Understanding and Improving Fairness-Accuracy Trade-offs in Multi-Task Learning

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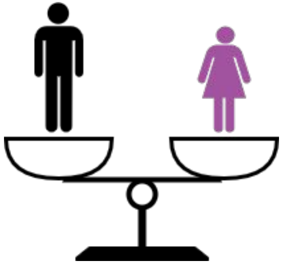
Fairness



Objective:
Subgroups are treated equally.

Why: Critical for decision making in employment, education, and criminal justice etc.

Mostly studied in **single-task learning** problems.

Multi-Task Learning

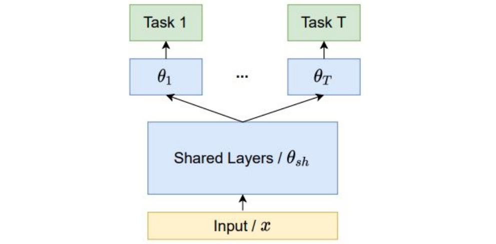


Figure 1: Shared-bottom architecture for a multi-task model.

Objective:
Jointly optimize the performance of multiple tasks.

Why: Transfer learning / regularization / model efficiency/...

Mostly only focused on optimizing **accuracy** across multiple tasks.

A largely unexplored question:
How does **fairness** play out in **multi-task learning** (MTL) scenarios?

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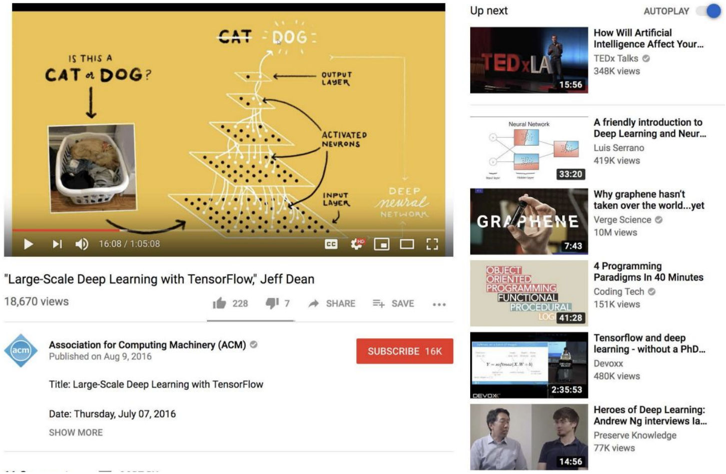
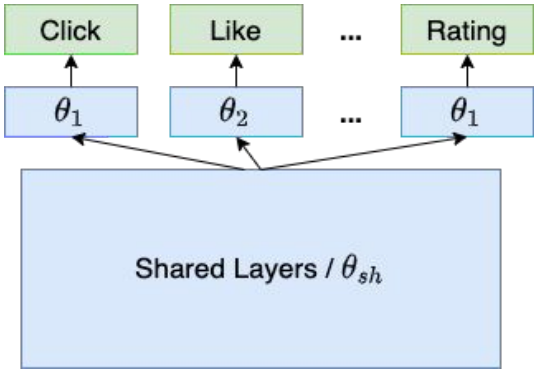
Fairness in MTL: Why do we care?

A content recommendation platform should treat different groups of users / content creators equally..



... And there are multiple types of user response (click, like, rating etc.) to be modeled [1].



In an MTL setting, can we ensure **fairness** of each individual task?

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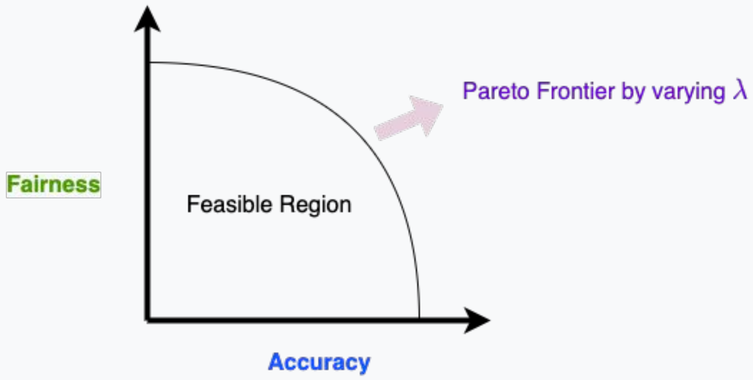
[1] Zhao et al. "Recommending what video to watch next: a multitask ranking system." Recsys 2019.

Fairness comes at a cost of accuracy

For a **single task**, there exists a Pareto frontier for fairness-accuracy trade-off.

$$\underbrace{\hat{\mathcal{L}}_{\text{task}}(\theta) = \hat{\mathcal{L}}(\theta)}_{\text{accuracy loss}} + \underbrace{\lambda \hat{\mathcal{F}}(\theta)}_{\text{fairness loss}}$$

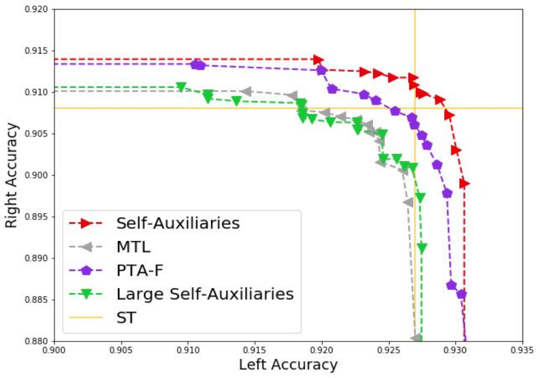


MTL comes with an accuracy trade-off

There exists a Pareto frontier for **accuracies** across different tasks.

$$\hat{\mathcal{L}}(\theta) := \sum_{t=1}^{T} \underbrace{w_t}_{\text{weight for task t}} \underbrace{\hat{\mathcal{L}}_t(\theta)}_{\text{accuracy loss for task t}}$$

Multi-MNIST Dataset [2].



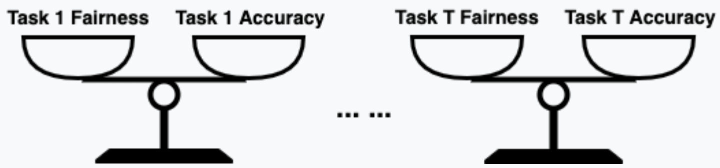
Accuracy trade-off between predicting **left** and **right** digits [2].

[2 Sener & Koltun. Multi-task learning as multi-objective optimization. NeurIPS 2018.
[3] Wang et al. Small Towers Make Big Differences. arXiv preprint arXiv:2008.05808.

Fairness in MTL: A multi-dimensional Pareto Frontier

Fairness is mostly studied in **single-task** settings.

MTL research mostly focused on optimizing **only the accuracy** across multiple tasks.



With ***T*** tasks each with a fairness objective and an accuracy objective, there is a ***2T***-dimensional Pareto frontier.

Research Questions:

1. How does fairness play out in the multi-task scenario?
2. How to characterize the multi-dimensional fairness-accuracy trade-off?
3. Can we improve the Pareto frontier?

Problem Framing

Fairness implications in Multi-Task Learning

Fairness implications in multi-task learning

	T1 Error	T1 FPR Gap	T2 Error	T2 FPR Gap
STL-T1	0.2030	0.2716	-	-
STL-T2	-	-	0.0784	0.0145
MTL	0.2035	0.2846	0.0783	0.0137
Difference	+0.24%	**+4.78%**	-0.08%	**-5.39%**

(a) CelebA: MTL hurts Task 1 fairness but improves Task 2 fairness.

	T1 Error	T1 FPR Gap	T2 Error	T2 FPR Gap
STL-T1	0.1659	0.1200	-	-
STL-T2	-	-	0.1313	0.0661
MTL	0.1656	0.1205	0.1299	0.0738
Difference	-0.20%	+0.34%	**-1.10%**	**+11.60%**

(b) UCI-Adult: MTL improves Task 2 accuracy but hurts its fairness.

STL-T1: single-task learning for Task 1;
STL-T2: single-task learning for Task 2;
MTL: multi-task learning with equal task weight.

- Datasets: MTL classification problems
  - **CelebA**: Attractive (T1) & Smiling (T2)
  - **UCI-Adult**: Income > $50k (T1) & Capital Gain > 0 (T2)
- Fairness attribute: ***Gender***
- Accuracy metric: prediction error rate
- Fairness metric: Equal opportunity [4] for group fairness
  - False Positive Rate (FPR) gap between male and female

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[4] Hardt, Price & Srebro. Equality of opportunity in supervised learning. NeurIPS 2016.

Fairness implications in multi-task learning (cont'd)

	T1 Error	T1 FPR Gap	T2 Error	T2 FPR Gap
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(a) CelebA: MTL hurts Task 1 fairness but improves Task 2 fairness.

MTL may have **larger** impacts on fairness goals than on accuracy goals...

	T1 Error	T1 FPR Gap	T2 Error	T2 FPR Gap
STL-T1	0.1659	0.1200	-	-
STL-T2	-	-	0.1313	0.0661
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Difference	-0.20%	+0.34%	**-1.10%**	**+11.60%**

(b) UCI-Adult: MTL improves Task 2 accuracy but hurts its fairness.

.. or **hurt** the fairness of some tasks while benefiting from its accuracy gains

STL-T1: single-task learning for Task 1;
STL-T2: single-task learning for Task 2;
MTL: multi-task learning with equal task weight.

Training multiple tasks together by simply pooling the accuracy objectives may lead to **unwanted fairness consequences.**

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[3] Hardt, Price & Srebro. Equality of opportunity in supervised learning. NeurIPS 2016.

New Metrics

Measuring fairness-accuracy trade-offs in MTL

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Measuring fairness in multi-task learning

- It's hard to visualize a Pareto frontier with > 3 dimensions
- Even with 2 tasks, we have a 4-dim Pareto frontier for fairness-accuracy trade-off
- Can we efficiently summarize and visualize this **multi-dimensional Pareto frontier**?
    - Moreover, fairness/accuracy metrics could differ largely across different tasks (e.g. some tasks are intrinsically harder to learn / have more bias)

Measuring **relative change** normalized by single-task learning (STL) baselines, and **average** across tasks:

Average Relative Fairness Gap (ARFG)

$$ARFG := \frac{1}{T}\sum_{t=1}^{T} FPRGap^{(t)} / \underbrace{FPRGap_S^{(t)}}_{\text{single-task FPR gap w/o fairness remediation}},$$

Average Relative Error (ARE)

$$ARE := \frac{1}{T}\sum_{t=1}^{T} Err^{(t)} / \underbrace{Err_S^{(t)}}_{\text{single-task error w/o fairness remediation}}.$$

Measuring fairness in multi-task learning (cont'd)

- ARFG and ARE are always positive, and
  - can be either smaller or greater than 1 as MTL could either improve or hurt accuracy / fairness for individual tasks;
  - ARFG < 1 (ARE < 1) suggests that MTL reduces relative FPR gap (error) on average, and vice versa.
- **ARFG-ARE Pareto frontier**: overall fairness-accuracy trade-off **across all tasks**.

Average Relative Fairness Gap (ARFG)

$$ARFG := \frac{1}{T}\sum_{t=1}^{T} FPRGap^{(t)} / \underline{FPRGap_S^{(t)}},$$

single-task FPR gap w/o fairness remediation

Average Relative Error (ARE)

$$ARE := \frac{1}{T}\sum_{t=1}^{T} Err^{(t)} / \underline{Err_S^{(t)}}.$$

single-task error w/o fairness remediation

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New Mitigation

Improving fairness-accuracy trade-offs in MTL

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Fairness loss: single-task learning (STL)

Using **FPR gap** for *equal opportunity* as the measure for group fairness...

set of negative examples

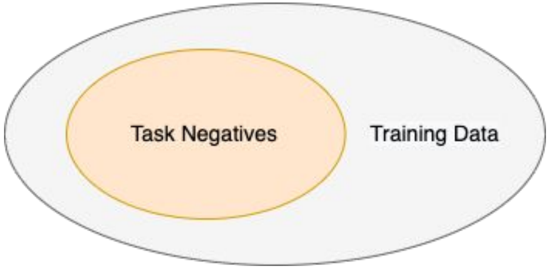
$$\hat{\mathcal{L}}_{STL}(f) = \hat{\mathcal{L}}(f) + \lambda \hat{\mathcal{F}}(f|N),$$

accuracy loss

group fairness loss

- correlation loss [5-6]
- Maximum Mean Discrepancy (MMD) [7]
- FPR difference [8-10]

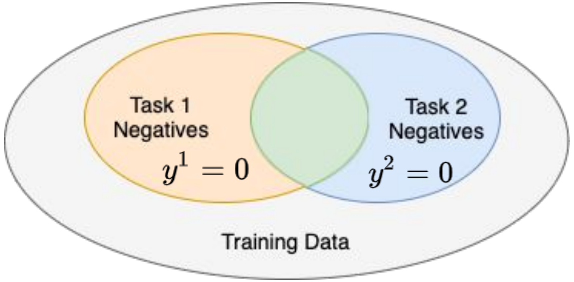
Measures the gap between predictions on **negative examples (Y=0)** of the two populations



[5] Beutel et al. Fairness in recommendation ranking through pairwise comparisons. KDD 2019.
[6] Beutel et al. Putting fairness principles into practice: Challenges, metrics, and improvements. AIES 2019.
[7] Prost et al. Toward a better trade-off between performance and fairness with kernel-based distribution matching. NeurIPS 2019 “ML with Guarantees” workshop.
[8] Feldman et al. Certifying and removing disparate impact. KDD 2015.
[9] Menon et al. The cost of fairness in binary classification. FAccT 2018.
[10] Zafar et al. Fairness Constraints: A Flexible Approach for Fair Classification. JMLR 2019.

Baseline: Fairness loss generalized to MTL

2-task learning as an example



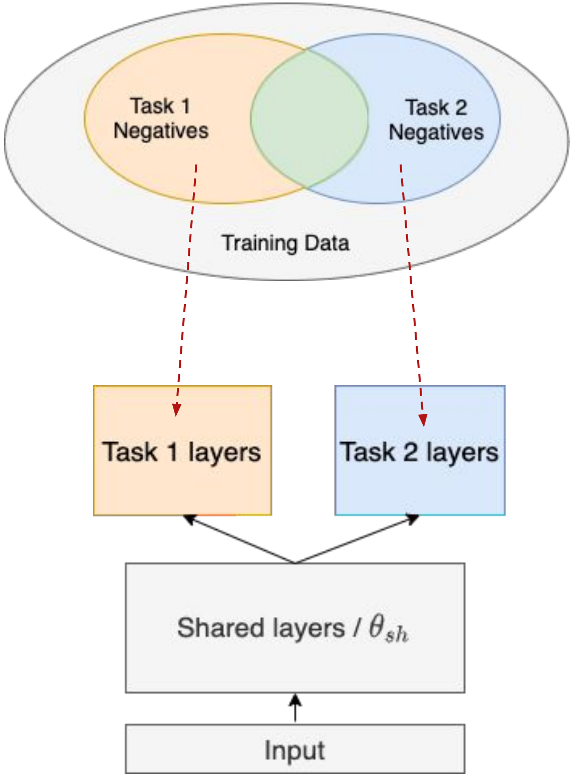
(x, y^1, y^2)

$y^1 \in \{0, 1\}$: Label for Task 1

$y^2 \in \{0, 1\}$: Label for Task 2

- Baseline: Fairness loss computed on  &  &  ;
- However,  is **only** relevant to Task 1 fairness;
- Likewise,  is **only** relevant to Task 2 fairness;
- But Baseline method does not distinguish between them => A **suboptimal** use of model capacity!

Our proposal: A redistribution of fairness losses



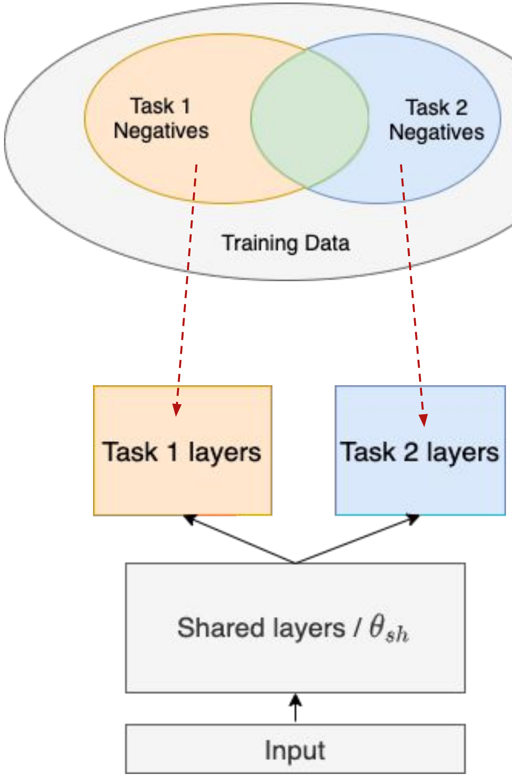
<u>MTA-F</u>: Multi-task-aware fairness treatment

Let's address the fairness in a more targeted way:

- Head layers address fairness issues that are ***specific*** to the task itself;
- Shared layers address fairness issues that are ***common*** to more than 1 tasks.

A more efficient allocation of model capacity → "saves" the model more capacity for accuracy objectives → a better overall fairness-accuracy trade-off

MTA-F: Multi-task-aware fairness treatment



Set of **negative** examples for task t

$$\hat{\mathcal{F}}_t^{head}(\theta) := \hat{\mathcal{F}}(\theta \,|\, N_t \cap (\bigcap_{k\neq t} N_k^c)),$$

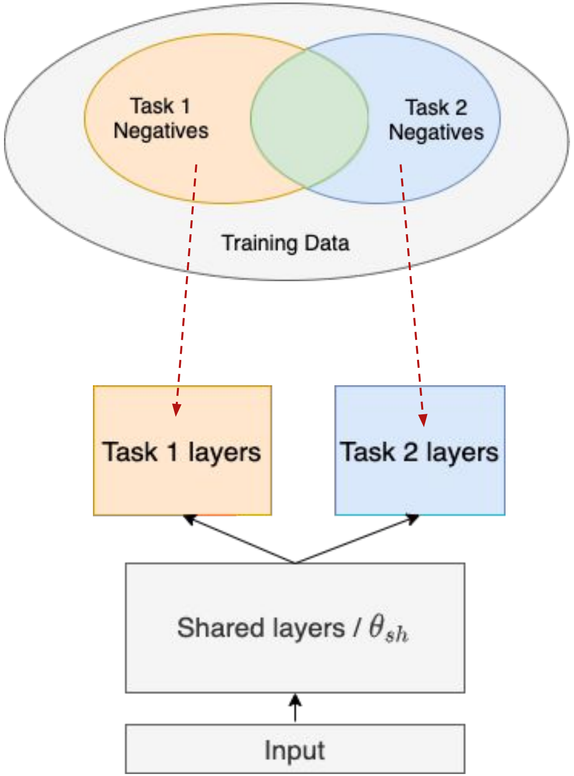
Set of **positive** examples for task k

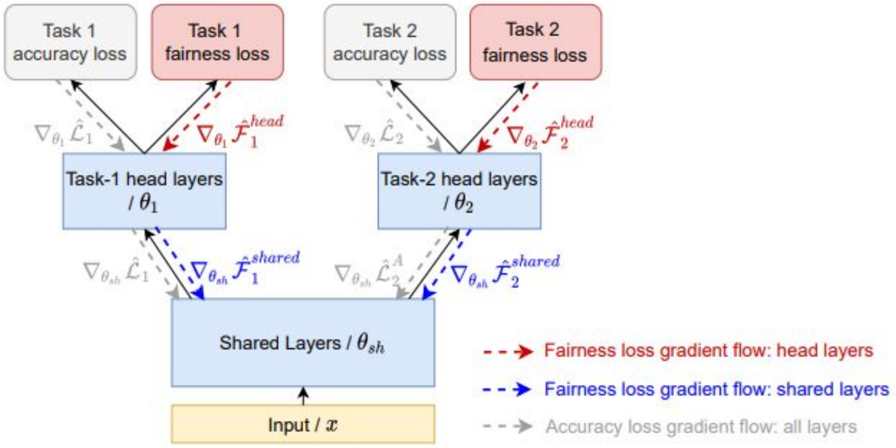
$$\hat{\mathcal{F}}_t^{shared}(\theta) := \hat{\mathcal{F}}(\theta|N_t) - \hat{\mathcal{F}}_t^{head}(\theta),$$

MTA-F: Multi-task-aware fairness treatment

$$\hat{\mathcal{F}}_t^{head}(\theta) := \hat{\mathcal{F}}(\theta \mid N_t \cap (\bigcap_{k \neq t} N_k^c)),$$

$$\hat{\mathcal{F}}_t^{shared}(\theta) := \hat{\mathcal{F}}(\theta \mid N_t) - \hat{\mathcal{F}}_t^{head}(\theta),$$





(b) Backpropagation with MTA-F: We backpropagate task-specific fairness losses $\hat{\mathcal{F}}_t^{head}$ to head layers, and the remaining fairness loss $\hat{\mathcal{F}}_t^{shared}$ to shared layers ($t = 1, 2$).

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MTA-F: Multi-task-aware fairness treatment

Algorithm 1: MTA-F Update Rule

Input: Mini-batch $\{(x_i, y_i^1, ..., y_i^T)\}_{i=1}^n$, model parameters $\theta = (\theta_{sh}, \theta_1, ..., \theta_T)$, task weights $\{w_t\}_{t=1}^T$, fairness weights $\{\lambda_t\}_{t=1}^T$, head-to-shared ratio $\{r_t\}_{t=1}^T$, and learning rate η

for $t = 1, ..., T$ **do**

iteratively update T tasks

$\hat{\mathcal{L}}_t(\theta_{sh}, \theta_t) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}_t(f_t(x_i; \theta_{sh}, \theta_t), y_i^t)$

▷ *Compute accuracy losses*

$\hat{\mathcal{F}}_t^{head}(\theta_{sh}, \theta_t)$ and $\hat{\mathcal{F}}_t^{shared}(\theta_{sh}, \theta_t)$ as in Eq. (10) / (11)

▷ *Compute fairness losses*

$\theta_t = \theta_t - \eta(w_t \nabla_{\theta_t} \hat{\mathcal{L}}_t(\theta_{sh}, \theta_t) + \lambda_t r_t \nabla_{\theta_t} \underline{\hat{\mathcal{F}}_t^{head}(\theta_{sh}, \theta_t)})$

▷ *Gradient descent on head parameters*

end

$\theta_{sh} = \theta_{sh} - \eta[\sum_{t=1}^T w_t \nabla_{\theta_{sh}} \hat{\mathcal{L}}_t(\theta_{sh}, \theta_t) + \lambda_t \nabla_{\theta_{sh}} \underline{\hat{\mathcal{F}}_t^{shared}(\theta_{sh}, \theta_t)}]$

▷ *Gradient descent on shared parameters*

Output: Updated model parameters $\theta = (\theta_{sh}, \theta_1, ..., \theta_T)$

MTA-F differs from baseline method in these places.

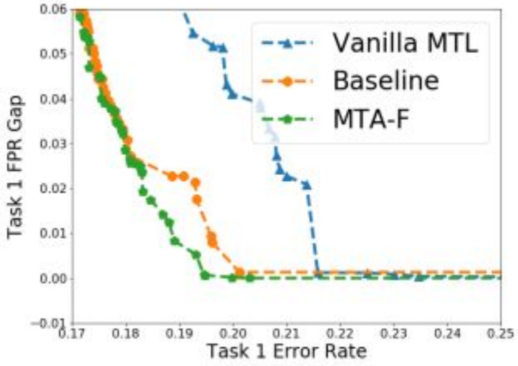
Experiments

- Datasets:
  - **UCI-Adult**: *Income > $50k* (T1), *Capital Gain > 0* (T2)
  - **German Credit Data**: *Good loans* (T1), *Credit > 2000* (T2)
  - **LSAC Law School**: *Pass bar* (T1), *high GPA* (T2)
- Methods:
  - **Vanilla MTL**: plain MTL **without** fairness mitigation
  - **Baseline**: Per-task fairness treatment
  - **MTA-F**: our proposed method
- Fairness loss: correlation loss / MMD loss / FPR gap loss
- Fairness metric: Equal Opportunity between females and males

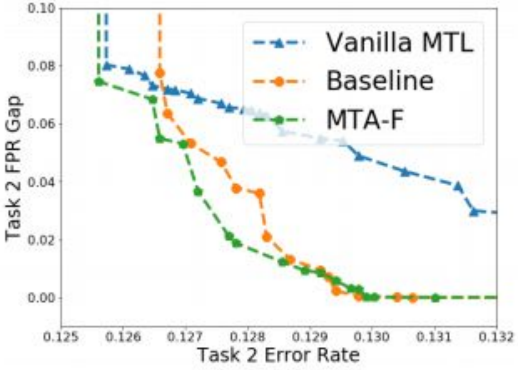
Experiments: UCI-Adult

Marginal Pareto frontiers (lower left is better)

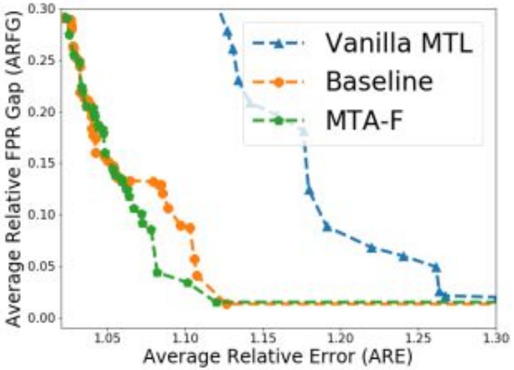
AFRG-ARE Pareto frontier



(a) Fairness-accuracy Pareto frontier for **Task 1**.



(b) Fairness-accuracy Pareto frontier for **Task 2**.



(c) *ARFG-ARE* Pareto frontier.

MTA-F improves **per-task** as well as **overall** fairness-accuracy Pareto frontiers.

Experiments: Numerical results

Overall fairness gap   Overall error rate

Dataset	UCI-Adult		German Credit		LSAC Law School	
Metric	*ARFG*	*ARE*	*ARFG*	*ARE*	*ARFG*	*ARE*
Vanilla MTL	0.3444	1.1040	0.1336	0.8367	0.3497	0.9778
Baseline	0.0871	1.1032	0.0999	0.8356	0.1126	0.9864
MTA-F	**0.0437**	**1.0820**	**0.0364**	**0.8264**	**0.0310**	**0.9731**

Table 3: Average relative fairness gap (*ARFG*) and average relative error (*ARE*) on **UCI-Adult**, **German Credit Data** and **LSAC Law School** datasets, as defined in Section 4. Lower metric values indicate better overall fairness / accuracy across all tasks.

Task 1   Task 2

		T_1 *Err*	T_1 *FPRGap*	T_2 *Err*	T_2 *FPRGap*
UCI-Adult	Vanilla MTL	0.1911	0.0715	0.1359	0.0091
	Baseline	0.1938	0.0186	0.1336	0.0020
	MTA-F	**0.1891**	**0.0083**	**0.1319**	**0.0016**
German Credit	Vanilla MTL	0.205	0.0150	0.220	0.0084
	Baseline	0.255	0.0879	**0.180**	0.0069
	MTA-F	**0.200**	**0.0033**	0.220	**0.0034**
LSAC Law School	Vanilla MTL	0.1555	0.0503	**0.1565**	**0.0004**
	Baseline	0.1568	0.0119	0.1580	0.0006
	MTA-F	**0.1540**	**0.0015**	**0.1565**	**0.0004**

Table 4: Per-task metrics for **UCI-Adult, German Credit Data** and **LSAC Law School** datasets.

MTA-F improves **per-task** as well as **overall** fairness-accuracy metrics, across all three datasets and with different fairness losses.

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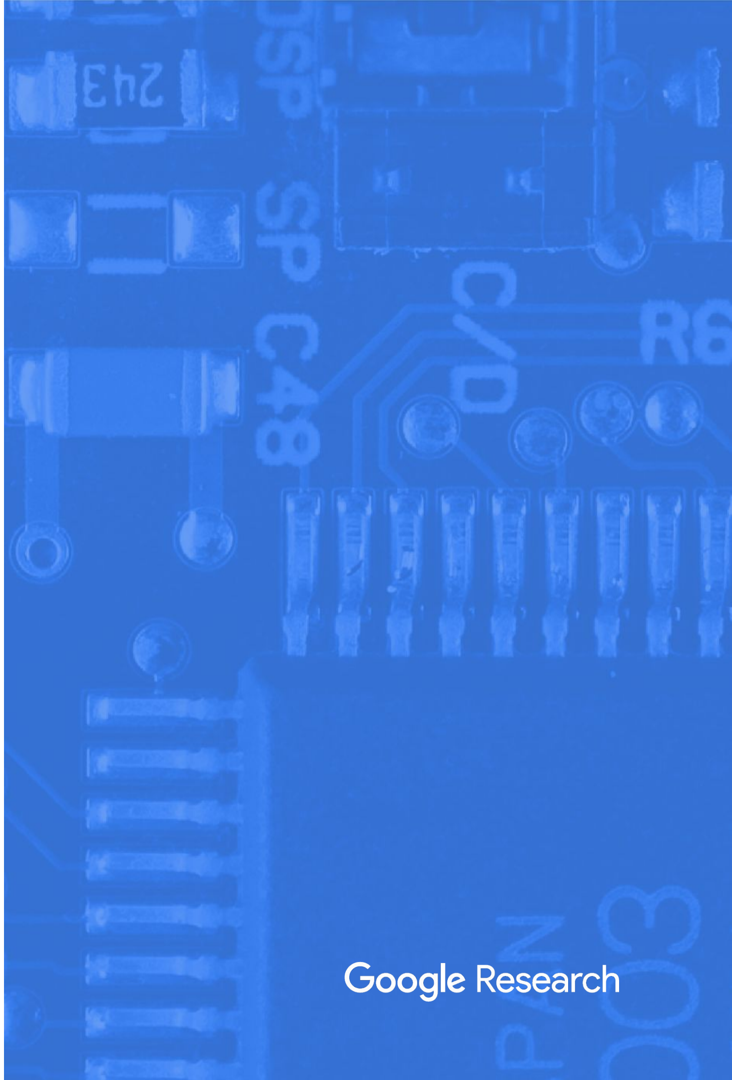
Key Takeaways

- ➢ Optimizing only for accuracy trade-off in MTL may lead to **unwanted fairness implications**.
- ➢ Quantify the **multi-dimensional trade-off**: we propose Average relative fairness gap (ARFG) and average relative error (ARE).
- ➢ MTA-F: a **data-dependent multi-task fairness mitigation** approach, which decomposes fairness losses for different model components by exploiting task relatedness and the shared architecture for multi-task models.



Thank You

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