Abstract

The subtle and typically unconscious use of patronizing and condescending language (PCL) in large-audience media outlets undesirably feeds stereotypes and strengthens power-knowledge relationships, perpetuating discrimination towards vulnerable communities. Due to its subjective and subtle nature, PCL detection is an open and challenging problem, both for computational methods and human annotators. In this paper we describe the systems submitted by the DH-FBK team to SemEval-2022 Task 4, aiming at detecting PCL towards vulnerable communities in English media texts. Motivated by the subjectivity of human interpretation, we propose to leverage annotators’ uncertainty and disagreement to better capture the shades of PCL in a multi-task, multi-view learning framework. Our approach achieves competitive results, largely outperforming baselines and ranking on the top-left side of the leaderboard on both PCL identification and classification. Noticeably, our approach does not rely on any external data or model ensemble, making it a viable and attractive solution for real-world use.

1 Introduction

Detecting patronizing and condescending language (PCL) is an open, challenging, and underexplored research area in natural language processing (Pérez-Almendros et al., 2020; Wang and Potts, 2019). A patronizing and condescending attitude is expressed as a good-natured and beneficial attitude from a person of authority towards others, who are typically depicted in a subtly compassionate way (Pérez-Almendros et al., 2020).

PCL is a mildly perceived phenomenon. It is often unconscious, driven by good intentions, and expressed through flowery wordings (Wong et al., 2014; Huckin, 2002). This makes PCL identification and classification difficult both for NLP systems and human annotators (cf. Figure 1), as it cannot be linked to specific words. Nonetheless, it undesirably conveys harmful messages in many ways, as it promotes stereotypes, and a superiority and discriminatory mindset (Fiske, 1993). This is particularly damaging when used by large-audience media outlets, since it drives greater exclusion of already vulnerable communities (Pérez-Almendros et al., 2020). Automatically detecting PCL has the potential to enable a range of applications and research directions, such as suggestion tools for news editors to mitigate condescension in writing before publication, and studies on the interplay between condescension and sociodemographic factors.

To encourage research on patronizing and condescending language detection, the SemEval-2022 Task 4 (Pérez-Almendros et al., 2022) has recently been proposed. The shared task aims at investigating methods for the identification of PCL (subtask 1; Figure 1, top) and the categorization of the linguistic techniques which are used to express it (subtask 2; Figure 1, bottom) on English news stories mentioning vulnerable communities (Section 2).

In this paper, we present the DH-FBK entry for the SemEval-2022 Task 4 (Pérez-Almendros et al., 2022). Motivated by the subtle nature of
patientizing language and the subjectivity of human interpretation, we propose a multi-task, multi-view learning approach which leverages annotators’ uncertainty and disagreement as auxiliary tasks (Section 3) in judging for PCL presence (subtask 1) or category (subtask 2). Further, we investigate the effectiveness of sequentially fine-tuning on subtasks of increasing complexity (subtask 1 $\rightarrow$ subtask 2), as well as the use of additional information such as the geographical provenance of news outlets.

Our systems achieve competitive results on the SemEval-2022 Task 4, outperforming the organizers’ RoBERTa (Liu et al., 2019) baseline by a large margin (subtask 1: +8.8 F$_1$; subtask 2: +26.9 F$_1$) and consistently ranking on the top-left side of the leaderboard (subtask 1: 18th out of 78 teams; subtask 2: 13th out of 49 teams) without using any external data or ensemble strategy, making it a viable solution for real-world use. We make our code publicly available to the research community to encourage future work on this direction.\footnote{The source code is available at https://github.com/dhfbk/pcl-detection-disagreement.}

## 2 Data and task description

In this section, we present relevant details on data and the associated shared task. We firstly summarize the dataset (Section 2.1) and describe the task setup (Section 2.2). Next, we focus on the data annotation process as it is central for understanding our methods (Section 2.3).

### 2.1 “Don’t Patronize Me!” data

The organizers of SemEval-2022 Task 4 provide participant teams with the “Don’t Patronize Me!” annotated dataset, originally introduced in Pérez-Almendros et al. (2020) and further updated for the purpose of the shared task (v1.4). The dataset comprises a selection of 10,469 paragraphs published in the news of 20 English-speaking countries\footnote{Covered English-speaking country codes: au, bd, ca, gb, gh, hk, ie, in, jm, ke, lk, my, nz, ph, pk, sg, tz, us, and za.} from all over the world between 2010 and 2018, and sampled from the “News on Web” corpus (NoW; Davies, 2013). Each paragraph mentions one of ten selected vulnerable communities (i.e., disabled, homeless, hopeless, immigrant, in need, migrant, poor families, refugee, vulnerable, and women). These communities have been chosen because they are often target of PCL. Notably, attention has been paid to balance paragraphs across communities and news outlets’ countries. For further details, we refer to Pérez-Almendros et al. (2022, 2020).

### 2.2 Task setup

The SemEval-2022 Task 4 challenge is divided into the following two subtasks:

1. **PCL identification**: given an input paragraph, identify whether it entails any form of PCL. Formally, this is a binary classification task;

2. **PCL classification**: given an input paragraph, decide what linguistic techniques are used to express the condescension (if any). This is a multi-label classification task, with 7 possible labels – i.e., unbalanced power relations (UNB), shallow solution (SHA), presupposition (PRE), authority voice (AUT), metaphor (MET), compassion (COM), and the poorer, the merrier (THE). These categories follow a validated PCL taxonomy (Pérez-Almendros et al., 2020) that we summarize in Appendix A. Examples for each category are in Table 1.

As PCL is a subtle and mild phenomenon, the annotation process was not straightforward (Pérez-Almendros et al., 2020). In the following section, the annotation scheme followed by dataset creators

| Example                                                                 | Category                      |
|------------------------------------------------------------------------|-------------------------------|
| “We can be extremely proud of the current women winemakers”           | Unbalanced power relations    |
| “The inclusion of a refugee team”                                     | Shallow solution              |
| “An immigrant to a developed country lives in two worlds”              | Presupposition                |
| “women must wake up”                                                   | Authority voice               |
| “trapped in the prison of poverty”                                     | Metaphor                      |
| “more than 400 suspected asylum seekers are awaiting their fate”      | Compass                       |
| “how talented disabled people can be”                                  | The poorer, the merrier       |

Table 1: Examples of text excerpts expressing patronizing and condescending language, along with their category.
is presented, as it is especially relevant for understanding the data itself and our methods.

2.3 Annotation process

The dataset has been manually labeled by expert annotators following a two-step process as described below. The resulting annotations are the gold-standard reference for the subtasks (Section 2.2).

**Subtask 1** The annotation was performed by three annotators. Two annotators labeled the whole dataset \( (a_1, a_2) \), while a third one \( a_3 \) intervened in case of clear disagreement between \( a_1 \) and \( a_2 \). Authors reported that “this annotation step proved more difficult than expected, stemming from the often subtle and subjective nature of PCL” (Pérez-Almendros et al., 2020). Because of this difficulty, annotators were given the possibility to assign each paragraph a value 0 (no PCL), 1 (mild PCL) or 2 (high PCL). Information about the annotation is available as a 5-point scale, which reflects a joint notion of uncertainty and agreement between annotators. For subtask 1, organizers map values into a binary form (i.e., \{0, 1\} ↦→ NO-PCL, \{2, 3, 4\} ↦→ PCL), evaluating systems accordingly. As anticipated, cases of total disagreement (i.e., \( a_1: 0 \) and \( a_2: 2 \), and viceversa) received a third independent annotation by \( a_3 \). If \( a_3 \) considered the paragraph not to contain PCL, a borderline case, or another clear PCL case, the paragraph was assigned a value of 1, 2 or 3, respectively. This has the effect to leave extreme values (0 and 4) reserved for clear-cut cases. The number of PCL-expressing paragraphs is 993 (9.5%). A summary of the annotation process for subtask 1 is in Table 2, top.

**Subtask 2** In the second round of annotation, paragraphs previously labeled as containing PCL were further characterized by \( a_1 \) and \( a_2 \). The aim is two-fold: (i) identify the paragraph segments (or spans) that express PCL, and (ii) categorize each of them into one or more PCL categories (cf. Section 2.2). As a consequence, each identified span exhibits one or multiple labels, depending on whether one or both annotators identified it, and on their agreement on the type(s) of condescension expressed by the text segment. This results in a per-span per-type agreement information on a 2-point scale (1 or 2). Organizers frame subtask 2 as a paragraph-level classification problem, and thus each paragraph can express zero or more condescension types based on the resulting 2,760 span annotations (2.8 annotations per paragraph, on average). An overview of the annotation process for subtask 2 is presented in Table 2, bottom.

### Table 2: The annotation process from individual annotators’ decisions to gold labels for both subtasks.

| Annotation task | Individual decisions \((a_1, a_2)\) | Score | Instances | Gold label |
|-----------------|----------------------------------|-------|-----------|------------|
| **Subtask 1:** “Does the paragraph contain any form of PCL?” | (0,0) \((0,1), (1,0), *\) | 0 | 8,529 | No |
| Values: 0, 1, 2 | (1,1), * | 2 | 144 | |
| | (2,1), (1,2), * | 3 | 458 | |
| | (2,2) | 4 | 391 | |
| **Subtask 2:** “Which PCL category does the span express (if any)?” | \((c_i, \text{NONE}), (\text{NONE}, c_i)\) | 1 | 1,359 | \(c_i\) |
| Values: \(c_i, c_j \in C\), NONE | \((c_i, c_j)_{c_i \neq c_j}, (c_j, c_i)_{c_i \neq c_j}\) | 2 | 1,401 | \(c_i, c_j\) |

3Dataset authors reported the annotators’ background is on the fields of communication, media, and data science.

4According to the first dataset release, these account for 5.5% of the annotations (Pérez-Almendros et al., 2020).

326
Then, we provide details on data- and task-specific components that we use in our systems, namely dataset views (Section 3.2) and auxiliary tasks (Section 3.3). Lastly, we present the composition of our final models (Section 3.4).

### 3.1 General framework

Our approach is based on multi-task learning, a learning paradigm that aims to leverage training signals of related tasks at the same time by exploiting a shared representation in the model (Caruana, 1997). In all our models, we employ a main task, namely PCL identification or classification, which is a task of direct interest. Additionally, we employ auxiliary tasks (see Section 3.3), namely tasks which can provide useful signals to potentially improve the performance on the main task.

All our models use RoBERTa-base (Liu et al., 2019) as shared encoder, and a separate decoder for each task. This way, all tasks benefit from mutual signals encoded by a shared contextualized representation that is jointly fine-tuned during training.

The input is a text instance that is encoded using byte-pair encoding (BPE; Sennrich et al., 2016), whereas the output label is given by task-specific decoders which consist of a linear classification layer and operate on the contextual embedding of the special [CLS] classification token.

In our models, each auxiliary task makes use of a specific form (or view) of the original dataset, which we introduce in the following (Section 3.2). When training with multiple views of data, each input batch to the model consists of examples from a single data view, and the loss function is only activated for tasks associated to that data view. For further details on multi-view (or multi-dataset) training, refer to van der Goot et al. (2021). An overview of the framework is presented in Figure 2.

### 3.2 Data views

Our models employ different forms (or views) of the original “Don’t Patronize Me!” dataset provided by organizers. Specifically, we use (i) paragraph and (ii) span views as detailed as follows.

**Paragraph data view (DP)** This corresponds to the dataset in its standard form – i.e., whole paragraphs – as provided by organizers (Section 2.1).

**Span data view (DS)** A dataset consisting of all text excerpts – i.e., paragraph substrings – that have been marked as expressing patronizing and condescending language. As a result, this dataset represents a different view of DP data, where only snippets of PCL are included. Examples of text instances in DS are reported in Table 1.

These different data views are used by specialized task decoders, as presented in Section 3.3.

### 3.3 Auxiliary tasks

In this section, we describe the auxiliary tasks we used in one or more of our final models (Section 3.4), along with the data view each task uses. For details on the interplay between main and auxiliary tasks, we refer the reader to Section 4.1.

**Paragraph uncertainty level (UNCERTAINTY)** This task is used for subtask 1 to consider different annotators’ point of view in identifying PCL. We use the aggregated 5-point scale score (cf. Section 2.3, subtask 1) assigned to each paragraph as auxiliary task. Although disaggregated annotators’ decisions have not been made available for the shared task, we argue that the combined annotation provided by organizers can be viewed as a joint notion of uncertainty and agreement between annotators in identifying PCL, and is thus valuable information that can inform PCL identification. Since this is a paragraph-level information, this auxiliary task uses the DP data view. For each paragraph, a label \( l \in \{0, 1, 2, 3, 4\} \) must be predicted.

**Span agreement level (AGREEMENT)** This task is used for subtask 2 as it potentially drives useful signals for PCL classification. We hypothesize that the number of annotators which agree on a particular PCL category for a span (cf. Section 2.3, subtask 2) is a crucial information as it can provide the main task with different shades of PCL based on annotators’ interpretation and sensibility. The
agreement level is a span-level information, and thus we use the $D_S$ view for the associated task. For each span, a label $l \in \{1, 2\}$ must be predicted.

**Span categorization (SPAN)** This auxiliary task is used for both subtask 1 and 2, as we argue that making use of small and focused units of information such as condescending text excerpts would be useful to inject knowledge in the encoder about which paragraph segments are important for recognizing PCL. The task uses the $D_S$ data view, and for each span a label $l \in \{\text{UNB}, \text{SHA}, \text{PRE}, \text{AUT}, \text{MET}, \text{COM}, \text{THE}\}$ has to be predicted (i.e., one among the condescending types in Section 2.2).

**News outlet country (COUNTRY)** We employ this auxiliary task for our subtask 2 model. We hypothesize that the diverse background culture of countries results in variation in language use, and thus could have an impact on the expression of patronizing and condescending language. The news outlet provenance is provided by organizers along with the original dataset. The auxiliary task uses the $D_P$ view, and the label to be predicted is a country code, i.e., $l \in \{\text{au, bd, ca, gb, gh, hk, ie, in, jm, ke, lk, my, ng, nz, ph, pk, sg, tz, us, za}\}$.

### 3.4 Models
Our approaches to PCL identification and classification are all centered on the hypothesis that leveraging annotators’ uncertainty and disagreement during training is beneficial for capturing the subtle language which characterizes PCL. This is in line with recent work emphasizing the importance of modeling annotators’ disagreement in subjective tasks (Davani et al., 2022; Leonardelli et al., 2021; Uma et al., 2021) and initiatives supporting the release of disaggregated annotations in NLP (Abercrombie et al., 2022).

We participated in the SemEval-2022 Task 4 challenge with two submissions for both subtasks. To this end, we built three models. Two models are our best systems – as evaluated on the development set (cf. Section 4.3) – on subtask 1 (Section 3.4.1) and subtask 2 (Section 3.4.2). We submit them for the corresponding subtasks. The third model was instead built aiming at a generic and unified solution, and represents our second submission for both subtasks (Section 3.4.3).

#### 3.4.1 MTMW(UNC+SPAN) model for PCL identification (subtask 1)
In this multi-task, multi-view model (MTMW), we consider PCL identification as the main (binary classification) task, and employ UNCERTAINTY and SPAN as auxiliary tasks, as described in Section 3.3. We refer to this model to as MTMW(UNC+SPAN). An overview of the resulting approach for PCL identification is presented in Figure 3a.

#### 3.4.2 MTMW(AGR+COU+SPAN) model for PCL classification (subtask 2)
In this multi-task, multi-view model (MTMW), the main task is PCL classification, whereas AGREEMENT, COUNTRY and SPAN are auxiliary tasks. For PCL classification, each label is modeled through a dedicated binary classification decoder. We use MTMW(AGR+COU+SPAN) to refer to this approach in the remainder of this paper. We graphically
present the model in Figure 3b, and refer the reader to Section 3.3 for details on auxiliary components.

### 3.4.3 Sequential PCL identification and classification (subtasks 1 & 2)

Given that PCL classification is a fine-grained version of the PCL identification task, we argue that sequentially fine-tuning encoder weights on tasks of increased complexity should be beneficial to improve the performance on both subtasks. This approach borrows the idea from modern data-centric adaptation methods in NLP (Ramponi and Plank, 2020) such as continued pretraining of language models (Gururangan et al., 2020), however employing it at the fine-tuning stage, similarly to intermediate-task transfer (Phang et al., 2018).

We firstly run the PCL identification model described in Section 3.4.1. Then, we use the resulting fine-tuned encoder weights as initialization for the encoder of the PCL classification model (Section 3.4.2) with SPAN auxiliary only.6 Finally, we fine-tune it on subtask 2. This results in a single model that has incrementally learnt the complexity of PCL detection as a whole. Prediction of labels for subtask 1 were done simply considering a paragraph as containing PCL if it exhibits at least a PCL category label in subtask 2. We refer to this approach to as SEQ. FINE-TUNING model.

### 4 Experiments

In this section, we first outline the experimental setup (Section 4.1). Then, we present the results of our models (Section 4.2), as well as additional analyses and discussion (Section 4.3).

#### 4.1 Experimental Setup

We implemented our models using the MaChAmp v0.2 toolkit (van der Goot et al., 2021) and employ RoBERTa-base (Liu et al., 2019) as shared encoder since it has been shown to outperform other commonly used pretrained language models on PCL detection tasks (Pérez-Almendros et al., 2020).

For training, we use default hyperparameters (Appendix B) and fine-tune each model – roughly 110M trainable parameters – for 10 epochs on a single GPU.7 We use a cross-entropy loss with balanced class weights to give equal importance to all classes during fine-tuning, and thus emphasizing underrepresented classes in training data. The multi-task learning loss is computed as $L = \sum_t \lambda_t L_t$, where $L_t$ is the loss for task $t$, and $\lambda_t$ the corresponding weighting parameter. In our experiments, we empirically set $\lambda_1 = 1$ for the main task, and $\lambda_t = 0.25$ for auxiliary tasks.8

We solely rely on data provided by organizers, and use the provided 80% train and 20% development split as one fold, additionally creating the remaining 80%/20% splits in a stratified fashion. To avoid confounding our results, we ensure training splits for the span data view do not contain any text excerpt appearing in development data of the paragraph data view. This results in 5 folds that we use for selecting models for our submissions. For official test set evaluation, we then submit the selected models trained on the provided data split.

For the purpose of the shared task, models for PCL identification (subtask 1) are evaluated using F1 score over the positive class, whereas models for PCL classification (subtask 2) are evaluated based on macro-average F1 score. We employ the same metrics at the model selection stage.

#### 4.2 Results

We present the official results for our proposed models for subtask 1 and 2 in Table 3 and Table 4, respectively. We also include scores of the organizers’ RoBERTa baseline for informed comparison based on the shared task metrics.

**Subtask 1** As shown in Table 3, our submitted MTMW(UNC+SPAN) model outperforms the RoBERTa baseline by a large margin, with most of the benefit coming from the precision metric. This indicates that the uncertainty and agreement

|                | P   | R   | F1  |
|----------------|-----|-----|-----|
| Organizers’ baseline | 39.35 | 65.30 | 49.11 |
| MTMW(UNC+SPAN)     | 64.23 | 52.68 | 57.89 |
| SEQ. FINE-TUNING   | 53.99 | 55.52 | 54.74 |

Table 3: Official test set results of our models compared to the organizers’ RoBERTa baseline on PCL identification (subtask 1). P: Precision; R: Recall; F1: F1 score over the positive class. Best results are in bold.

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6This choice is motivated by the need for a simpler and unified solution for both subtasks. We decided to leave country and agreement auxiliaries out for this submission due to negligible differences in performance on subtask 2 (Section 4.3).

7NVIDIA Tesla V100-SXM2.

8Except for AGREEMENT, for which we empirically set $\lambda = 0.125$ since it is actually auxiliary of an auxiliary task. A thorough investigation on the impact of the weighting parameter on individual auxiliary tasks is left for future work.
level as well as the use of focused text excerpts do play a positive role in PCL identification. On the other hand, while also the SEQ. FINE-TUNING approach provides better results compared to the baseline, it scores lower than MTMW (UNC+SPAN). A reason for this behavior can be attributed to the way we infer labels for this subtask (i.e., based on predictions for subtask 2, as anticipated in Section 4.3.3), or due to catastrophic forgetting (McCloskey and Cohen, 1989), a phenomenon in which prior knowledge is largely forgotten when learning a new task. On the shared task leaderboard, MTMW (UNC+SPAN) ranked 18th out of 78 teams.

**Subtask 2** Similarly to results for subtask 1, both our submitted systems largely outperform the RoBERTa baseline, as shown in Table 4. We notice that the SEQ. FINE-TUNING approach still scores lower than a tailored approach for subtask 2, i.e., MTMW (AGR+COU+SPAN). Specifically, MTMW (AGR+COU+SPAN) shows an absolute improvement of +26.9 points in macro-average F1 score over the RoBERTa baseline, with a clear advantage over the SEQ. FINE-TUNING model on underrepresented classes (i.e., AUT, MET and THE). Our MTMW (AGR+COU+SPAN) model ranked 13th out of 49 participating teams on the official leaderboard. Overall, our models do not require any external data or model ensemble, and we think this makes them viable approaches for real-world use.

### 4.3 Analysis and discussion

In order to provide insights for future work on PCL detection, we conduct analyses on the contribution of auxiliary tasks to performance of our models (Section 4.3.1), and an in-depth study on the role of uncertainty and disagreement (Section 4.3.2).

#### 4.3.1 Contribution of auxiliary tasks

Our submitted models for PCL identification and classification leverage training signals coming from selected auxiliary tasks (cf. Section 3.4). These model variants have been chosen after a thorough performance evaluation on the development splits. In Table 5 we report the mean and standard deviation of F1 scores for each model with different auxiliary task configurations. We denote with “Our single task baseline” our baseline RoBERTa model with no multi-task nor multi-view learning. Note that this is different from organizers’ RoBERTa baseline, since we employ a different hyperparameter setup with the addition of class weights (Section 4.1). We do not include the organizers’ baseline here due to incomparability –

| Model                                      | F1 score     |
|--------------------------------------------|--------------|
| **subtask 1**                              |              |
| Our single task baseline                   | 56.73±3.2    |
| Multi-task setup                           |              |
| + COUNTRY                                  | 55.99±2.7    |
| + UNCERTAINTY                              | 56.92±3.2    |
| + COUNTRY, UNCERTAINTY                     | 57.74±3.5    |
| Multi-task, multi-view setup               |              |
| + COUNTRY                                  | 55.69±2.0    |
| + UNCERTAINTY                              | 57.35±1.9    |
| + COUNTRY, UNCERTAINTY                     | **58.38±3.7**|
| **subtask 2**                              |              |
| Our single task baseline                   | 37.02±2.8    |
| Multi-task setup                           |              |
| + COUNTRY                                  | 36.26±2.3    |
| Multi-task, multi-view setup               |              |
| + COUNTRY                                  | 38.25±3.6    |
| + AGREEMENT                                | 37.16±2.3    |
| + COUNTRY, AGREEMENT                       | 38.81±2.9    |

Table 5: Contribution of auxiliary tasks to performance of models for subtask 1 (top) and subtask 2 (bottom). We report mean and standard deviation of F1 scores on development splits. The multi-task, multi-view setups use SPAN by default. Results for AGREEMENT and its combinations in the multi-task setup of subtask 2 are omitted, since they would require the D5 view, and thus only refer to the multi-task, multi-view configuration.
we only have access to results on a single development split. For reference, organizers reported 48.29 F1 on subtask 1, and 13.40 F1 on subtask 2 for their baseline. Multi-task setups refer to configurations where \( D_P \)-based auxiliaries are used, whereas multi-task, multi-view setups also exploit the \( D_S \) view, thus using \textsc{span} as default auxiliary task on all experiments.

**Subtask 1** Table 5 (top) shows the results of models with different auxiliary task combinations on subtask 1 development data. All multi-task, and multi-task multi-view setups outperform the baseline, with the only exception of the multi-task configuration solely using \textsc{country} as auxiliary task. Overall, the use of \textsc{uncertainty} as auxiliary task consistently improves the performance over the baseline, even when coupled with other auxiliaries. The best results are obtained when employing a multi-task, multi-view setup with \textsc{uncertainty} only (58.38 F1), suggesting that information coming from the \textsc{country} auxiliary is not as useful as in the multi-task scenario. We hypothesize this behaviour could be attributed to the use of \textsc{span} in the multi-task, multi-view setup, which indirectly provides a more useful inductive bias for \textsc{pcl} identification. In future work we aim to further dig into this aspect, exploring various loss weight configurations to assess the strength of this finding.

**Subtask 2** We present in Table 5 (bottom) the contribution of auxiliary tasks on subtask 2 development data. Similarly to subtask 1, \textsc{country} in the multi-task setup is the only auxiliary task that does not improve the performance over our single task RoBERTa baseline. However, when coupled with agreement in the multi-task, multi-view configuration, it provides the best overall performance over all model variants (38.81 F1). This suggests that the agreement auxiliary provides signals orthogonal to \textsc{country}, as shown by the multi-task, multi-view alternatives employing these auxiliaries in isolation. By a closer look, the performance of the multi-task, multi-view setup alone (i.e., \textsc{span} only) are highly competitive, confirming our hypothesis that using \textsc{pcl}-expressing text excerpts is beneficial for \textsc{pcl} detection as a whole.

### 4.3.2 Role of uncertainty and disagreement

To delve into the role of agreement and uncertainty, we further study performance of our best systems on subtask 1 and 2 as a function of the agreement/uncertainty level. To the goal, we use the predictions of our models on development splits.

#### Subtask 1

To investigate the impact of uncertainty/agreement on the performance of our model for subtask 1, we first divided each development split by uncertainty/agreement level (cf. “Score”, Table 2, top). Then, we calculated the per-level F1 score on each split. Finally, we averaged the per-level performance on all folds. We report the experimental results in Table 6. It is interesting to observe how in this task the uncertainty/agreement levels 0, 2 and 4 reflect agreement between annotators (0+0, 1+1, or 2+2), but performance for score 2 – where both annotators agree in being uncertain – is much worse. This suggests a prominent role of uncertainty in worsening classifier’s performance, rather than disagreement. On the other hand, uncertainty and disagreement represent two sides of the same coin, as the less certain and clear a decision is, the greater probability is to have disagreement between annotators.

#### Subtask 2

We perform a similar analysis for subtask 2. The agreement level (cf. “Score”, Table 2, bottom) has a clear effect on model’s performance: out of the 2,760 \textsc{pcl}-expressing spans, only 44% of 1,359 spans with an agreement level of 1 are correctly labeled, compared to 56% of 1,401 spans for which both annotators signaled a form of \textsc{pcl}. Considering paragraphs with a single \textsc{pcl}-expressing span only, this results to 35% of 801 examples for agreement level 1, and 52% of 798 examples for agreement 2, further confirming that instances exhibiting disagreement are more difficult to classify.

### 5 Conclusion

In this paper, we presented our submitted systems to SemEval-2022 Task 4. We showed that leveraging annotators’ uncertainty and disagreement during training in a multi-task, multi-view framework is beneficial for the identification and classification of patronizing and condescending language, and achieves competitive results on the official leaderboard without relying on any external data or model.
ensemble. We also showed that sequential fine-tuning is a viable alternative to tackle PCL identification and classification jointly, with the goal of reducing the use of computational resources during inference, although it obtains lower performance compared to our tailored solutions. A thorough analysis on the impact of diverse auxiliary tasks on the performance of our models for PCL detection, and an investigation on the role of uncertainty and disagreement further confirmed the importance of considering annotators’ point of view in PCL detection. As future work, we aim to test the presence and assess the impact of spurious lexical biases in the dataset (Ramponi and Tonelli, 2022) and extend our models to other genres, such as social media (Wang and Potts, 2019). We hope this work will encourage future efforts towards annotators-centric NLP, on PCL detection and other subjective tasks more broadly.

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Appendix

A PCL categories

In the following, we provide the precise definitions of the PCL categories according to Pérez-Almendros et al. (2020).

Unbalanced power relations “By means of the language, the author distances themselves from the community or the situation they are talking about, and expresses the will, capacity or responsibility to help them. It is also present when the author entitles themselves to give something positive to others in a more vulnerable situation, especially when what the author concedes is a right which they do not have any authority to decide to give.”

Shallow solution “A simple and superficial charitable action by the privileged community is presented either as life-saving/life-changing for the unprivileged one, or as a solution for a deep-rooted problem.”

Presupposition “When the author assumes a situation as certain without having all the information, or generalises their or somebody else’s experience as a categorical truth without presenting a valid, trustworthy source for it (e.g. a research work or survey). The use of stereotypes or cliches are also considered to be examples of presupposition.”

Authority voice “When the author stands themselves as a spokesperson of the group, or explains or advises the members of a community about the community itself or a specific situation they are living.”

Metaphor “[Metaphors] can conceal PCL, as they cast an idea in another light, making a comparison between unrelated concepts, often with the objective of depicting a certain situation in a softer way. [...] Euphemisms are considered as an example of metaphors.”

Compassion “The author presents the vulnerable individual or community as needy, raising a feeling of pity and compassion from the audience towards them. It is commonly characterized by the use of flowery wording that does not provide information, but the author enjoys the detailed and poetic description of the vulnerability.”

The poorer, the merrier “The text is focused on the community, especially on how the vulnerability makes them better (e.g. stronger, happier or more resilient) or how they share a positive attribute just for being part of a vulnerable community. People living vulnerable situations have values to admire and learn from. The message expresses the idea of vulnerability as something beautiful or poetic. We can think of the typical example of ‘poor people are happier because they don’t have material goods.’”

B Hyperparameters

The hyperparameter setting for all our models is presented in Table 7. This reflects the default MaChAmp’s hyperparameter values (van der Goot et al., 2021), with the addition of loss weights, as introduced in Section 4.1, and 10 epochs of training as suggested in the original RoBERTa publication (Liu et al., 2019).

C Credits

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