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Optimizing Real-Time Data Processing: Balancing Resource Constraints and Quality-of-Service

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Real-time data processing

Deep neural networks (DNNs) increasingly used to deliver instant insights



Al traffic monitoring



Augmented reality for hospitality



Real-time sport analytics



Al-enabled financial trading

Quality-of-Service (QoS) in DNN-based Data Processing

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QoS tradeoffs: Performance-Accuracy-Reliability



Periodic inference: DNN latency < time to next arrival



Event-driven inference: buffer losses!



Model tuning and adaptive architectures

- DNN model tuning
 - Weight pruning
 - Quantization
 - Knowledge distillation
 - Lossy compression
 - Neural Architecture Search (NAS)
- Adaptive DNN models
 - How shall we leverage these capabilities for DNN inference serving?



D Liu, H Kong, X Luo, W Liu, R Subramaniam. Bringing AI To Edge: From Deep Learning's Perspective. Neurocomputing. Eshratifar, A. E., et al. BottleNet: A Deep Learning Architecture for Intelligent Mobile Cloud Computing Services, IEEE/ACM ISLPED.



Controlling QoS tradeoffs in DNN-based data processing Early exits and their scheduling policies

Extension: QoS tradeoffs in collaborative DNN inference Predicting QoS in distributed DNN deployments

- \Box
- Scheduling early exits in distributed DNN deployments



DSN'24

INFOCOM'25

Early exit DNN job scheduling

TC'23

Joint work with:



Manuel Roveri (Politecnico di Milano, Italy)



Yichong Chen (Imperial College London, UK)

Early exit in CNNs

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- Intermediate Classifiers (IC) produce an early classification avoiding "overthinking"
- Early exit is controlled by a confidence threshold for each EC

Output classification



• Example – forcing exit at layer *l*:



IC thresholds trained with the CNN or decided post-training.

Scheduling early exits for QoS

How to schedule early exit online to control data loss?



- Early exit scheduling problem: choose IC thresholds for each incoming job *i*
- QoS metrics: latency, accuracy, loss ratio (i.e., fraction of lost jobs).
- **Issue**: difficult to predict accuracy and processing time for arbitrary threshold combinations

Casale, G., & Roveri, M. (2023). Scheduling Inputs in Early Exit Neural Networks. *IEEE Transactions on Computers*.

Accuracy in adaptive DNNs

Accuracy and latency change with the data distribution!



• **Single-exit schedulers**: restrict feasible threshold values to {0,1}



Single-exit scheduling

- Knapsack-based policy:
 - Similar to discrete scheduling with compressible resources (NP-hard)



Single-exit scheduling

- Queueing model based policy:
 - DNN latency from steady-state M/GI/1/K queue
 - Service seen as a mixture distribution (GI) based on exit layer probabilities
- Optimal schedule obtained via a Linear Program (LP)
 - Maximize accuracy
 - Constraint maximum loss ratio





Loss ratio approximation

 $L = \frac{\rho^{(\sqrt{\rho}s^2 - \sqrt{\rho} + 2K)/(2 + \sqrt{\rho}s^2 - \sqrt{\rho})}(\rho - 1)}{\rho^{2(1 + \sqrt{\rho}s^2 - \sqrt{\rho} + K)/(2 + \sqrt{\rho}s^2 - \sqrt{\rho})} - 1}$

Simulation of real technological scenarios

• 6 CNNs (28-56 processing layers; 8-24 exit points; CIFAR10/100 data)



Extension: dealing with out-of-distribution data

- How to generalize the approach when offline profiling is not viable?
- AdaEE: multi-armed bandit (MAB) to schedule early exits
 - Reward metric: **Confidence gain** Performance overhead



- Driving early-exits with confidence gains
 - Single-exit: <1s to update the policies
 - Data-driven: Bayes optimization based



$$\tau_{i,l} \leftarrow \arg \max_{\tau_{i,l} \in \mathcal{A}} \left(Q_{i-1} + c \sqrt{\frac{\ln(i)}{N_{l-1}}} \right)$$





R. G. Pacheco et al. AdaEE: Adaptive Early-Exit DNN Inference Through Multi-Armed Bandits. ICC 2023.

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Key takeaways

- 1. Early-exit ICs a new control knob to dynamically tune QoS trade-offs
- 2. Knapsack based policy are highly robust
- 3. Queueing based policy highly effective to reduce latency (but under assumptions)
- 4. Confidence gain can help dealing with out-of-distribution data

Distributed early-exit optimization

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Joint works with:



Yichong Chen (Imperial College London, UK)



Zifeng Niu (Imperial College London, UK)



Manuel Roveri (Politecnico di Mllano, Italy)

DNNs & Resource Constraints

- Many DNN deployment models
 - Fog, MEC, 3G/4G/5G/Wi-Fi/..., private vs public, Cloud-to-Edge, ...
- Common challenges and themes:
 - Processing data closer to where it is generated

1.0

0.8

6.0 (s) 4.0

0.2

0.0

Cloud Cloud Cloud

LTE Wi-Fi

3G

QoS vs. resource constraints

Data transfer latency vs. Local processing

0.8

0.2

Mobile Mobile

GPU

CPU



Y. Kang et al. Neurosurgeon: Collaborative intelligence between the cloud and mobile edge, Proceedings of ASPLOS.

Cloud

GPU

State-of-the-art: DNN layer-wise partitioning

• Many popular DNNs have a linear topology (chain)





- Ideal split point determined from layer characteristics
 - Convolutional: large output data, Pooling: smaller output data; FC layers: high latency
 - Prediction on processing time on target hardware obtained via regression



Y. Kang *et al.* Neurosurgeon: Collaborative intelligence between the cloud and mobile edge, Proceedings of ASPLOS. H. Liang *et al.* DNN Surgery: Accelerating DNN Inference on the Edge Through Layer Partitioning, IEEE TCC 2023.

Designing a DNN-based data processing system

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- DNN placement is critical, e.g. IoT devices without on-air update
- State-of-the-art mainly relies on integer-linear programming (ILP)
 - Binary variables map layers to edge & IoT nodes
 - Constraints on memory, processing time, DNN layer dependencies, network range, ...



S. Disabato, M. Roveri, C. Alippi. Distributed Deep Convolutional Neural Networks for the Internet of Things. IEEE TC, 2021.

Modelling data loss ratio

- ILP models are appropriate for periodic workloads
- The same approach cannot easily capture stochastic arrivals



DNN-based collaborative inference system as a graph



• We focus on linear DNN pipelines (referred to as a service chain)



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Example: a shared deployment with two DNN-based services G. Casale - Slide 21/31

• DNN deployment described by heterogeneous graph



Graph neural networks for QoS trade-off prediction

- GNN surrogates can address the problem
 - Input features: system and workload parameters: arrival rates, RAM size, CPU GHz, ...
 - Output features performance metrics: throughputs, latencies, loss ratio, ...



ChainNet GNN: predicting QoS in collaborative inference

- GNN surrogate trained on simulation and/or system data
 - Input features: arrival rates, RAM size, CPU GHz, ...
 - Output features performance metrics: throughputs, latencies, loss ratio, ...
- Modelling throughput in ChainNet



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ChainNet: results

- 71% loss ratio reduction in real-world technological scenario
 - 2×OrangePi Zero, 2×Raspberry Pi A+, and 1×Raspberry Pi 3A+
- Systematic reduction also visible in generalization tests via simulation



Extending ChainNet for early-exit scheduling

- How can we generalize early-exit scheduling to the distributed setting?
- Jobs assigned upon arrival to a given path (chain) and coupled with (arbitrary) IC thresholds



CEEN distributed early-exit scheduler

- Maximize the accuracy of the early-exit DNN while minimizing the data loss
- Control policy:
 - IC threshold configuration
 - chain assignment probability



- EENN Predictor
 - Decoder-only transformer
 - Characterizes IC dependencies using empirical data
 - Input: EENN thresholds
 - Output: confidence scores and early exit frequencies

EENN Performance predictor



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Loss Ratio Predictor with Early Exit

- GNN that predicts throughput
 and loss ratio
 - Extended version of ChainNet
- System seen as a queueing networ
 - Early-exit modelled as chain
 - Considers blocking and CPU contention
- Memory constraints as limits on queue buffer capacity
 - Fixed-point use of ChainNet



Evaluation

- Multiple ReNet50 deployments, e.g., gateway only, near edge (NE) + far edge (FE)
- Baselines: AdaEE, Knapsack, Exit last
- Load factor = theoretical device utilization (1=100%) without job loss



• Similar results when results are considered for other EENNs (e.g., ResNet101)

Conclusion

Output classification

Summary

• We can recast early-exits as a mechanism to tune performance and reliability

- We can tallor GINNS to performance prediction tasks: <u>https://github.com/imperial-qore/ChainNet</u> $\underbrace{IIII}_{h_i^{(N),0}} \underbrace{[E_1]}_{I_1} \xrightarrow{[E_2]}_{h_i^{(N),1}} \underbrace{[E_2]}_{h_i^{(N),2}} \xrightarrow{[E_{T_i}]}_{h_i^{(N),2}} \underbrace{MLP_{tput}}_{h_i^{(N),T_i}} \xrightarrow{MLP_{tput}}_{h_i^{(N),T_i}}$
- Early-exit scheduling in DNN-based distributed data processing



Open challenges

- Generalize early-exit approach to job priorities
- Generalize early-exit approach to cope with non-i.i.d. data and bursts
- Generalize scheduling for QoS to other types of adaptive DNNs
- Early-exit aware DNN topology adaptation and placement reconfiguration