Cartel: A System for Collaborative Transfer Learning at the Edge

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What is Transfer Learning

“Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task.”

Use of knowledge gained while solving one problem and applying it to a different related problem
Problem

- Introduction of Multi-access Edge Computing + 5G has created a 47% increase in network traffic since 2016
  - 7 – 49 exabytes per month
- Deploying Machine Learning on this amount of data has become increasingly difficult
  - Network traffic concerns
  - Training speed and accuracy concerns
Multi-access Edge Computing (MEC)

“Cloud services, running at the edge”

“Mini Data Centers, deployed near communication points”

- Compute & Storage closer to the end user
- Provides ultra-low latency
Machine Learning @ Edge

- There is tremendous growth of data generated at the edge from end-user devices and IoT.

- We explore machine learning in the context of MEC:
  - Results are only needed locally
  - Latency is critical
  - Data volume must be reduced
Existing Solution

Centralized System

Problems

- **Data movement** is time consuming and uses a lot of backhaul network bandwidth.
- **Distributed ML** across geo-distributed data can **slow down** the execution up to 53X[1].
- **Regulatory constraints** (GDPR)

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An Alternative Approach

Isolated System

- Train machine learning models independently at each edge, in isolation from other edge nodes.
- The isolated model performance gets heavily impacted in scenarios where there is a need to adapt to changing workload.
Motivation

Can we achieve a balance between centralized and isolated system?

Leverage the resource-constrained edge nodes to train customized (smaller) machine learning models in a manner that reduces training time and backhaul data transfer while keeping the performance closer to a centralized system?

Opportunity

- Each edge node has its own attributes / characteristics → a full generic model trained on broad variety of data may not be required at an edge node.

Backhaul: The sending of data to the backbone of the network... Kinda like sending all the way to the “cloud”
Cartel maintains **small customized models** at each edge node.

- When there is change in the environment or variations in workload patterns, Cartel provides a jump start to **adapt** to these changes by transferring knowledge from other edge(s) where similar patterns have been observed.
Key Challenges

C1 : When to request for model transfer?
C2 : Which node (logical neighbor) to contact?
C3 : How to transfer knowledge to the target edge node?
Solution Design

**Raw-data v/s Metadata**

- Do not share raw data between any edge nodes or with the cloud.
- Use Metadata
  - Statistics about the network
  - Software configuration
  - Active user distribution by segments
  - Estimates of class priors (probability of certain classes), etc.

Cartel maintains and aggregates metadata locally and in the metadata server (MdS).
C1: When to request for model transfer?

Drift Detection

- Determine when to send a request to collaborate with edge nodes for a model transfer.
- In our prototype we use a threshold-based drift detection mechanism.

When data drift reaches a certain percentage
Use the Meta Data Service to check which neighbors have data most similar to themselves

C2: Which neighbors to contact?

Logical Neighbor

- Find the neighbor that has similar class priors to the target node.
- We call them as “logical neighbors” as they can be from anywhere in the network.
- In our prototype class priors are undergoing some shift, the empirical distributions from the target node is compared with those from the other nodes at the MdS to determine which subset of edge nodes are logical neighbors of the target node.
C3: How to transfer knowledge to the target?

Knowledge Transfer

- Two steps process
  1. Partitioning
  2. Merging
Transfer Learning: Partition + Merge

Partition + Merge is good for adaptability to many ML algorithms

### Online Random Forest (ORF)
- Bagging Approach: Remove a percentage of your existing tree structure and merge in a percentage of a neighbor's tree structure to your random forest

### Online Support Vector Machine (OSVM)
- One-Versus-Rest: Drop the weight vectors from your data set that are proving to be inseparable in N-dimensions and inherit the weight vectors from your neighbor
Solution Overview

Edge Node

Collaborative Component

Existing ML Library*

Data

[Diagram showing the relationship between collaborative components and an existing ML library within an edge node.]
Solution Overview
Experiment

Tested image classification and network monitoring (instruction classification)

Tested ORF and OSVM algorithms

5 edge nodes, 1 central node

Intel Xeon’s w/ 48 GB ram
Evaluation

Goals

• How effectively does the system adapt to the change in workload?
• How effective is Cartel in reducing data transfer costs, while providing lightweight and accurate models?
• What are the costs in the mechanisms of Cartel and the design choices?
• How does Cartel perform in a real-world scenario?

Methodology

• Workload

- Class 1
- Class 2

Time

Introduction Workload

Fluctuation Workload

• Machine Learning Model – ORF & OSVM
• Datasets used - MNIST & CICIDS2017
Evaluation

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Able to achieve normalized error rates as fast as centralized training and far better than isolated.
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Evaluation

Adaptability to Change in the Workload

- When changes in the environment or variations in workload patterns require the model to adapt, Cartel provides a jump start by transferring knowledge from other edge(s) where similar patterns have been observed.

- Cartel adapts to the workload changes up to 8x faster than isolated system while achieving similar predictive performance compared to a centralized system.
Evaluation

Data Transfer Cost

- Data/Communication cost includes the transfer of raw data or metadata updates.

- Model transfer cost captures the amount of data transferred during model updates to the edge (periodically in case of centralized system or partial model request from a logical neighbor in Cartel).

- Cartel reduces the total data transfer cost up to 1500x when compared to a centralized system.

SIGNIFICANTLY lower transfer cost
Summary

- We introduce **Cartel**, a system for sharing customized machine learning models between edge nodes.

- Benefits of Cartel include:
  - Adapts quickly to changes in workload (up to 8x faster compared to an isolated system).
  - Reduces total data transfer costs significantly (1500x ↓ compared to a centralized system).
  - Enables use of smaller models (3x ↓) at an edge node leading to faster training (5.7x ↓) when compared to a centralized system.
Questions

- What is the added cost of aggregating the meta data?
  - They leave this as a black box but it could be significant
- What are some real-world scenarios where we would actually have MEC’s that are training on related data?