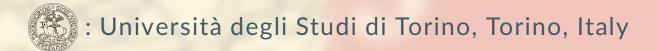
# Fair Pairwise Learning to Rank



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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

# 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

# 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)

$$ext{rND} = rac{1}{Z} \sum_{i \in \{10, 20, ...\}}^{N} rac{1}{log_2 i} \mid rac{|S^+_{1...i}|}{i} - rac{|S^+|}{N} \mid s$$

 $\frac{|S_{1...i}^+|}{i}$ : 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.

# **Group-Dependendent 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.

$$|A_{G_i>G_i}-A_{G_i>G_i}|$$
 should be close to 0.

#### 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.

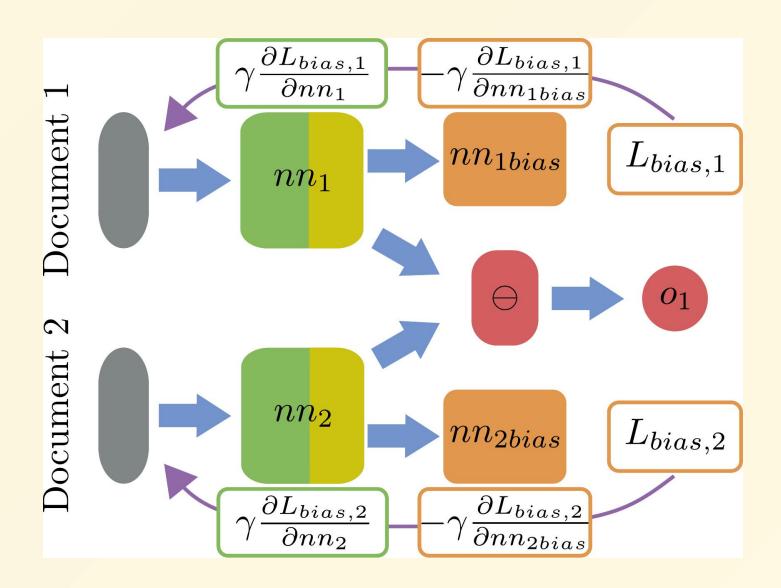
- The Gradient Reversal Layer of Ganin et al., 2016
- The Noise Module by Cerrato et al., 2020

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

#### The Fair DirectRanker Framework

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

#### Fair Adversarial DirectRanker



#### Fair Adversarial DirectRanker

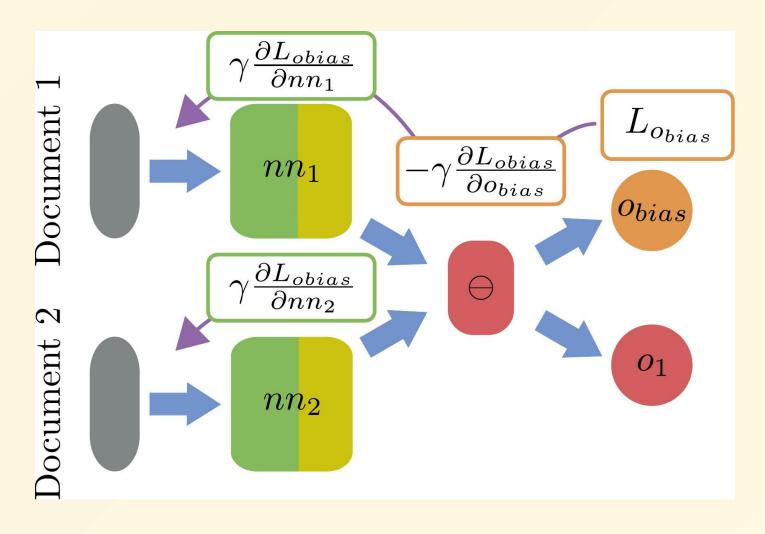
- Two debiasing networks try to predict the sensitive attribute/group the individual belongs to
- The gradient is *inverted* when backpropagating into the main network (Ganin et al. 2016)

#### Fair Adversarial DirectRanker

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

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

# Fair Flipped DirectRanker



# 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

$$egin{aligned} L(\Delta y, \Delta s, x_1, x_2) &= L_{ ext{rank}}(\Delta y, x_1, x_2) \ &+ \gamma L_{o_{bias}}(\Delta s, x_1, x_2) \end{aligned}$$

space for experimental results and discussion...