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Reinforcement Guided Multi-Task Learning Framework for Low-Resource Stereotype Detection

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Overview

Motivation

- Empirical success of large Pretrained Language Models led to them being ubiquitously used in daily-life applications that interact with humans. Unsupervised training on huge, uncurated datasets results in harmful text and societal bias creeping in their outputs

- This motivates a two-pronged solution:
  1) To diagnose and de-noise the bias in the PLMs
  2) To identify & regulate harmful text externally at the output

- This work focuses on the task of identifying *stereotypical associations* in text
- *Stereotypes* differ from other harmful text such as *hate speech, misogyny, abuse, threat, insult* etc., in two important ways:
  1) They could also express a positive sentiment towards the target
  2) We require knowledge of their existence in the society to identify them

Asians are good at math

My African-American friend loves watermelons

Contributions

- We devise a focused annotation effort for *"Stereotype Detection"* to construct a fine-grained evaluation dataset
- We leverage the existence of several correlated neighboring tasks to propose a *reinforcement-learning guided multitask framework* that identifies and leverages neighboring task data examples that are beneficial for the target task

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Dataset

Existing Datasets

- There are two existing datasets for mitigating Stereotypical bias. Both of them are diagnostic in nature:
    1) *Stereoset (Nadeem et al. 2020* [1])
    2) *CrowS-Pairs (Nangia et al. 2020* [2])

- Blodgett et al. (2021) [3] demonstrate that both the datasets suffer from conceptual and operational issues

- In addition, diagnostic datasets, by nature, also suffer from lack of coverage of subtle manifestations of stereotypes in text

Annotation Approach

- We address the coverage issue by collecting potential data samples for annotation from two subreddits: */r/Jokes* (stereotype-rich) and */r/AskHistorians* (stereotype-poor)

- To avoid operational and conceptual pitfalls, we use *Cardwell 1996* [4]'s definition of *Stereotype*: *"a fixed, over-generalized belief about a particular group or class of people"*

- We ask the annotators to answer three questions for each sample:
  1) Is an over-simplified belief about a type of person "intentionally" expressed in the text?
  2) Is there an "unintentional", widely-known stereotypical association present in the text?
  3) Does the sentence seem made up (unlikely to occur in regular discourse)?

Our Dataset

➢ This focused annotation approach allows us to categorize the examples into three classes: *explicit stereotypes, implicit stereotypes* and *non-stereotypes*. We use *anti-stereotypes* from existing datasets.

1) Ethiopians like stew (*explicit stereotype*)
2) The lawyer misrepresented the situation and tricked the person (*implicit stereotype*)
3) Jews spend money lavishly (*anti-stereotype*)
4) There is an Asian family that lives down the street (*non-stereotype*)

Data Type	Size
Explicit Stereotypes	742
Implicit Stereotypes	282
Non-Stereotypes	1197

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Model

Neighbor Tasks

- Several datasets for harmful language identification such as *hate speech detection, offensive language detection, misogyny detection* and *toxicity detection* are widely available. They often contain overlapping objectives. For example:

  1) She may or may not be a jew but, she's certainly cheap! (insult, stereotype)

  2) Burn in hell, you Asian bastard! (abuse, stereotype)

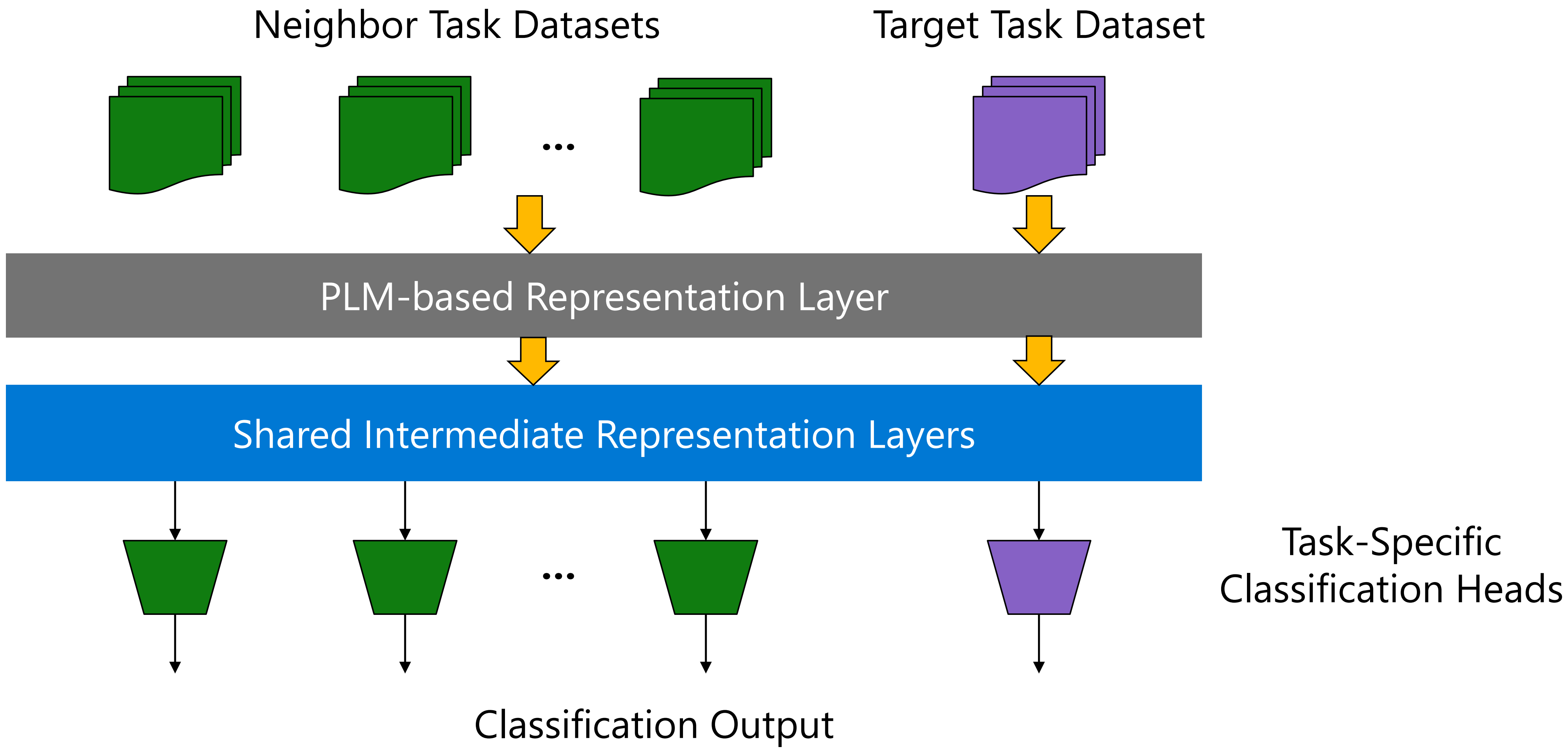
- We hypothesize that solving these tasks require understanding largely similar linguistic characteristics of the text. We call these tasks *"neighbor tasks"*.

Multi-Task Learning Model

- **Motivation:** Leverage the transfer learning gains from the neighbor tasks to improve the target task.

- As the tasks have "*overlapping objectives*" and largely require "*understanding similar linguistic characteristics*" of text, leveraging the *intermediate representations* from the neighbor tasks should benefit the target task.

Multi-Task Learning Architecture



RL-Guided Multi-Task Learning Model

- **Intuition:** *Not all examples from the neighbor task are equally useful in learning the target task*

- We train an RL-agent on top of the MTL model to identify examples from neighbor tasks, which are beneficial for the target task

  - **Step 1:** For each example in the neighbor task, RL-actor makes a *select*/*reject* decision
  - **Step 2:** MTL model is trained on the selected examples from the neighbor task
  - **Step 3:** The RL-actor is rewarded based on the *change in performance on the target task*
  - **Step 4:** The loss between *RL-actor's actual reward* and *RL-critic's expected reward* is used to train the RL-agent

4 Experiments

Experimental Setup

- We perform experiments using *six* datasets in *three* phases:
  - Phase 1: Fine-tune PLM-based classifier
  - Phase 2: Train a multi-task learning (MTL) model for all the datasets
  - Phase 3: Train RL-guided MTL model for each task as target task

- We experiment with *four* PLMs as base-classifiers: BERT-base, BERT-large (Devlin et al., 2019 [5]), BART-large (Lewis et al., 2020 [6]) and XLNet-large (Yang et al., 2019 [7])

- We use the following *six* datasets for our experiments:

1) Hate Speech Detection (de Gilbert et al., 2018 [8])
2) Offensive Language Detection (Davidson et al., 2017 [9])
3) Misogyny Detection (Fersini et al., 2018 [10])
4) Coarse-Grained Stereotype Detection: combination of *StereoSet* and *CrowS-Pairs* datasets
5) Fine-Grained Stereotype Detection (*our dataset*)
6) Jigsaw Toxicity Dataset [11] (*used only for training*)

Results

Model	Hate Speech Detection	Offense Detection	Misogyny Detection	Coarse-grained Stereotypes	Fine-grained Stereotypes
BERT-base	66.47	66.13	74.16	65.71	61.36
BERT-large	67.05	63.90	72.13	59.63	55.42
BART-large	68.91	65.86	73.12	63.40	54.64
XLNet-large	59.14	48.33	63.16	63.71	53.80
Multi-Task Learning					
BERT-base + MTL	69.21	68.57	73.48	68.29	65.00
BERT-large + MTL	69.78	65.14	73.94	61.96	61.65
BART-large + MTL	67.79	68.03	74.40	65.77	64.90
XLNet-large + MTL	61.68	46.35	64.42	65.21	57.00
RL-guided Multi-Task Learning					
BERT-base + RL-MTL	**72.06**	**68.97**	74.48	**74.18**	65.72
BERT-large + RL-MTL	69.82	65.97	**75.21**	70.88	64.74
BART-large + RL-MTL	69.60	66.76	75.14	74.11	**67.94**
XLNet-large + RL-MTL	61.97	47.60	63.21	67.98	56.37

5 Analysis

Impact of MTL Prior on RL-MTL

- In our experiments, we initialize the parameters of RL-MTL model with trained parameters from the MTL model.

- In this ablation, we initialize the RL-MTL model randomly and observe the difference in performance

Task	MTL Initialization	Random Initialization
Hate Speech Detection	72.06	70.23
Offense Detection	68.97	67.23
Misogyny Detection	74.78	71.10
Coarse-grained Stereotypes	74.18	60.42
Fine-grained Stereotypes	65.72	57.32

Neighbor Task Impact

- In this ablation, we study the impact of each neighbor task with each task as a target task

- It is interesting to note that *coarse-grained stereotype* data doesn't contribute as significantly to the performance improvement on *fine-grained stereotype detection task*. This might be due to the presence of anti-stereotypes and several other issues pointed out in Blodgett et al. (2021) [3].

Target \ Neighbor	Hate Speech Detection	Offense Detection	Misogyny Detection	Coarse-grained Stereotype
Hate Speech	-	69.69	70.07	**71.10**
Offensive Language	66.71	-	66.56	**67.39**
Misogyny	70.98	**75.87**	-	73.89
Coarse Stereotype	66.15	**67.40**	63.82	-
Fine Stereotype	**63.80**	63.65	59.94	56.12

Conclusion

- We tackle the problem of *Stereotype Detection* from *data annotation* and *low-resource computational framework* perspectives

- We devise a *focused annotation task* in conjunction with selective data candidate collection to create a fine-grained evaluation set for the task

- We utilize neighbor tasks with abundance of high-quality gold data in our *multi-task learning model*. We further propose an *RL-guided multi-task learning model* that learns to select examples from the neighbor tasks which benefit the target task.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Thank you

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