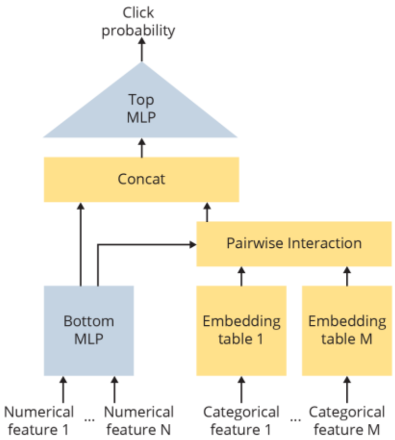
slow – DRAM Access



fast – Vector Math

fast – Vector Math

fast – Vector Math



CMU SEI Contributions: Spiral AI/ML

- CMU ECE Prof. Tze Meng Low, student Elliot Binder
- Low’s group develops hardware performance models to write optimal code for various platforms
  - Models incorporated into Spiral (Franchetti, CMU ECE) to automatically generate optimal code
- AI models are overwhelmingly implemented in Python frameworks such as PyTorch and Tensorflow
  - Python front ends link to high performance, hardware specific back ends
  - High-level abstractions introduce performance tradeoffs
- Compare performance of model-driven, hand-tuned code with vendor-submitted results to MLPerf

CMU SEI Contributions: Spiral AI/ML (cont.)

- Exploit knowledge of memory systems and frameworks to minimize data motion
- Reduce, reuse, recycle
- Eliminate unnecessary framework-induced overheads
  - Fuse operations
- Loops determine data motion
  - Interplay between vector sizes and cache sizes determines optimal ordering
- Effect of optimizations applied to both CPU and GPU implementations
- Present results at conferences to show the best possible performance to the community

Improving Recommendation Systems: Impact on DoD

Financial savings

- Back of the envelope – commercial
  - Hyperscale data center market in 2025: **~$100B**
  - ~10% of data center time spent on recommender systems: **~$10B**
  - 4x faster model would save **~$7.5B**
- DoD FY21 AI budget proposal: **$841M**
  - DoD will spend **~$100M** on inference and training in coming years
  - Savings with these techniques: **~$10M**

Advanced Computing in the Emerging Technology Center

John Wohlbier

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Jason Larkin

Daniel Justice

Tze Meng Low

CMU ECE

Elliot Binder

CMU ECE

DARPA

- Software Defined Hardware

Spiral

- Spiral AI/ML
- Spiral Graph

Quantum

- Quantum Advantage Evaluation Framework
- Quantum versus Classical
- Near Term Quantum Computing for Software Verification and Validation

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