Fair Pairwise Learning to Rank

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The Fairness Problem

Neural Network models are being increasingly employed in learning to rank tasks

These models are inherently **opaque**, as their huge parameter space prevents a clear understanding of their decisions

When dealing with sensitive data such as race and gender, there is no guarantee about their **fairness**

The Fairness Problem

If the data contains **biases** against a specific group of people, those can also be learned by a ML model

- **Disparate impact**: positive outcomes are assigned with different rates to people belonging to different groups
- **Disparate treatment**: the model takes different decisions for individual belonging to different groups *who are otherwise similar*
- **Disparate mistreatment**: a decision system has different error rates for different groups

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

The Fairness Problem in Ranking

$$D = \{(q_i, x_i, s_i, y_i)\ i \in \{1..N\}\}$$

q_i : queries

x_i: features

y_i: document relevance

s_i: sensitive attribute

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

The Fairness Problem in Ranking

- Singh and Joachims, 2018: **average exposure** of groups should be balanced, i.e. the average probability of individuals from each group to be ranked at the top of the list
- Yang, Stoyanovich, 2017: the proportion of people belonging to different groups should be balanced at the top-i positions
- Narashiman et al., 2020: difference in rank accuracy should be balanced between different groups

Normalized Discounted Difference (rND)

$$\text{rND} = \frac{1}{Z} \sum_{i \in \{10,20,\ldots\}}^{N} \frac{1}{log_2 i} \left| \frac{|\ S^+_{1\ldots i}\ |}{i} - \frac{|\ S^+\ |}{N} \right|$$

$\frac{|S^+_{1\ldots i}|}{i}$: proportion of protected individuals in the top-i documents

$\frac{|S^+|}{N}$: proportion of protected individuals in the overall population/query

Values close to 0 are desirable.

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

Group-Dependent Pairwise Accuracy (GPA)

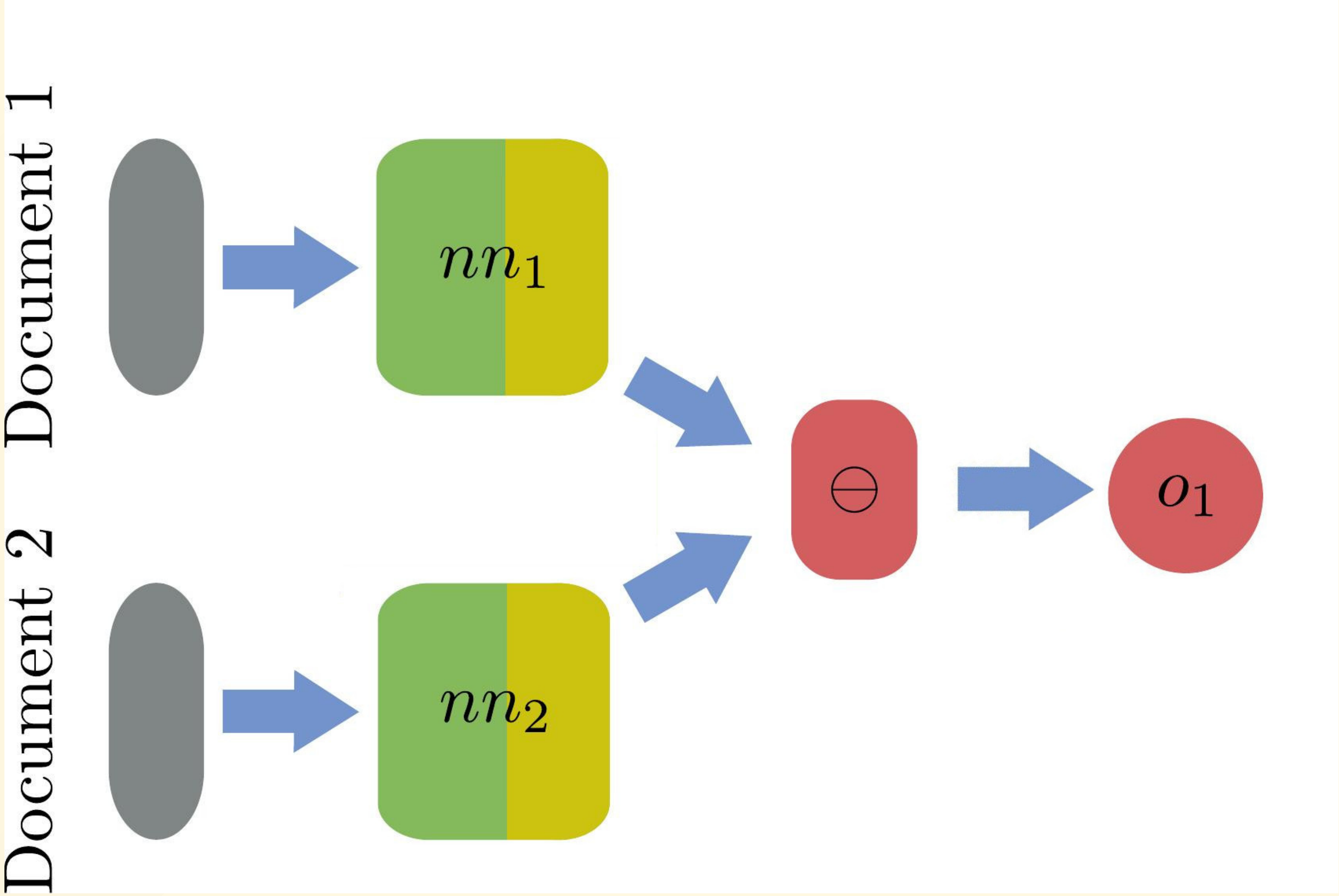
$G_1, ..., G_K$: a set of K groups

$A_{G_i > G_j}$: group-dependent pairwise accuracy - i.e. ranker accuracy on documents which are labelled more relevant and belong to group i; and ranker accuracy on documents which are labelled less relevant and belong to group j.

$\left|A_{G_i > G_j} - A_{G_j > G_i}\right|$ **should be close to 0**.

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

DirectRanker



Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

The Fair DirectRanker Framework

We build on a fast, *pairwise* ranking model (DirectRanker, Köppel et al. 2019) by employing different strategies to encourage fair outputs.

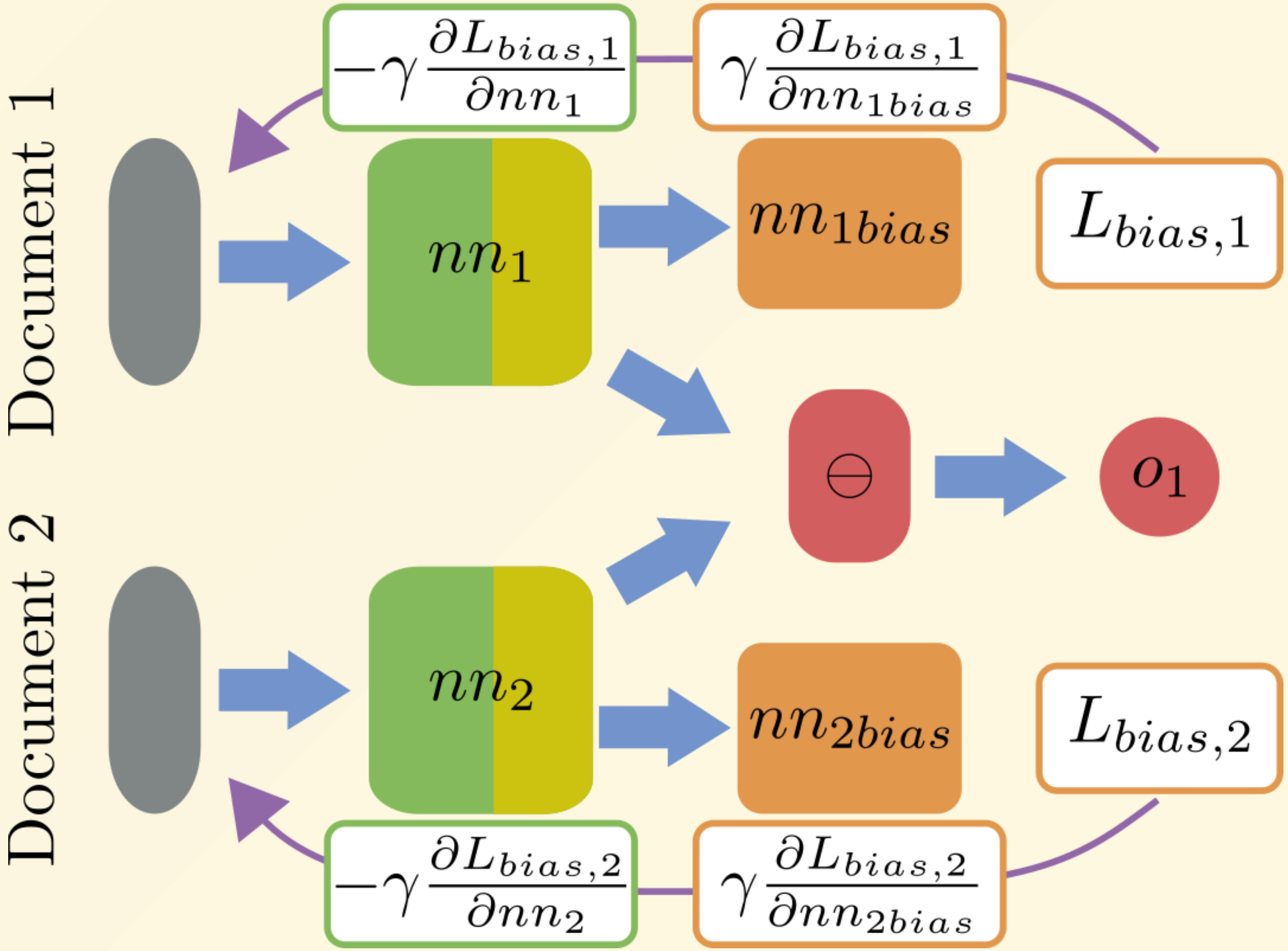
- The Gradient Reversal Layer of Ganin et al., 2016
- The Noise Module by Cerrato et al., 2020

We introduce a family of neural architectures that are able to **rank without discriminating**.

The Fair DirectRanker Framework

$$L(\Delta y, x_1, x_2, s_1, s_2) = L_{\text{rank}}(\Delta y, x_1, x_2) + \gamma \sum_{i=1}^{2} L_{\text{bias},i}(s_i, x_i),$$

Fair Adversarial DirectRanker



Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

Fair Adversarial DirectRanker

- Two **debiasing networks** try to predict the sensitive attribute/group the individual belongs to
- The gradient is *inverted* when backpropagating into the main network (Ganin et al. 2016)

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

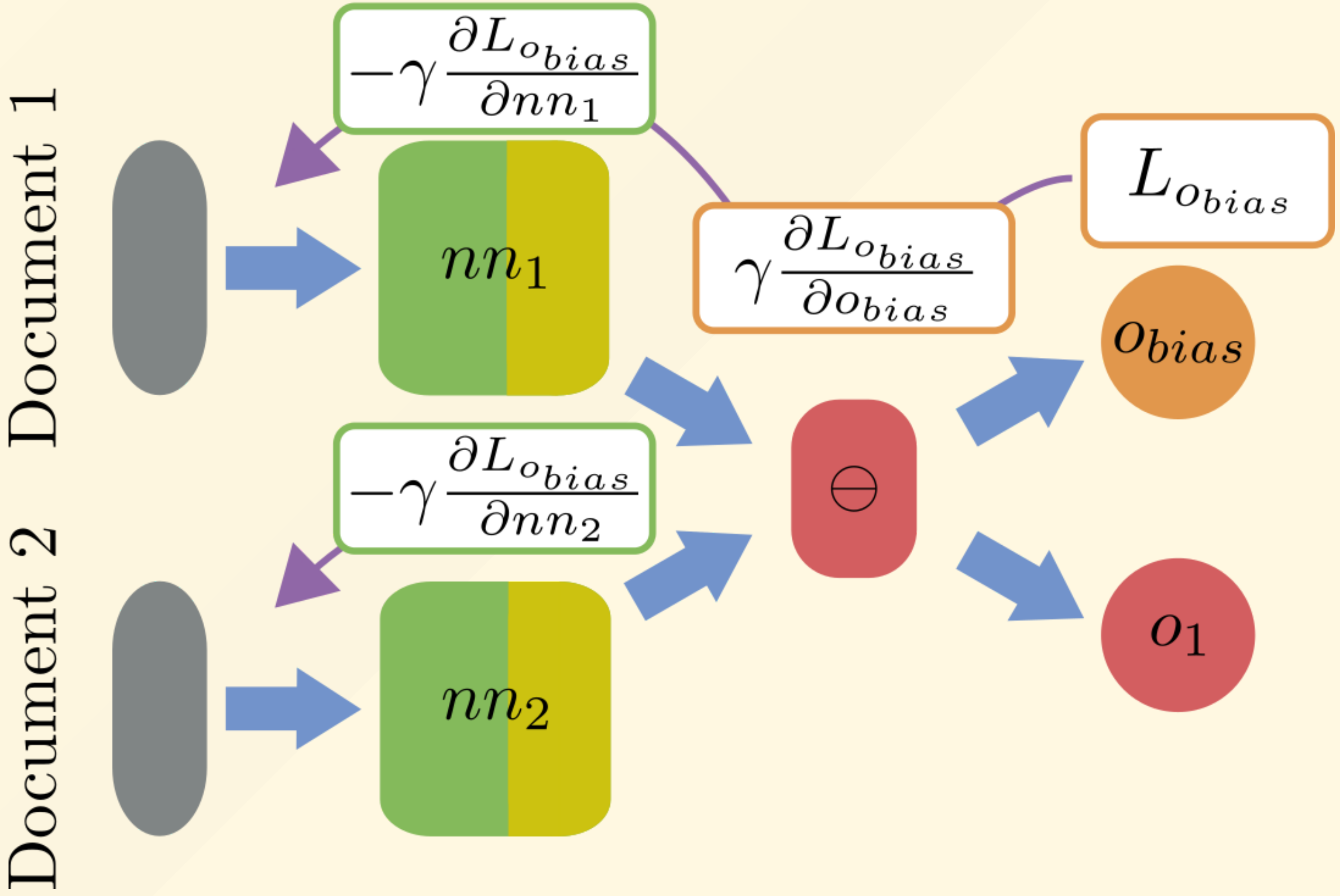
Fair Adversarial DirectRanker

$$L_{\text{rank}}(\Delta y, x_1, x_2) = (\Delta y - o_1(x_1, x_2))^2$$

$$\begin{aligned} L_{\text{bias},i}(s, x) = & -s \log(nn_{i\,bias}(x)) \\ & - (1 - s) \log(1 - nn_{i\,bias}(x)), \end{aligned}$$

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

Fair Flipped DirectRanker



Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.

Fair Flipped DirectRanker

- The features extracted from the main network are **ranked** according to the sensitive attribute
- The gradient information is again **flipped** when backpropagating into the main network

Fair Flipped DirectRanker

$$
\begin{aligned}
L(\Delta y, \Delta s, x_1, x_2) = &(\Delta y - o_1(x_1, x_2))^2 \\
&+ \gamma * (\Delta s - o_{bias}(x_1, x_2))^2
\end{aligned}
$$

Adversarial, Flipped DirectRanker

$$
\begin{aligned}
L(\Delta y, \Delta s, x_1, x_2) = {} & (\Delta y - o_1(x_1, x_2))^2 \\
& + \gamma_1 * (\Delta s - o_{bias}(x_1, x_2))^2 \\
& + \gamma_2 * (-s \log(nn_{i\,bias}(x)) - (1 - s) \log(1 - nn_{i\,bias}(x)))
\end{aligned}
$$

Cerrato et al., Fair Pairwise Learning to Rank. DSAA 2020.