At the Intersection of NLP and Sustainable Development: Exploring the Impact of Demographic-Aware Text Representations in Modeling Value on a Corpus of Interviews.

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Demographic Rich Qualitative UPV-Interviews (DR-QI) corpus

DR-QI (data sheet) contains extracts of qualitative interviews conducted in rural communities in India and Uganda, which are annotated for UPV classification [1]. For each speaker, 10 self-reported categorical demographic features are included.

Motivation

Most research on demographic-aware text representation examines only a handful of features which are often modelled separately: while in reality identities are composite, resulting from the mutual influence of different demographic elements [2]. This study addresses this gap by investigating text classification with a rich set of demographic features.

Data Analysis and Models

We investigate the effect of adding 10 one-hot encoded demographic features (Fig 2) as model input for UPV classification. We use DistilBERT as the main encoder. In order to protect the privacy of speakers, we train an autoencoder to obscure demographic information.

Experiments

Including demographic information benefits UPV classification (Tab 1) even if this information is encoded, suggesting that autoencoders can be useful for protecting speakers’ identity. Further, an ablation study (Tab2) shows a large impact of economic features, while the popular features age and gender have little impact. This suggests that broadening the range of demographic features can be a promising research direction.

Fig 1: UPV interview in Uganda

Fig 2: Statistical features of demographic features in the DR-QI dataset

Fig 3: Demographic-aware models. Module 2 represents the UPV classifier. We experiment with encoding demographic vectors by a separately trained autoencoder (module 1).

<table>
<thead>
<tr>
<th>Experiments</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>65.43</td>
<td>81.84</td>
<td>69.12</td>
</tr>
<tr>
<td>Demographic</td>
<td>67.53</td>
<td>83.41</td>
<td>70.74</td>
</tr>
<tr>
<td>Encoded Dem.</td>
<td>69.33</td>
<td>82.52</td>
<td>72.01</td>
</tr>
</tbody>
</table>

Tab 1: Model performances for the baseline model (no demographic features), demographic model and the encoded demographic model

Tab 2: Ablation study. Model performance by removing one of the ten considered features at a time

Literature
