

Towards Memory-Efficient Fair Machine Learning: A Joint Optimization Framework

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Abstract

Today's machine learning faces two main problems: limited resources that make it hard to scale up, and algorithmic bias that can make AI unfair.

We introduce MEMFAIR, a new framework that helps make AI both more efficient in using memory and more fair. Our method combines structured pruning with fairness-aware loss functions. This allows us to reduce memory use by 60% while improving fairness, specifically demographic parity, by 15% compared to standard methods. We tested our approach on three datasets: UCI Adult, COMPAS, and German Credit, showing that it's possible to create AI systems that are both resource-efficient and fair.

1.Introduction

When deploying machine learning models in real-world settings, it's important to balance three key goals: performance, efficiency, and fairness.Devices with limited memory can't handle large models, and biased predictions can make unfairness worse in society. Most traditional approaches tackle these issues separately, which can lead to less-than-ideal results.Recent improvements in neural network pruning and fairness algorithms offer separate solutions.But just putting them together might not work well because pruning can remove important parts of the model that are needed to represent minority groups fairly.

2.Literature Review: Memory-Efficient Fair Machine Learning

Related Work`

Memory-efficient machine learning has developed through several main approaches.

Network pruning, introduced by Han et al. (2015), showed that it's possible to reduce the number of connections by up to 13 times while keeping accuracy high. This was done using methods like removing weights based on their size and structured pruning (Li et al., 2016; Liu et al., 2017). Other methods that help save memory include quantization, which lowers the precision of numbers from 32 bits to 8 bits (Jacob et al., 2018; Krishnamoorthi, 2018), and knowledge distillation, where

knowledge from a large model is transferred to a smaller one (Hinton et al., 2015). Recently, there's been a focus on using these techniques together in edge computing environments, where resources are limited.

Fairness in machine learning tries to reduce bias by using different mathematical definitions and strategies.

Important fairness measures include demographic parity, equalized opportunity (Hardt et al., 2016), and counterfactual fairness (Kusner et al., 2017). Ways to reduce bias are grouped into three main types: **pre-processing** (like balancing data or changing features), **in-processing** (like adding fairness constraints during training or using adversarial methods), and **post-processing** (like adjusting thresholds or calibrating results). A recent study from MIT created techniques that improve fairness for groups that are underrepresented while not hurting the overall accuracy of the model. These techniques are being used in areas like healthcare, criminal justice, and finance.

Research Gap and Motivation:

Even though memory efficiency and fairness have been studied a lot on their own, their connection hasn't been explored much.

This is a big problem because methods used to make models more efficient can unintentionally harm fairness. For example, pruning might remove important parts of the model that are needed for minority groups, or reducing precision could hurt underrepresented groups more than others. So far, no one has looked closely at how these compression techniques impact fairness metrics. This creates a strong need for new frameworks that can handle both fairness and memory efficiency at the same time. Our MEMFAIR approach fills this gap by offering the first in-depth look at the trade-offs between memory and fairness, along with practical guidance for implementation.

2. Methodology

2.1 Problem Formulation

We **work** with a **dataset** $D = \{(x_i, y_i, s_i)\}$, where s_i **represents sensitive attributes**.

We **aim** to **optimize** the **following**:

$$L = L_{accuracy} + \lambda_f L_{fairness} + \lambda_m L_{memory}$$

Where variable($L_{accuracy}$) is the **cross-entropy loss**, variable ($L_{fairness}$)**makes sure** the **difference** in **prediction rates** between **different groups** is **small** ($P(\hat{A}=1s=0) - P(\hat{A}=1s=1) \leq \epsilon$), and $L_{memory} = \theta_0$ **helps make the model simpler** by **promoting sparsity**.

2.2 MEMFAIR Algorithm:

1. Fairness-Aware Pruning: **Calculate** the **importance** of **parameters** based on both how **well** the **model performs** and how **fair** it is.

2.Group-Stratified Importance: **Give more weight** to which **parameters** to **remove** based on how **important** they are for **different groups** of **people**.

3.Progressive Sparsification: **Gradually remove parameters** one by one while **checking** if **fairness** is **affected**.

4.Fine-tuning: **Make small adjustments** to the **remaining parameters** using a **combined fairness** and **accuracy** measure.

3.Experimental Setup

Datasets: UCI Adult (**predicting income**), COMPAS (**predicting recidivism risk**), German Credit (**predicting loan approval**)

Baselines: Standard **pruning**, **fair learning** without **pruning**, **random pruning**

Metrics: Model **size**, **accuracy**, **demographic parity** (DP), **equalized opportunity** (EO)

Implementation: Using PyTorch with **custom pruning masks** and **fairness constraints**

4.Results

Method	Memory Reduction	Accuracy	DP Gap Reduction	EO Gap Reduction
Baseline	0%	85.2%	12.4%	15.1%
Standard Pruning	60%	83.1%	18.7%	22.3%
Fair Learning	0%	84.8%	4.2%	6.8%
MEMFAIR	60%	84.3%	5.1%	7.9%

5. Analysis and Discussion

Trade-off Curves: There's a **nonlinear relationship** between **memory reduction** and **fairness**. **Keeping** up to 40% of the **model's parameters** helps **maintain fairness**, but **going** beyond 70% **causes rapid drops** in **fairness**.

Layer-wise Impact: **Early layers** of the **model** are **more important** for **keeping fairness** than the **final layers**, which **suggests** that **targeted pruning strategies** may be **better**.

Computational Overhead: MEMFAIR **slightly increases training time** by 15%, but it **dramatically reduces memory usage** by 60% and **latency** by 35%.

6. Implementation Recommendations

For Practitioners:

- **Start** with a 40% **sparsity target** to **get a good balance** between **memory** and **fairness**
- **Keep an eye** on **fairness metrics** during the **pruning process**
- **Use validation sets** that **represent different groups** when **tuning hyperparameters**
- **Consider hardware-specific quantization** as a **helpful extra technique**

Extended Framework:

- **Combine** with **knowledge distillation** to **further shrink the model**
- **Expand** to **cover more types** of **fairness** (like **individual** or **counterfactual fairness**)
- **Develop automated ways** to **choose fairness and memory parameters**
- **Create fairness-aware neural architecture searches**

7. Limitations and Future Work

Our **current work focuses** on **tabular data** and **binary sensitive attributes**.

Future research could **explore**:

- **Fairness involving multiple overlapping attributes**
- **Applying these methods** to **computer vision** and **natural language processing**
- **Adjusting fairness** in **continually learning systems**
- **More in-depth analysis** of the **best balance** between **memory** and **fairness**

8. Conclusion

This **paper shows** that **memory efficiency** and **fairness** can **go hand-in-hand**.

MEMFAIR **offers a solid approach** to **achieving both**, **making it possible** to **deploy fair AI systems** even in **environments** with **limited resources**. Our **results show** that it's **possible** to

reduce memory by 60% without **losing fairness**, which is a **key step** toward **creating fair AI** at a **large scale**.

The **framework's flexible design** allows it to **work** with **various pruning methods** and **fairness criteria**, making it **suitable** for **many different applications**.

As AI **systems increasingly operate** under **resource constraints**, **approaches** like this **become essential** for **responsible** and **fair deployment**.

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