InfoDCL: A Distantly Supervised Contrastive Learning Framework for Social Meaning

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Abstract

Existing supervised contrastive learning frameworks suffer from two major drawbacks: (i) they depend on labeled data, which is limited for the majority of tasks in the real-world, and (ii) they incorporate inter-class relationships based on instance-level information, while ignoring corpus-level information, for weighting negative samples. To mitigate these challenges, we propose an effective distantly supervised contrastive learning framework (InfoDCL) that makes use of naturally occurring surrogate labels in the context of contrastive learning and employs pointwise mutual information to leverage corpus-level information. Our framework outperforms an extensive set of existing contrastive learning methods (self-supervised, supervised, and weakly supervised) on a wide range of social meaning tasks (in-domain and out-of-domain), in both the general and few-shot settings. Our method is also language-agnostic, as we demonstrate on three languages in addition to English.

1 Introduction

Contrastive learning (CL) aims at bringing semantic representations of instances of a given class (e.g., positive pairs of the same objects in images or same topics in text) closer and representations of negative class(es) instances farther away (Fang and Xie, 2020; Liu et al., 2021a; Gao et al., 2021; Wang and Liu, 2021). One way most CL frameworks differ is how positive pairs are defined. In self-supervised contrastive learning (SSCL), a positive pair is typically formed by pairing an anchor sample with its transformation (e.g., cropping an image (Cubuk et al., 2018; Caron et al., 2020; Chen et al., 2020), replacing some words in a sentence with their synonyms (Wang et al., 2021)). On the other hand, supervised contrastive learning (SCL) not only uses the transformation of an anchor but also samples from the same class as its positive samples exploiting gold-labeled data. Existing SCL frameworks (Khosla et al., 2020; Gunel et al., 2021; Suresh and Ong, 2021; Gao et al., 2021; Zhang et al., 2021b) suffer from two major drawbacks. The first drawback is SCL’s dependence on task-specific labeled data (which is required to identify positive samples in a batch). Recently, Zheng et al. (2021) introduced a weakly-supervised contrastive learning (WCL) objective for computer vision, which generates a similarity-based 1-nearest neighbor graph in each batch and assigns weak labels for samples of the batch (thus clustering vertices in the graph). It is not clear, however, how much an WCL method with augmentations akin to language would fare for NLP. We propose a framework that does not require model-derived weak labels, which outperforms a clustering-based WCL approach. The second drawback with SCL is related to how negative samples are treated. Gao et al. (2021); Khosla et al. (2020); Gunel et al. (2021) treat all the negatives equally, which is sub-optimal since confusable negatives should be more informative. To rectify this, Suresh and Ong (2021) introduce a label-aware contrastive loss (LCL) where they feed the anchor sample to a task specific model and assign higher weights to confusable negatives based on this model’s confidence on the class corresponding to the negative sample. The LCL solution introduced by Suresh and Ong (2021) is costly since it requires an auxiliary task-specific model to be trained with the main model. We introduce a variant of LCL that does not depend on an additional task-specific model (Section 3.3). LCL also only considers instance-level information (i.e., instance representation) to capture relationships between different classes. In this work, we introduce an effective contrastive loss that takes into account corpus-level information (Section 3.4).

Concretely, to overcome existing drawbacks, we propose InfoDCL, a novel distantly supervised contrastive learning (DCL) framework that exploits...
surrogate labels as a proxy for gold labels and incorporates corpus-level information to capture inter-class relationships alongside an enhanced version of instance-level information proposed by Suresh and Ong (2021). Without loss of generality, we apply the proposed framework for learning task-agnostic text representations that are transferable to a wide range of particularly social meaning tasks (e.g., emotion, hate speech, humor, sarcasm). To instantiate the proposed framework, we use emojis naturally occurring in tweets as surrogate labels, where a positive pair is created by pairing a tweet with another tweet that shares the same emoji and negative samples are picked from the same batch using tweets that employ different emojis. For weighing negative samples, besides an instance-level measure, we propose a corpus-aware measure based on pointwise mutual information (PMI) of class pairs (emoji pairs) obtained from co-occurrence of the emoji classes from large unlabeled social media text (tweets). Our corpus-aware weighting method (based on PMI) is on par with our enhanced instance-level weighting strategy. When we combine the two, we acquire an overall better model performance (see our ablation studies in Section 6). Our proposed framework also exploits cross-entropy based distantly supervised learning and self-supervised training, i.e., masked language modeling (MLM). More generally, we show that other surrogate labels such as hashtags can be used successfully with our proposed approach (Section E.4 in Appendix). Since surrogate labels are abundant (e.g., hashtags accompanying images or videos), we hypothesize our approach can be extended beyond language tasks (although we leave this for future research). Our method provides sizable gains on both in-domain social media data, but also out-of-domain data (Section 5). We also show the utility of our method on several tasks on three languages, in addition to English (Section E.3). Our framework is also strikingly successful in few-shot learning (Section 5).

We evaluate the quality of short text representations learned by our proposed framework on 24 social meaning datasets and compare against an extensive set of competitive frameworks (11 baselines). Our proposed framework outperforms all competitive frameworks on 14 (out of 16) in-domain tasks and seven (out of eight) out-of-domain tasks. In few-shot experiments, our framework also consistently outperforms our baselines (by a large margin) for different percentages of training data. We further perform ablation studies to understand sources of improvement in our proposed framework and qualitative studies on the quality of learned sequence-level representations. Our major contributions are as follows: (1) We introduce InfoDCL, a novel framework that exploits surrogate labels, which is abundant especially in social media language, image, and video. (2) Our novel approach makes use of both instance-level and corpus-level information to weigh negative samples within a contrastive learning framework. (3) Our framework outperforms several competitive methods on a wide range of social meaning tasks (both in-domain and out-of-domain, and for general and few-shot settings). (4) Our framework is language-independent, as demonstrated by its utility on various tasks on four languages. (5) We offer an extensive number of ablation studies that show the contribution of each component in our framework, as well as a qualitative analysis that demonstrates the superiority of the representation our model learns.

2 Related Work

Our work combines advances in representation learning and contrastive learning. Representation learning. Pre-trained language models (PLM) such as BERT (Devlin et al., 2019) encode discrete language symbols into a continuous representation space. BERT employs a self-supervised learning objective, i.e., masked language modeling (MLM), that predicts tokens masked in the input sequences exploiting bi-directional context (along with next sentence prediction). Since BERT is pre-trained on standard text that is not ideal for social media, Nguyen et al. (2020) propose an alternative model pre-trained on a large-scale corpus of English tweets (BERTweet). Previous studies (Chen et al., 2018; Corazza et al., 2020; Zhang et al., 2021a) have also utilized distant supervision (e.g., use of emoji) to obtain better representations for one or another task. For example, Corazza et al. (2020) introduce an emoji-based masking strategy to enhance performance on abusive language detection. Other work such as Felbo et al. (2017) pre-train an encoder model on the emoji prediction task, showing improvements in sentiment, emotion, and sarcasm prediction. Our work differs in that we make use of distant supervision in the context of contrastive learning. Our goal is to acquire richer representations suited to the whole class of social meaning tasks, as opposed to only one or more of
these tasks. **Contrastive learning.** There has been a flurry of recent contrastive learning frameworks introducing self-supervised (Giorgi et al., 2021; Liu et al., 2021a; Gao et al., 2021), semi-supervised (Yu et al., 2021), weakly-supervised (Zheng et al., 2021), and strongly supervised (Gunel et al., 2021; Suresh and Ong, 2021; Gao et al., 2021) learning objectives. These frameworks differ across a number of dimensions that we summarize in Table 4 in Appendix A. Our proposed framework learns high-quality text representations exploiting surrogate labels. Compared to existing frameworks, our proposed approach is the first to exploit both instance-level weighing (confidence) and corpus-level weighing (PMI) of negative samples.

### 3 Proposed Framework

The goal of contrastive learning is to learn efficient representations by pulling samples from the same class together and pushing samples from other classes apart (Hadsell et al., 2006). We will formalize the framework now. Let \( C \) denote the set of class labels. Let \( D = \{(x_i, y_i)\}_{i=1}^m \) denote a randomly sampled mini-batch of size \( m \), where \( x_i \) and \( y_i \in C \) denote a sample and its label respectively. Many contrastive learning frameworks construct the similar (a.k.a., positive) sample \( (x_{m+i}) \) for an anchor sample \( (x_i) \) by applying a data augmentation technique (\( T \)) such as back-translation (Fang and Xie, 2020), token masking (Liu et al., 2021a), and dropout masking (Gao et al., 2021) on the anchor sample \( (x_i) \). Let \( B = \{(x_i, y_i)\}_{i=1}^{2m} \) denote the augmented mini-batch, where \( x_{m+i} = T(x_i) \) and \( y_{m+i} = y_i \) (\( i = \{1, \ldots, \frac{m}{2}\} \)).

#### 3.1 Self-Supervised Contrastive Loss

For self-supervised contrastive learning, we consider \( |C| = N \), where \( N \) is the total number of training samples. Hence, the representation of the anchor sample \( x_i \) is pulled closer to that of its augmented (positive) sample \( x_{m+i} \) and pushed away from the representations of all the other \( 2m - 2 \) (negative) samples in the mini-batch. The semantic representation \( h_i \in \mathbb{R}^d \) for each sample \( x_i \) is computed by an encoder, \( \Phi \), where \( h_i = \Phi(x_i) \). Chen et al. (2017) calculate the contrastive loss in a batch as follows:

\[
\mathcal{L}_{SSCL} = 2^m \sum_{i=1}^m \log e^{\text{sim}(h_i, h_{m+i})/\tau} - \sum_{a=1}^{2m} \sum_{a \neq i}^m e^{\text{sim}(h_i, h_a)/\tau}, \tag{1}
\]

where \( \tau \in \mathbb{R}^+ \) is a scalar temperature parameter, and \( \text{sim}(h_i, h_j) \) is the cosine similarity \( \frac{h_i^T h_j}{\|h_i\| \|h_j\|} \).

#### 3.2 Supervised Contrastive Loss

The contrastive loss in Eq. 1 is unable to handle the case of multiple samples belonging to the same class when utilizing a supervised dataset (\( |C| < N \)). Positive samples in SCL (Khosla et al., 2020) is a set composed of not only the augmented sample but also the samples belonging to the same class as \( x_i \). The positive samples of \( x_i \) are denoted by \( \mathcal{P}_i = \{\rho \in B : y_p = y_i \land \rho \neq i\} \) and \( |\mathcal{P}_i| \) is its cardinality. The SCL is formulated as:

\[
\mathcal{L}_{SCL} = \sum_{i=1}^{2m} \log \frac{1}{|\mathcal{P}_i|} \sum_{\rho \in \mathcal{P}_i} e^{\text{sim}(h_i, h_\rho)/\tau} - \sum_{a=1}^{2m} \sum_{a \neq i}^m e^{\text{sim}(h_i, h_a)/\tau}. \tag{2}
\]

In our novel framework, we make use of SCL but employ surrogate labels instead of gold labels to construct the positive set.

#### 3.3 Label-Aware Contrastive Loss

Suresh and Ong (2021) further extend the SCL objective to capture the fine-grained relations between negative samples. They hypothesize that not all negatives are equally difficult for positive samples and that the more confusable negatives should be emphasized in the loss. Such a loss function forces the model to learn more distinguishable representations for the confusable examples. Hence, they propose LCL, which introduces a weight \( w_i, y_a \) to indicate the confusability of class label \( y_a \) w.r.t anchor \( x_i \):

\[
\mathcal{L}_{LCL} = \sum_{i=1}^{2m} \sum_{\rho \in \mathcal{P}_i} \log \frac{w_i, y_a}{|\mathcal{P}_i|} e^{\text{sim}(h_i, h_\rho)/\tau} - \sum_{a=1}^{2m} \sum_{a \neq i}^m w_i, y_a e^{\text{sim}(h_i, h_a)/\tau}. \tag{3}
\]

The weight vector \( w_i \in \mathbb{R}^{|C|} \) comes from the class-specific probabilities (confidence score) outputted by an auxiliary task-specific supervised model after consuming the anchor \( x_i \). LCL assumes that the highly confusable classes w.r.t anchor receive higher confidence scores, while the lesser confusable classes w.r.t anchor receive lower confidence scores. In this work, we argue that a major limitation of LCL is that it attempts to capture inter-class relationships based *only* on instance-level information without exploiting corpus-level information. We also introduce a variant of LCL where we use our main model to derive the weight vector \( w_i \) from our main model through an additional loss (i.e., weighting is performed end-to-end in our main model).
3.4 Corpus-Aware Contrastive Loss

We propose a new contrastive learning method that relies on distant supervision to obtain class labels and incorporates corpus-level information to capture inter-class relationships. Since we have a large number of fine-grained classes, we assume that each class is not equally distant from all other classes. For example, the class ‘ 😂 ’ shares similar semantics with the class ‘ 😅 ’, but is largely distant to the class ‘ 😍 ’. This motivates us to propose a distantly supervised contrastive loss that exploits the nuanced knowledge provided by the large number of our surrogate class labels. Concretely, our proposed framework exploits a simple and effective corpus-level measure based on PMI to extract relations between emojis from a large amount of unlabeled tweets.\(^1\) Unlike LCL (which requires an additional task-specific model), the PMI method is relatively cheap to compute as it requires neither labeled data nor model training: PMI is based only on the co-occurrence of emoji pairs. We hypothesize that PMI scores of emoji pairs could provide globally useful semantic relations between emojis. Our proposed CCL based on PMI can be formulated as:

\[
L_{CCL} = \sum_{i=1}^{2n} -\frac{1}{|P_i|} \sum_{p \in P_i} \log \frac{e^{\gamma \text{pmi}(h_i, h_p)/\tau}}{\sum_{a \in \{0, 1\}} e^{\gamma \text{pmi}(h_i, h_a)/\tau}},
\]

where the weight \(w_{y_i, y_a} = 1 - \max(0, \text{npmi}(y_i, y_a))\), and \(\text{npmi}(y_i, y_a) \in [-1, 1]\) is normalized point-wise mutual information (Bouma, 2009) between \(y_a\) and \(y_i\).\(^2\)

3.5 Epoch-Wise Re-Pairing

Rather than augmenting a batch \(D\) with using some data augmentation technique, in our framework, the positive sample \(x_{m+1}\) of the anchor \(x_i\) is a sample that uses the same emoji. To alleviate any potential noise in our distant labels, we introduce an epoch-wise re-pairing (EpW-RP) mechanism where the pairing of a positive sample with a given anchor is not fixed for epochs: at the beginning of each epoch, we flexibly re-pair the anchor with a new positive pair \(x_{m+1}\) randomly re-sampled from the whole training dataset using the same emoji as \(x_i\). This ensures that each anchor in a given batch will have at least one positive sample.\(^3\)

3.6 Overall Objective

Our proposed framework exploits the instance-aware, confidence-based contrastive loss \(L_{DCL}\) alongside the corpus-aware, PMI-based contrastive loss \(L_{CCL}\). The resulting loss, which we collectively refer to as distantly supervised contrastive loss \(L_{DCL}\), steers the encoder to learn a representation that can distinguish confusable samples but also recognize corpus-level inter-class relations. Distantly-supervised contrastive loss is given by:

\[
L_{DCL} = \gamma L_{CCL} + (1 - \gamma) L_{CCL},
\]

where \(\gamma \in [0, 1]\) is a hyper-parameter that controls the relative importance of each of the contrastive losses. Unlike Suresh and Ong (2021), we weigh the samples in \(L_{CCL}\) using classification probabilities from our main model rather than training an additional weighting model. We hypothesize this sharing strategy where a single model is trained end-to-end on an overall objective incorporating negative class weighting could facilitate model efficiency (e.g., training speed, energy efficiency). Our ablation study in Section 6 confirms that using the main model as the weighing network is effective for overall performance.

Our proposed framework also exploits a surrogate label prediction (SLP) objective \(L_{SLP}\), where the encoder \(\Phi\) is jointly optimized for the emoji prediction task using cross entropy loss. To mitigate the effect of any catastrophic forgetting of token-level knowledge, the proposed framework includes an MLM objective defined by \(L_{MLM}\).\(^4\) The overall objective function of the proposed InfoDCL framework can be given by:

\[
L = \lambda_1 L_{MLM} + \lambda_2 L_{SLP} + (1 - \lambda_1 - \lambda_2) L_{DCL},
\]

where \(\lambda_1\) and \(\lambda_2\) are the loss scaling factors.

4 Experiments

4.1 Data for Representation Learning

In this paper, we exploit emojis as surrogate labels for our proposed framework. We randomly extract 350M English tweets\(^5\) each with at least one emoji from a larger in-house dataset (collected between 2014 and 2020). We appropriately pre-process the tweets and only keep ones with a unique type of emoji.

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\(^1\)We experiment with a relatively sophisticated approach that learns class embeddings to capture the inter-class relations in Section F.1 in Appendix, but find it to be sub-optimal.

\(^2\)Equation for NPMI is in Appendix B.1.

\(^3\)Note that each sample in the training dataset is used only once at each epoch, either as the anchor or as a positive sample of the anchor.

\(^4\)The Equations of \(L_{SLP}\) and \(L_{MLM}\) are listed in Appendix B.2 and B.3, respectively.

\(^5\)Language identification is from Twitter metadata.
emoji (following Felbo et al. (2017); Barbieri et al. (2018); Bamman and Smith (2015)) with one emoji at the end. We exclude emojis occurring less than 200 times, which gives us a set of 1,067 emojis in 32M tweets. We call this dataset TweetEmoji-EN and split it into a training set (31M) and a validation set (1M). In addition, we acquire representation learning data for (1) our experiments on three additional languages (i.e., Arabic, Italian, and Spanish) and to (2) investigate of the utility of hashtags as surrogate labels. More information about all our representation learning data is in Appendix C.1.

4.2 Evaluation Data and Splits

In-Domain Data. We collect 16 English language Twitter datasets representing eight different social meaning tasks. These are (1) crisis awareness, (2) emotion recognition, (3) hateful and offensive language detection, (4) humor identification, (5) irony and sarcasm detection, (6) irony type identification, (7) sentiment analysis, and (8) stance detection. We also evaluate our framework on nine Twitter datasets, three from each of Arabic, Italian, and Spanish. More information about our English and multilingual datasets is in Appendix C.2. Out-of-Domain Data. We were also able to identify eight datasets of social meaning involving emotion, sarcasm, and sentiment derived from outside the Twitter domain (e.g., data created by psychologists, debate fora, Reddit posts, YouTube comments, movie reviews). We provide more information about these datasets in Appendix C.2. Pre-Processing and Data Splits. We lightly normalize these evaluation datasets by replacing user mentions and hyperlinks with ‘USER’ and ‘URL’. For datasets without Dev splits, we use 10% of the respective training samples as Dev. For datasets originally used in cross-validation, we randomly split into 80% Train, 10% Dev, and 10% Test. Table 5 in Appendix C describes our evaluation datasets, including the percentages of samples with emojis.

4.3 Implementation and Baselines

For experiments on English, we initialize our model with the pre-trained English RoBERTa\textsubscript{Base} (Liu et al., 2019) from Huggingface’s Transformers (Wolf et al., 2020) library. For multi-lingual experiments (reported in Appendix E.3), we use the pre-trained XLM-RoBERTa\textsubscript{Base} model (Conneau et al., 2020) as our initial checkpoint. We further train PLMs with our proposed objectives for three epochs, and, then, fine-tune the trained models on each downstream task for five times with different random seeds and report the averaged model performance. Our main metric is macro-averaged $F_1$ score. To evaluate the overall ability of a model, we also report an aggregated metric that averages over the 16 Twitter datasets, eight out-of-domain tasks, and the nine multi-lingual Twitter datasets. More details about our training hyper-parameters are in Appendix D.2.

NPMI Weighting Matrix. We randomly sample 150M tweets from our original 350M Twitter dataset, each with at least one emoji. We extract all emojis in each tweet and count the frequencies of emojis as well as co-occurrences between emojis. To avoid noisy relatedness from low frequency pairs, we filter out emoji pairs $(y_i, y_o)$ whose co-occurrences are less than 20 times. We employ Eq. 7 (Appendix B.1) to calculate NPMI for each emoji pair.

Baselines. We compare our proposed method against 11 strong baselines, which we describe here. (1) RB: The original pre-trained RoBERTa, fine-tuned on downstream tasks with standard cross-entropy loss. (2) MLM: We continue pre-training RoBERTa on our TweetEmoji-EN dataset with solely the MLM objective in Eq. 9 (Appendix B.3), then fine-tune on downstream tasks. (3) Emoji-Based MLM (E-MLM): Following Corazza et al. (2020), we mask emojis in tweets and task the model to predict them, then fine-tune on downstream tasks. (4) SLP. A RoBERTa model fine-tuned on the surrogate label prediction task (emoji prediction) with cross-entropy loss, then fine-tuned on downstream tasks. Supervised Contrastive Learning: We also compare to state-of-the-art supervised contrastive fine-tuning frameworks. We take the original pre-trained RoBERTa and fine-tune it on each task with (5) SCL (Gunel et al., 2021) and (6) LCL (Suresh and Ong, 2021), respectively. Both works combine supervised contrastive loss with standard cross-entropy as well as augmentation of the training data to construct positive pairs. We follow the augmentation technique used in Suresh and Ong (2021), which replaces 30% of words in the input sample with their synonyms in WordNet dictionary (Miller, 1995).

Self-Supervised Contrastive Learning. We further train RoBERTa on different recently proposed self-supervised contrastive learning frameworks.
(7) SimCSE-Self. Gao et al. (2021) introduce SimCSE where they produce a positive pair by applying different dropout masks on input text twice. We similarly acquire a positive pair using the same dropout method. (8) SimCSE-Distant. Gao et al. (2021) also propose a supervised SimCSE that utilizes gold NLI data to create positive pairs where an anchor is a premise and a positive sample is an entailment. Hence, we adopt the supervised SimCSE framework to our distantly supervised data and construct positive pairs applying our epoch-wise re-pairing strategy. Specifically, each anchor has one positive sample that employs the same emoji as the anchor in a batch. (9) Mirror-BERT. (Liu et al., 2021a) construct Mirror-BERT by random span masking as well as different dropout masks. After contrastive learning, sentence-encoder models are fine-tuned on downstream tasks with the cross-entropy loss.

(10) Weakly-supervised Contrastive Learning. We simplify and adapt the WCL framework of Zheng et al. (2021) to language: We first encode unlabelled tweets to sequence-level representation vectors using the hidden state of the ‘[CLS]’ token from the last layer of RoBERTa. All unlabelled tweets are clustered by applying k-means to their representation vectors. We then use the cluster IDs as weak labels to perform an SCL to pull the tweets assigned to the same cluster closer. Following Zheng et al. (2021), we also include an SSCL loss by augmenting the positive sample of an anchor using random span as well as dropout masking. We jointly optimize the SCL and SSCL losses in our implementation. (11) Domain-Specific PLM (BTw): We compare to the SoTA domain-specific PLM, BERTweet (Nguyen et al., 2020). BERTweet was pre-trained on 850M tweets with RoBERTaBase architecture. We download the pre-trained BERTweet checkpoint from Huggingface’s Transformers (Wolf et al., 2020) library and fine-tune it on each downstream task with cross-entropy loss. More details about hyper-parameters of these baselines are in Appendix D.2.

5 Main Results

Table 1 shows performance of our InfoDCL model compared to our 11 baselines on the 16 Twitter social meaning datasets and eight out-of-domain datasets. In-Domain Results. InfoDCL outperforms Baseline (1) on each of the 16 in-domain datasets, with 1.93 average $F_1$ improvement. Similarly, our InfoDCL method outperforms all other baselines on average and achieves better performance on almost all individual datasets for both in-domain and out-of-domain tasks. InfoDCL also outperforms both the MLM and surrogate label prediction (SLP) methods with 1.19 and 0.46 average $F_1$ scores, respectively. Our proposed method is thus able to learn more effective representations for social meaning. We observe that both Mirror-BERT and SimCSE negatively impact downstream task performance, suggesting that even though these are useful for semantic similarity tasks (Gao et al., 2021; Liu et al., 2021a), they may not be as beneficial to social meaning tasks. We also observe that our proposed variant of SimCSE, SimCSE-Distant, achieves sizable improvements over both Mirror-BERT and SimCSE-Self (3.20 and 4.49 average $F_1$, respectively). This further shows the effectiveness of the distantly supervised objective we propose. SimCSE-Distant, however, cannot surpass our proposed InfoDCL method on average $F_1$ on the 16 tasks (in spite of acquiring best performance on two tasks). InfoDCL outperforms Mirror-BERT, SimCSE-Self, and SimCSE-Distant with 3.56, 4.85, and 0.36 average $F_1$, respectively. We also note that InfoDCL outperforms SCL, LCL, and WCL with 2.05, 1.87, and 1.90 average $F_1$, respectively. Overall, our proposed framework (InfoDCL) obtains the best performance in 12 out of 16 tasks and the best average $F_1$. We further investigate the relation between model performance and emoji presence, finding that our proposed approach not only improves tasks involving high amounts of emoji content (e.g., the test set of EmoMoham has 23.43% tweets containing emojis) but also those without any emoji content (e.g., Hate_Day). 7 Compared to the original BERTweet, the BERTweet we continue training with our method obtains an average improvement of 0.77 $F_1$ (outperforms it on 14 individual tasks). The results demonstrate that our method is able to enhance the domain-specific LM as well.

Out-of-Domain Results. InfoDCL achieves an average improvement of 1.01 $F_1$ ($F_1 = 75.54$) over the eight out-of-domain datasets compared to Baseline (1), as Table 1 shows. Our InfoDCL model also surpasses all baseline models on average, and achieves highest on six out of eight datasets. We notice the degradation of BERTweet when we eval-

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7 Statistics of emoji presence of each downstream task is shown in Table 5 in the Appendix.


Table 1: Fine-tuning results on our 24 social media datasets. We report average macro-$F_1$ over five runs. RB: Fine-tuning on original pre-trained RoBERTa (Liu et al., 2019); MLM: Further pre-training RoBERTa with masked language modeling objective; SCLS: Surrogate classification fine-tuning; Mir-B: Mirror-BERT (Liu et al., 2021a); Sim-S: SimCSE-Self (Gao et al., 2021); Sim-D: (Ours) SimCSE-Distant trained with distantly supervised positive pairs with SSCL loss; LCL: label-aware contrastive loss (Suresh and Ong, 2021); BTw: BERTweet (Nguyen et al., 2020); a: Sota Twitter-specific PLM; Ours-R: WCL: Weakly-supervised contrastive learning; Ours-B: continue training RoBERTa and BERTweet, respectively, with our proposed InfoDCL method.

| Task                      | RB       | MLM | E-MLM | SLP | Sim-S | Sim-D | SCLS | LCL | Ours-R | Ours-B | BTw       | Ours-R | Ours-B |
|---------------------------|----------|-----|-------|-----|-------|-------|------|-----|--------|--------|-----------|--------|--------|
| NLI                       | 95.89    | 95.81 | 95.91 | 95.89 | 95.79 | 95.71 | 95.94 | 95.88 | 95.87 | 95.83 | 96.01 | 95.76 | 95.84 |
| EmoMatt                   | 78.67    | 79.68 | 80.79 | 81.25 | 78.27 | 77.20 | 81.05 | 78.79 | 77.66 | 76.65 | 81.34 | 80.25 | 81.96 |
| Hate                       | 57.01 | 57.46 | 56.65 | 57.05 | 57.09 | 57.35 | 57.13 | 56.94 | 56.96 | 57.19 | 57.30 | 57.32 | 57.65 |
| HateMat                   | 76.04    | 77.29 | 79.79 | 75.50 | 75.88 | 73.40 | 73.15 | 77.70 | 77.20 | 77.39 | 79.36 | 79.30 | 79.63 |
| HateSim                   | 47.85    | 52.56 | 52.33 | 52.58 | 45.49 | 46.81 | 52.32 | 48.24 | 49.83 | 50.68 | 52.84 | 53.62 | 53.95 |
| HateSimMat                | 93.28    | 93.62 | 93.73 | 93.31 | 93.37 | 91.55 | 93.42 | 92.82 | 91.00 | 92.45 | 93.75 | 94.43 | 94.04 |
| InfoDCL                   | 72.87    | 74.15 | 75.94 | 76.89 | 70.62 | 66.40 | 75.36 | 73.58 | 73.86 | 72.14 | 76.31 | 77.05 | 78.72 |
| InfoDCL-BERT              | 53.20    | 52.85 | 55.58 | 56.38 | 49.60 | 46.26 | 54.06 | 50.68 | 53.63 | 52.80 | 57.22 | 56.73 | 59.15 |
| InfoDCL-OffSetSim         | 79.93    | 80.75 | 80.97 | 80.97 | 75.79 | 77.28 | 80.80 | 79.96 | 79.48 | 81.21 | 79.35 | 79.83 |
| SentiEm                    | 73.71    | 74.87 | 77.34 | 79.77 | 66.60 | 64.41 | 80.27 | 73.92 | 74.82 | 73.68 | 78.31 | 78.76 | 80.52 |
| SentiEmNew                | 95.99    | 95.87 | 96.02 | 95.89 | 95.62 | 95.27 | 96.07 | 95.89 | 95.62 | 95.72 | 96.10 | 96.40 | 96.67 |
| SentiEmSim                | 85.21    | 86.19 | 86.38 | 86.89 | 84.31 | 84.06 | 87.20 | 85.18 | 84.74 | 85.97 | 88.00 | 87.13 | 87.20 |
| SentiEmSimMat             | 79.79    | 80.84 | 80.66 | 81.08 | 79.02 | 77.58 | 81.40 | 79.32 | 76.92 | 75.93 | 81.49 | 81.76 | 83.20 |
| SentiLmath                | 71.41    | 71.31 | 71.50 | 71.79 | 71.23 | 70.11 | 71.68 | 70.57 | 70.10 | 71.30 | 71.87 | 71.64 | 71.98 |
| SentiLmathSim             | 49.44    | 49.97 | 50.50 | 49.54 | 49.83 | 49.86 | 50.88 | 49.14 | 49.55 | 49.30 | 51.13 | 48.33 | 48.52 |
| SentiLmathSimMat          | 79.67    | 79.48 | 78.76 | 78.27 | 77.41 | 77.25 | 78.31 | 77.25 | 77.41 | 77.25 | 78.57 | 77.61 | 77.88 |

Table 2: Few-shot results in average $F_1$ on downstream tasks with $N = 20, 100, 500, 1000$ labelled samples.

| Task                      | N 20 | 100  | 500  | 1000 |
|---------------------------|------|------|------|------|
| In-Domain                 |      |      |      |      |
| RoBERTa                   | 35.22| 41.92| 70.06| 72.20|
| BERTweet                  | 39.14| 38.23| 68.35| 73.50|
| Ours-SimCSE-RoBERTa       | -45.97| -51.06| -71.56| -73.89|
| Ours-InfoDCL-RoBERTa      | 46.88| 59.44| 72.72| 74.47|
| Ours-InfoDCL-BERTweet     | 45.29| 52.64| 71.31| 74.03|
| Out-of-Domain             |      |      |      |      |
| RoBERTa                   | 27.07| 41.12| 69.26| 71.42|
| BERTweet                  | 30.69| 39.40| 62.53| 68.22|
| Ours-SimCSE-RoBERTa       | -39.02| -53.55| -76.87| -77.70|
| Ours-InfoDCL-RoBERTa      | 40.66| 58.51| 69.36| 71.92|
| Ours-InfoDCL-BERTweet     | 38.72| 48.87| 63.64| 69.25|

Table 2: Few-shot results in average $F_1$ on downstream tasks with $N = 20, 100, 500, 1000$ labelled samples.

6 Ablation Studies and Analyses

Ablation Studies. In this section, we investigate the effectiveness of each of the ingredients of

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3Data splits for our few-shot experiments are in Appendix C.

Similarly, InfoDCL-RoBERTa is 13.88 and 17.39 over RoBERTa with 20 and 100 training samples over RoBERTa for out-of-domain tasks. These gains also persist when we compare our method to all other strong baselines, including as we increase data sample size, as Table 2 shows. This demonstrates that our proposed method remarkably alleviates the challenge of labelled data scarcity even under severely few-shot settings.9

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9We offer additional few-shot results in Appendix E.2.
our proposed framework. To facilitate the training, we randomly extract 5M samples from our TweetEmoji-EN dataset for our ablation experiments. We evaluate on the 16 Twitter benchmark datasets with the same hyper-parameters we identify in Section D.2 and report an average of five runs with different random seeds. Table 3 presents our aggregated $F_1$ scores. As Table 3 shows, our InfoDCL outperforms all other settings, which indicates that all the components in our model are necessary. The results show that the most important ingredient in our model is the emoji surrogate label prediction (SLP) objective, which results in a 1.13 drop of average $F_1$ score when removed. We also train an additional network to produce the weight vector, $w_i$, in LCL loss as Suresh and Ong (2021) proposed instead of using our own main model to assign this weight vector end-to-end. We observe a drop of 0.66 averaged $F_1$ with the additional model, showing the superiority of our end-to-end approach (which is also less computational costly). Our epoch-wise re-pairing (EpW-RP) strategy is also valuable, as removing it results in a drop of 0.59 average $F_1$. We believe EpW-RP helps regularize our model as we dynamically repair an anchor with a new positive pair for each training epoch. Our results also show that our proposed CCL is as effective as LCL. Removing either of these results in $\sim 0.55$ average $F_1$ drop. We surprisingly find that the model is relatively less impacted (i.e., $\sim 0.38$ $F_1$ drop) when we remove both CCL and LCL, which implies that use of vanilla SCL loss along with other model ingredients partially complement both of these combined. We also adapt a simple self-augmentation method introduced by Liu et al. (2021a) to our distant supervision setting: given an anchor $x_i$, we acquire a positive set $\{x_i, x_{m+i}, x_{2m+i}, x_{3m+i}\}$ where $x_{m+i}$ is a sample with the same emoji as the anchor, $x_{2m+i}$ is an augmented version (applying dropout and masking) of $x_i$, and $x_{3m+i}$ is an augmented version of $x_{m+i}$. As Table 3 shows, this InfoDCL+Self-Aug method does not help our model (0.10 $F_1$ drop). Finally, we investigate further issues as to how to handle surrogate labels in our models. We provide this analysis in Appendix F.1.

**Qualitative Analysis.** To further illustrate the effectiveness of the representation learned by our InfoDCL framework, we compare a t-SNE (Van der Maaten and Hinton, 2008) visualization of it to that of two strong baselines on two downstream tasks. From Fig 1, we can observe that our model has clearly learned to cluster the samples with similar semantics and separate semantically different clusters before fine-tuning on the gold downstream samples, for both in-domain and out-of-domain tasks. We provide more details about how we obtain the t-SNE visualization and provide another visualization study in Appendix F.2.

| Model                  | Avg $F_1$ | Diff |
|------------------------|-----------|------|
| InfoDCL                | 77.70     | -    |
| w\$ LCL                | 77.14     | -0.56|
| wo CCL                 | 77.15     | -0.55|
| wo LCL & CCL           | 77.32     | -0.38|
| wo SLP                 | 76.58     | -1.13|
| wo MLM                 | 77.45     | -0.25|
| wo EpW-RP              | 77.12     | -0.59|
| w additional weighting model | 77.04 | -0.66|
| InfoDCL+Self-Aug       | 77.60     | -0.10|

Table 3: Results of ablation studies. Results are average macro-$F_1$ across 16 Twitter tasks. All the models in this table are trained on 5M tweets, thus the result of InfoDCL is different to its in Table 1. For model removed SLP objective, we train a additional weighting model to provide the weights of LCL loss.

7 Conclusion and Future Work

We proposed InfoDCL, a novel method to adapt a pre-trained language model to social meaning tasks exploiting surrogate labels (e.g., emojis, hashtags)
in a contrastive learning framework. We demonstrated the effectiveness of our proposed method on 16 in-domain and eight out-of-domain social meaning datasets and nine non-English datasets. Our method outperforms 11 strong baselines and exhibits strikingly powerful performance in few-shot learning. In the future, we will seek to extend distantly supervised contrastive learning to tasks involving image and video where surrogate labels are abundant.

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Appendices

A Survey of Contrastive Learning Frameworks.

There has been a flurry of recent contrastive learning frameworks introducing self-supervised, semi-supervised, weakly-supervised, and strongly supervised learning objectives. These frameworks differ across a number of key dimensions: (i) type of the object (e.g., image, sentence, document), (ii) positive example creation method (e.g., same class as anchor, anchor with few words replaced with synonyms), (iii) negative example creation method (e.g., random sample, anchor with few words replaced with antonyms), (iv) supervision level (e.g., self, semi, weakly, hybrid, strong), and (v) weighing of negative samples (e.g., equal, confidence-based). Table 4 provides a summary of previous frameworks, comparing them with our proposed method.

B Method

B.1 Normalized Point-Wise Mutual Information

The normalized point-wise mutual information (Bouma, 2009) (NPMI) between $y_a$ and $y_i$, $npi(y_i, y_a) \in [-1, 1]$ is formulated as:

$$npi(y_i, y_a) = \left(\frac{\log \frac{p(y_i, y_a)}{p(y_i)p(y_a)}}{\log(p(y_i)p(y_a))}\right) - \log(p(y_i)p(y_a)).$$

When $npi(y_i, y_a) = 1$, $y_a$ and $y_i$ only occur together and are expected to express highly similar semantic meanings. When $npi(y_i, y_a) = 0$, $y_a$ and $y_i$ never occur together and are expected to express highly dissimilar (i.e., different) semantic meanings. We only utilize NPMI scores of related class pairs, i.e., $npi(y_i, y_a) > 0$. As the NPMI score of $y_a$ and $y_i$ is higher, the weight $w_{y_i, y_a}$ is lower. As a result of incorporating NPMI scores into the negative comparison in the SCL, we anticipate that the representation model would learn better inter-class correlations and cluster the related fine-grained classes.

B.2 Surrogate Label Predication

Our proposed framework also exploits a surrogate label prediction (SLP) objective, where the encoder $\Phi$ is optimized for the emoji prediction task using cross entropy. Specifically, we pass the hidden representation $h_i$ through two feed-forward layers with Tanh non-linearity in between and obtain the
prediction \( \hat{y}_i \). Then, the surrogate classification loss based on cross entropy can be formalized as:

\[
L_{SLP} = - \frac{1}{2m} \sum_{i=1}^{2m} \sum_{c=1}^{C} \hat{y}_{i,c} \cdot \log \hat{y}_{i,c},
\]

(8)

where \( \hat{y}_{i,c} \) is the predicted probability of sample \( x_i \) w.r.t class \( c \).

B.3 Masked Language Modeling Objective

Our proposed framework also exploits a MLM objective to mitigate the effect of catastrophic forgetting of the token-level knowledge. Following Liu et al. (2019), we randomly corrupt an input sentence by replacing 15\% of its tokens with the ‘[MASK]’ token. Given the corrupted input sequence, we then train our model to predict original tokens at masked positions. Formally, given an input sequence, \( x_i = \{t_1, \ldots, t_n\} \), the loss function of MLM is formulated as:

\[
L_{MLM} = - \frac{1}{2m} \sum_{i=1}^{2m} \log(p(t_j|t_{\text{cor}}(x_i))),
\]

(9)

where \( mk(x_i) \) indicates the set of masked tokens of the input sequence \( x_i \) and \( cor(x_i) \) denotes the corrupted input sequence \( x_i \).

C Data

C.1 Representation Learning Data and Pre-Processing.

Emoji Pre-Training Dataset. We normalize tweets by converting user mentions and hyperlinks to ‘USER’ and ‘URL’, respectively. We keep all the tweets, retweets, and replies but remove the ‘RT USER’ string in front of retweets. We filter out short tweets (< 5 actual English word without counting the special tokens such as hashtag, emoji, USER, URL, and RT) to ensure each tweet contains sufficient context. Following previous works (Felbo et al., 2017; Barbieri et al., 2018; Bamman and Smith, 2015), we only keep the tweet that contains only a unique type of emoji (regardless of the number of emojis) and that uses a emoji at the end of the tweet. We then extract the emoji as a label of the tweet and remove the emoji from the tweet. We exclude emojis occurring less than 200 times, which gives us a set of 1,067 emojis in 32M tweets. Moreover, we remove few tweets overlapped with Dev and Test sets of our evaluation tasks by Twitter ID and string matching. We split the tweets into a training (31M) and validation (1M) set and refer to this dataset as TweetEmoji-EN.

Hashtag Pre-Training Dataset. We also explore using hashtags as surrogate labels for InfoDCL training. Following our data pre-processing procedure on TweetEmoji-EN, we randomly extract 300M English tweets each with at least one hashtags from a larger in-house dataset collected between 2014 and 2020. We only keep tweets that contain a single hashtag used at the end. We then extract the hashtag as a distant label and remove it from the tweet. We exclude hashtags occurring less than 200 times, which gives us a set of 12,602 hashtags in 13M tweets. We split the tweets into a training set (12M) and a validation (1M) set. We refer to this dataset as TweetHashtag-EN.

Multilingual Emoji Pre-Training Dataset. We collect a multilingual dataset to train multilingual models with our proposed method. We apply the same data pre-processing and filtering conditions used on English data, and only include tweets that use the 1,067 emojis in TweetEmoji-EN. We extract 1M tweets from our in-house dataset for three languages, i.e., Arabic, Italian, and Span-
ish. We refer to these datasets as TweetEmoji-AR, TweetEmoji-IT, and TweetEmoji-ES. We also randomly extract 1M English tweets from our TweetEmoji-EN and refer to it as TweetEmoji-EN-1M. We then combine these four datasets and call the combined dataset TweetEmoji-Multi.

C.2 Evaluation Data

In-Domain Datasets. English Language Data.

We collect 16 twitter datasets representing eight different social meaning tasks to evaluate our models, including (1) crisis awareness task (Olteanu et al., 2014), (2) emotion recognition (Mohammad et al., 2018), (3) hateful and offensive language detection (Waseem and Hovy, 2016; Davidson et al., 2017; Basile et al., 2019; Zampieri et al., 2019a), (4) humor identification (Meaney et al., 2021), (5) irony and sarcasm detection (Hee et al., 2018; Riloff et al., 2013; Ptácek et al., 2014; Rajadesingan et al., 2015; Bamman and Smith, 2015), (6) irony type identification (Hee et al., 2018) (7) sentiment analysis (Thelwall et al., 2012; Rosenthal et al., 2017), and (8) stance detection (Mohammad et al., 2016). We present the distribution, the number of labels, and the short name of each dataset in Table 5.

Out-of-Domain Datasets.

We evaluate our model on downstream tasks from diverse social media platforms and domains. For emotion recognition task, we utilize (1) PsychExp (Wallbott and Scherer, 1986), a seven-way classification dataset of self-described emotional experiences created by psychologists, and (2) GoEmotion (Demszky et al., 2020), a dataset of Reddit posts annotated with 27 emotions (we exclude neutral samples). For sarcasm detection task, we use two datasets from the Internet Argument Corpora (Walker et al., 2012; Oraby et al., 2016) that posts from debate forums. For sentiment analysis, we utilize (1) five-class and binary classification versions of the Stanford Sentiment Treebank (Socher et al., 2013) (SST-5 and SST-2) that include annotated movie reviews with sentiment tags, (2) movie review (MR) for binary sentiment classification (Pang and Lee, 2005), and (3) SentiStrength for YouTube comments (SS-YouTube) (Thelwall et al., 2012).

Multilingual Datasets.

As explained, to evaluate the effectiveness of our methods on different languages, we collect nine Twitter tasks in three languages: Arabic, Italian, and Spanish. For each language, we include three emotion-related tasks, (1) emotion recognition (Abdul-Mageed et al., 2020; Bianchi et al., 2021; Mohammad et al., 2018), (2) irony identification (Ghanem et al., 2019; Cignarella et al., 2018; Ortega-Bueno et al., 2019), and (3) offensive language/hate speech detection (Mubarak et al., 2020; Bosco et al., 2018; Basile et al., 2019).

Few-Shot Data.

We conduct our few-shot experiments only on our English language downstream data. We use different sizes from the set {20, 100, 500, 1,000} sampled randomly from the respective Train splits of our data. For each of these sizes, we randomly sample five times with replacement (as we report the average of five runs in our experiments). We also run few-shot experiments with varying percentages of the Train set of each task (i.e., 1%, 5%, 10%, 20%...90%). We randomly sample five different training sets for each percentage, evaluate each model on the original Dev and Test sets, and average the performance over five runs.

D Experiment

D.1 Implementation

For experiments on English language datasets, we initialize our model with a pre-trained English RoBERTaBase (Liu et al., 2019) model from Huggingface’s Transformers (Wolf et al., 2020) library. RoBERTaBase consists of 12 Transformer Encoder layers, 768 hidden units each, 12 attention heads, and contains 110M parameters in entire model. RoBERTa uses a byte-pair-encoding vocabulary with a size of 50,265 tokens. RoBERTa was pre-trained on large English corpora (e.g., Bookcorpus) with the MLM objective. In accordance with convention (Liu et al., 2019; Gao et al., 2021), we pass the hidden state corresponding to the ‘[CLS]’ token from the last layer through a feed-forward layer with hidden size of 768 and a hyperbolic tangent function and, then, use the output as the sentence-level embedding, $h_i$. For the classification objective, we feed $h_i$ into a feed-forward layer with hidden size of 1,067\(^\text{14}\), a softmax function and a dropout of 0.1. For multilingual experiments, we utilize the pre-trained XLM-RoBERTaBase model\(^\text{15}\) (Conneau et al., 2020).

\(^{14}\)The number of Emoji classes is 1,067.

\(^{15}\)For short, we refer to the official released XLM-RoBERTaBase as XLM-R in the rest of the paper.
Table 5: Description of benchmark datasets. We include 16 English in-domain datasets, eight English out-of-domain datasets, and nine Twitter datasets in three different languages. To facilitate reference, we give each dataset a name as Task column shows. 

| Task                          | Study                          | Cls | Domain       | Lang | Data Split (Train/Dev/Test) | % of Emoji Samples (Train/Dev/Test) |
|-------------------------------|--------------------------------|-----|--------------|------|-----------------------------|-------------------------------------|
| Crisis2009                    | Ohe et al. (2014)               | 2   | Twitter      | EN   | 48.00%5/6/8.00 9/0.010/20.00 |                                      |
| EmoAffect2016                 | Mohammad et al. (2018)          | 3   | Twitter      | EN   | 3.257/37/41.22 11.39/27.81/23.43 |                                    |
| Hate2016                      | Waseem and Hovy (2016)          | 3   | Twitter      | EN   | 19,856/0/74/4.79 2.23/0.03/7.62 |                                    |
| HateX2019                     | Davidson et al. (2017)          | 2   | Twitter      | EN   | 11,325/60/70.49 6.50/10.11/5.77 |                                    |
| HateX2019                     | Basile et al. (2019)            | 2   | Twitter      | EN   | 8,000/0/100/0.00 0.55/0.01/0.00 |                                    |
| Humor2019                     | Meane et al. (2021)             | 2   | Twitter      | EN   | 3,450/0/74/8.74 10.58/10.94/11.22 |                                    |
| Irony2019-A                   | Hee et al. (2018)               | 2   | Twitter      | EN   | 3,450/0/74/8.74 10.58/10.94/11.22 |                                    |
| Irony2019-B                   | Hee et al. (2018)               | 4   | Twitter      | EN   | 0.00/0.01/0.00 0.55/0.01/0.00 |                                    |
| Offense-Zone                  | Zampieri et al. (2019a)         | 2   | Twitter      | EN   | 11.916/1,324/860 11.43/10.88/13.37 |                                    |
| Senti-Humor                   | Riloff et al. (2012)            | 3   | Twitter      | EN   | 1.143/177/177 3.63/0.94/5.82 |                                    |
| Senti-Offense                 | Puic et al. (2014)              | 2   | Twitter      | EN   | 71,433/9/69/9.03 4.34/3.64/9.9  |                                    |
| Senti-Offense                 | Rajadesingan et al. (2015)      | 2   | Twitter      | EN   | 41,261/5/158/5.158 16.94/18.01/17.10 |                                |
| Sentiment                      | Bamman and Smith (2015)         | 2   | Twitter      | EN   | 11,864/1,483/1,484 8.47/2.99/6.49 |                                    |
| Sentiment                      | Rosenthal et al. (2017)         | 3   | Twitter      | EN   | 42,764/752/12,284 0.000/0.06/0.59 |                                    |
| Sentiment                      | Thelwall et al. (2012)          | 2   | Twitter      | EN   | 900/100/1,113 0.000/0.00/0.00 |                                    |
| Stance-2018                   | Mohammad et al. (2016)          | 3   | Twitter      | EN   | 2.622/292/1,249 0.000/0.00/0.00 |                                    |
| Emo-2018                      | Denscky et al. (2020)           | 27  | Reddit       | EN   | 23.486/957/2,985 0.000/0.00/0.00 |                                    |
| Sem-2018                      | Walker et al. (2012)            | 3   | Debate Forums | EN | 900/100/995 0.000/0.00/0.00 |                                    |
| SemA-2018                     | Oraby et al. (2016)             | 2   | Debate Forums | EN | 900/100/2,260 0.000/0.00/0.10 |                                    |
| Senti-MR                      | Pang and Lee (2005)             | 2   | Movie reviews | EN | 8,529/1,066/1,067 2.01/1.76/1.84 |                                    |
| Sem-2018                      | Socher et al. (2013)            | 2   | Movie reviews | EN | 8,544/1,020/209 0.000/0.00/0.00 |                                    |
| Senti-Offense                 | Thelwall et al. (2012)          | 2   | Movie reviews | EN | 6,918/671/12,800 0.000/0.00/0.00 |                                    |
| Irony2019                      | Moit et al. (2017)              | 2   | Twitter      | EN   | 1,434/177/177 3.62/4.94/5.82 |                                    |
| Irony2019                      | Mohammad et al. (2016)          | 3   | Twitter      | EN   | 2,622/292/1,249 0.000/0.00/0.00 |                                    |
| Irony2019                      | Balas et al. (2018)             | 2   | Twitter      | EN   | 3,450/0/74/8.74 10.58/10.94/11.22 |                                    |
| Irony2019                      | Hee et al. (2018)               | 4   | Twitter      | EN   | 2,622/292/1,249 0.000/0.00/0.00 |                                    |
| Irony2019                      | Ortega-Bueno et al. (2019)      | 2   | Twitter      | EN   | 2,622/292/1,249 0.000/0.00/0.00 |                                    |
| Offense-Multistran-2018        | Mabar et al. (2020)             | 2   | Twitter      | EN   | 6,839/1,000/2,000 38/79/36/58/75 |                                    |

Table 5: Description of benchmark datasets. We include 16 English in-domain datasets, eight English out-of-domain datasets, and nine Twitter datasets in three different languages. To facilitate reference, we give each dataset a name as Task column shows. Cls column indicate the number of classes. Lang: Language, % of Emoji Samples: Percentage of samples of downstream tasks containing emojis.

as our initial checkpoint. XLM-RBase has the same architecture as RoBERTa. XLM-R includes a vocabulary of 250,002 BPE tokens for 100 languages and is pre-trained on 2.5TB of filtered CommonCrawl.

We fine-tune pre-trained models on each downstream task for five times with different random seeds and report the averaged model performance. Our main metric is macro-averaged $F_1$ score. To evaluate the overall ability of a model, we also report an aggregated metric that averages over the 16 Twitter datasets, eight out-of-domain tasks, and the nine multi-lingual Twitter datasets.

NPMI weighting matrix. We randomly sample 150M tweets from the 350M tweets with at least one emoji each. We extract all emojis in each tweet and count the frequencies of emojis as well as co-occurrences between emojis. To avoid noisy relatedness from low frequency pairs, we filter out emoji pairs, $(y_i, y_k)$, whose co-occurrences are less than 20 times or $0.02 \times$ frequency of $y_i$. We employ Eq. 7 to calculate NPMI for each emoji pair. Similarly, we calculate the NPMI weighting matrix using $150M$ with at least one hashtag each and filtering out low frequency pairs.

D.2 Hyper-Parameters

InfoDCL Training Hyper-Parameters. For hyper-parameter tuning of our proposed InfoDCL framework, we randomly sample 5M tweets from our TweetEmoji-EN dataset. We continue training the pre-trained RoBERTa for three epochs with Adam optimizer with a weight decay of 0.01 and a peak learning rate of $2e^{-5}$. The batch size is 128, and the total number of input samples is 256 after constructing positive pairs. As Gao et al. (2021) find contrastive learning is not sensitive to the learning rate nor batch size when further training a PLM, we do not fine-tune these (i.e., the learning rate and batch size) in this paper. Following (Liu et al., 2019), we mask 15% of tokens for our MLM objective. We fine-tune the loss scaling weights $\lambda_t$ in a set of $\{0.1, 0.3, 0.4\}, \lambda_2$ in a set of $\{0.1, 0.3, 0.5\}$, and $\gamma$ in a set of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$. To reduce search space, we use the same temperature value for the $\tau$ in Eq. 3 and Eq. 4 and fine-tune in a set of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$. We use grid search to find the best hyper-parameter set and evalu-
uate performance on the Dev set of the 16 English language Twitter datasets.\footnote{We fine-tune the learned model on each downstream task with an arbitrary learning rate of $5e-6$, a batch size of 16, and a training epoch of 20. The performance is macro-$F_1$ over three runs with random seeds.} We select the best hyper-parameter set that achieves the best macro-$F_1$ averaged over the 16 downstream tasks. Our best hyper-parameter set is $\lambda_1 = 0.3$, $\lambda_2 = 0.1$, $\gamma = 0.5$, and $\tau = 0.3$. We continue training RoBERTa/BERTweet on TweetEmoji-EN dataset with the InfoDCL objective and the best hyper-parameters. We train each InfoDCL model for three epochs and utilize 4 Nvidia A100 GPU (40GB each) and 24 CPU cores. Each epoch takes around 3 hours.

**Downstream Task Fine-Tuning Hyper-Parameters.** Furthermore, we take the model trained with the best hyper-parameters and search the best hyper-parameter set of downstream task fine-tuning. We search the batch size in a set of $\{8, 16, 32, 64\}$ and the peak learning rate in a set of $\{2e-5, 1e-5, 5e-6\}$. We identify the best fine-tuning hyper-parameters based on the macro-$F_1$\footnote{We run three times and use the mean of them.} on Dev sets averaged over the 16 English language Twitter datasets. Our best hyper-parameters for fine-tuning is a learning rate of $1e-5$ and a batch size of 32. For all the downstream task fine-tuning experiments in this paper, we train a model on the task for 20 epochs with early stop ($\textit{patience} = 5$ epochs). We use the same hyper-parameters identified in this full data setting for our few-shot learning. For each dataset, we fine-tune for five times with a different random seed every time, and report the mean macro-$F_1$ of the five runs. Each downstream fine-tuning experiment use a single Nvidia A100 GPU (40GB) and 4 CPU cores.

**Baseline Hyper-Parameters.** Our Baseline (1) is directly fine-tuning RoBERTa on downstream tasks. We fine-tune Baseline (1) hyper-parameters as follows: The batch size is chosen from a set of $\{8, 16, 32, 64\}$ and the peak learning rate in a set of $\{2e-5, 1e-5, 5e-6\}$. The best hyper-parameters for RoBERTa fine-tuning is a learning rate of $2e-5$ and a batch size of 64.

For Baseline (2-3), we further pre-train the RoBERTa model for three epochs (same as our InfoDCL) with the MLM objective with an arbitrary learning rate of $5e-5$ and a batch size of 4,096. We mask 15% of tokens in each input tweet. For Baseline (3), we give priority to masking emojis in a tweet: if the emoji tokens are less than 15%, we then randomly select regular tokens to complete the percentage of masking to the 15%. Baseline (4) is about surrogate label prediction (with emojis). We also train Baseline (4) for three epochs with a learning rate of $2e-5$ and a batch size of 4,096. After training, models are fine-tuned on downstream tasks using the same hyper-parameters as our proposed model.

**Baselines (5-7).** SimCSE (Gao et al., 2021) was trained in two setups, i.e., self-supervised and supervised by label data. We also train RoBERTa on both settings. For self-supervised SimCSE, we train RoBERTa on our TweetEmoji dataset for three epochs with a learning rate of $2e-5$, a batch size of 256, and $\tau = 0.05$. For the distantly-supervised SimCSE, we construct positive pairs as described in Section 3.5. Similar to self-supervised SimCSE, we train RoBERTa for three epochs with a learning rate of $2e-5$ but with a batch size of 128.\footnote{After pairing, each batch include 256 unique tweets.} The pre-training of Mirror-BERT is similar to the pre-training of self-supervised SimCSE. We set the span masking rate of $k = 3$, a temperature of 0.04, a learning rate of $2e-5$, and a batch size of 256. Trained models, then, are fine-tuned on downstream tasks. For downstream task fine-tuning with baselines 2-7, we use the same hyper-parameters identified with InfoDCL downstream task fine-tuning.

**Baselines (8-9).** SCL (Gunel et al., 2021) and LCL (Suresh and Ong, 2021) directly fine-tune on downstream tasks with cross-entropy loss. We reproduce these two methods on our evaluation tasks. For SCL, we follow Gunel et al. (2021) and fine-tune each task with a temperature of $\tau = 0.3$, a SCL scaling weighting of 0.9, and a learning rate of $2e-5$. For LCL, we fine-tune each task with a temperature $\tau$ of 0.3, a LCL scaling weighting of 0.5, and a learning rate of $2e-5$.

**Baselines (10).** We implement WCL (Zheng et al., 2021) to continue train RoBERTa with our emoji dataset. We remove all emojis in the 31M tweets and encode tweets using the hidden state of `[CLS]` token from the last layer of RoBERTa. The tweets are then clustered by $k$-means clustering algorithm.\footnote{We use mini-batch $k$-means clustering from scikit-learn (Pedregosa et al., 2011).} For hyper-parameter tuning of WCL, we randomly sample 5M tweets from TweetEmoji-EN and train a model for three epochs with dif-
different hyper-parameter sets. We search the number of clusters in a set of \{200, 500, 1067, 2000\} and temperature \(\tau\) in a set of \{0.1, 0.3\}. To reduce the search space, we use the same temperature value for SSCL and SCL losses. We evaluate performance on the Dev set of the 16 English language Twitter datasets\(^{20}\) and find the best hyper-parameter set is \(k = 1067\) and \(\tau = 0.1\). We then train WCL on the TweetEmoji-EN dataset for three epochs with our best hyper-parameters and fine-tune the model on 24 downstream tasks with the same hyper-parameters identified for InfoDCL downstream fine-tuning.

**Baseline (11).** We fine-tune BERTweet with hyper-parameters utilized in (Nguyen et al., 2020) that are a fixed learning of \(1e - 5\) and a batch size of 32.

| Hyper-parameters | \(\lambda_1\) | \(\lambda_2\) | \(\gamma\) | \(\tau\) | \(lr\) | batch size |
|------------------|-------------|-------------|---------|---------|-------|-----------|
| InfoDCL pre-training | 0.3 | 0.1 | 0.5 | 0.30 | \(2e - 5\) | 128 |
| InfoDCL fine-tuning | - | - | - | - | \(1e - 5\) | 32 |
| RoBERTa | - | - | - | - | \(2e - 5\) | 64 |
| MLM | - | - | - | - | \(5e - 5\) | 4.096 |
| E-MLM | - | - | - | - | \(5e - 5\) | 4.096 |
| SLP | - | - | - | - | \(2e - 5\) | 4.096 |
| SimCSE-Self | - | - | - | - | 0.05 | \(2e - 5\) | 256 |
| SimCSE-Distant | - | - | - | - | 0.05 | \(2e - 5\) | 128 |
| Mirror-BERT | - | - | - | - | 0.04 | \(2e - 5\) | 256 |
| SCL | - | - | - | - | \(30e - 5\) | 32 |
| LCL | - | - | - | - | \(30e - 5\) | 32 |
| WCL | - | - | - | - | \(10e - 5\) | 256 |
| BERTweet | - | - | - | - | \(1e - 5\) | 32 |

Table 6: Hyper-parameter values using in this paper.

**Multi-Lingual Experiment Hyper-Parameters.** For multi-lingual experiments, we utilize the pre-trained XLM-RoBERTa\(_{Base}\) model (Conneau et al., 2020) as our initial checkpoint. We continue training XLM-R on multi-lingual tweets with our methods and the best hyperparameters identified for English. For the downstream fine-tuning, we use as same as the best hyperparameters identified for English tasks.

**Hashtag Experiment Hyper-Parameters.** For the hashtag-based experiments presented in Section E.4, we train our model on the TweetHashtag-EN dataset with the best hyper-parameters identified in emoji-based InfoDCL training and use the same hyper-parameters identified with InfoDCL downstream task fine-tuning.

**E Results**

**E.1 Comparisons to Individual SoTAs.**

Although the focus of our work is on producing effective representations suited to the whole class of social meaning tasks, rather than to one or another of these tasks, we also compare our methods on each dataset to other reported task-specific SoTA models on that particular dataset in Table 7. We compare our methods on each dataset to other reported task-specific SoTA models on that particular dataset as shown. Due to diverse metrics used in previous studies, we compare models of each task reporting the corresponding metric of the SoTA method. Some SoTA models are trained on different data splits or use different evaluation approaches (e.g., Olteanu et al. (2014) is evaluated by cross-validation). To provide meaningful comparisons, we thus fine-tune BERTweet on our splits and report against our models. Our methods outperform SoTA on 11 out of 16 in-domain datasets and four out of eight out-of-domain datasets. We achieve the best average score over 16 in-domain datasets applying our model on BERTweet.

Further training RoBERTa with our methods obtains the best average score across the eight out-of-domain datasets. We note that some SoTA models adopt task-specific approaches and/or require task-specific resources. For example, Ke et al. (2020) utilize SentiWordNet to identify the sentiment polarity of each word. In this work, our focus on producing effective representations suited for the whole class of social meaning tasks, rather than one or another of these tasks. Otherwise, we hypothesize that task-specific approaches can be combined with our InfoDCL methods to yield even better performance on individual tasks.

**E.2 Few Shot Learning**

Since InfoDCL exploits an extensive set of cues in the data that capture a broad range of fine-grained social meaning concepts, we hypothesize it will be also effective in few-shot learning. Hence, we test this hypothesis for both in-domain and out-of-domain tasks. Figure 2 and Table 14 compare our models to three strong baselines when they are trained with different percentages of training samples. Results show that our proposed InfoDCL model always outperforms all baselines on average \(F_1\) scores across both in-domain and out-of-domain tasks. For 16 in-domain tasks, our InfoDCL-RoBERTa remarkably surpasses the RoBERTa baseline with a sizable 12.82 average \(F_1\) scores when we only provide 1% training data from downstream tasks. Compared to other strong baselines, fine-tuning BERTweet and SimCSE-
Distant (also our method), InfoDCL-RoBERTa outperforms these with 12.91 and 3.55 average $F_1$ scores, respectively, when we use 1% training data for downstream fine-tuning. With only 5% of gold data, InfoDCL-RoBERTa improves 5.76 points over the RoBERTa baseline. For eight out-of-domain tasks, InfoDCL-RoBERTa outperforms the RoBERTa, BERTweet, and SimCSE-Distant baselines with 16.23, 15.52, and 2.89 average $F_1$ scores, respectively, when the models are only fine-tuned on 1% training data of downstream tasks. As Figure 2b and Table 14 show, InfoDCL-RoBERTa consistently outperforms all the baselines given any percentage of training data. Tables 15, 16, 17, 18, and 19, respectively, present the performance of RoBERTa, BERTweet, SimCSE-Distant, InfoDCL-RoBERTa, InfoDCL-BERTweet on all our 24 English downstream datasets and various few-shot settings.

E.3 Multilingual Tasks

We also investigate the effectiveness of our proposed model on multi-lingual tasks. Table 8 shows the performance on nine downstream tasks in three different languages. Here, we continue training XLM-R with our proposed objectives. We experiment with three settings: (1) English only: training on the TweetEmoji-1M and evaluating on the nine multilingual datasets, (2) Target mono-lingual: training on each 1 mono-lingual tweets in the target language independently (i.e., TweetEmoji-AR for Arabic, TweetEmoji-IT for Italian, and TweetEmoji-ES for Spanish) and evaluating on the respective dataset corresponding to the same language as training data, and (3) Multilingual: training on the TweetEmoji-Multi dataset and evaluating on the nine multilingual datasets. We still use the NPMI weighting matrix generated from English tweets in these experiments. 21 Table 8 shows that our models outperform the original XLM-R on all the datasets and obtains improvements of 1.44 and 0.85 average $F_1$ across the nine datasets under the multilingual and target mono-lingual settings, respectively. Training on English mono-lingual data helps four datasets, but cannot benefit all the

21We plan to explore generating the NPMI weighting matrix from multilingual data in the future work.
Table 8: Results of multi-lingual tasks on macro-F1. SoTA: Previous SoTA performance on each respective dataset. **Underscore** indicates that our models are trained on different data splits to the SoTA model. **L:** Language, **XLM:** XLM-R. Downstream task: **AR:** Arabic, **IT:** Italian, **ES:** Spanish. Pre-ranking data: **EN:** English monolingual tweets, **Mono:** monolingual tweets in corresponding language, **Mult:** combined data that includes four languages and a total number of 4.5M tweets. * (Abdul-Mageed et al., 2020), † (Ghanem et al., 2019), ‡ (Mubarak et al., 2020), § (Bianchi et al., 2021), ¶ (Cignarella et al., 2018), ◆ (Bosco et al., 2018), ○ (Ortega-Bueno et al., 2019), ✶ (Basile et al., 2019).

| L. Task XLM | InfoDCL-XLMR | EN | Mono | Mult | SoTA |
|------------|--------------|----|------|------|------|
| Emo$_{en}$ | 72.23 | 72.08 | 72.59 | 72.56 | 60.32* |
| Irony$_{en}$ | 81.15 | 78.75 | 81.85 | 82.23 | 84.40‡ |
| OffProf$_{en}$ | 84.87 | 85.08 | 85.61 | 87.10 | 90.50† |
| Emo$_{en}$ | 70.37 | 73.51 | 75.58 | 74.56 | 71.60* |
| Irony$_{en}$ | 73.22 | 73.52 | 74.07 | 73.42 | 76.16♣ |
| Hat$_{en}$ | 78.63 | 78.06 | 79.44 | 79.77 | 79.83* |
| Emo$_{en}$ | 76.85 | 76.92 | 78.08 | 77.66 | 76.47♣ |
| Hat$_{en}$ | 73.22 | 73.11 | 72.98 | 74.91 | 71.67♣ |
| Average | 76.23 | 76.02 | 77.08 | 76.76 | 73.00* |

Table 9: Results of using hashtags as distant labels. We continue training RoBERTa (RB) and BERTweet (BTw) with our proposed framework InfoDCL on TwitterHashtag-EN respectively. Models are evaluated on 24 social media benchmarks. We report average macro-F1 over five runs.

| Task | RB | BTw | InfoDCL-RB | InfoDCL-BTw |
|------|----|-----|------------|-------------|
| Emo$_{en}$ | 95.87 | 95.81 | 95.94 | 95.84 |
| Irony$_{en}$ | 78.76 | 79.68 | 80.58 | 80.22 |
| Hat$_{en}$ | 57.01 | 58.87 | 56.64 | 57.11 |
| OffProf$_{en}$ | 76.94 | 77.55 | 77.17 | 78.31 |
| Emo$_{en}$ | 47.85 | 52.56 | 49.99 | 53.75 |
| Irony$_{en}$ | 93.28 | 93.62 | 93.88 | 94.25 |
| Hat$_{en}$ | 72.87 | 74.15 | 73.94 | 79.51 |
| OffProf$_{en}$ | 53.20 | 52.87 | 55.74 | 58.78 |
| Humor$_{en}$ | 79.93 | 80.75 | 80.65 | 79.36 |
| Sentiment | 73.71 | 74.87 | 74.51 | 78.83 |
| Sentiment | 95.99 | 95.87 | 95.98 | 96.66 |
| Sentiment | 85.21 | 86.19 | 86.77 | 87.43 |
| Sentiment | 79.79 | 80.48 | 80.33 | 83.87 |
| Sentiment | 89.55 | 89.69 | 90.93 | 89.59 |
| Stance$_{en}$ | 71.41 | 71.31 | 71.93 | 71.82 |
| Average | 76.28 | 76.08 | 77.05 | 76.29 |

E.4 Using Hashtag as Distant Supervision

As Table 9 presents, our proposed method also can enhance the representation quality using hashtags as distantly supervised labels. InfoDCL-RoBERTa, the model further training RoBERTa with our method, obtains average F1 of 77.36 and 75.43 across the 16 in-domain and eight out-of-domain datasets, respectively, when we use Tweet-Hashtag. InfoDCL-BERTweet, the further pre-trained BERTweet with our method, obtains average F1 of 78.29 and 74.44 across the 16 in-domain and eight out-of-domain datasets, respectively.

F Analyses

F.1 On Treating Surrogate Labels

Should we cluster or push apart the large number of fine-grained (correlated) classes? In previous works, contrastive learning is used to push apart samples from different classes. Suresh and Ong (2021) propose the LCL to penalize samples that is more confusable. In this paper, we hypothesize that we should also incorporate inter-class relations into learning objectives (our CCL). Hence, we introduce the PMI score into SCL to scale down the loss of a pair belonging to semantically related classes (emojis) as defined in Section 3.4 (which should help cluster our fine-grained classes). Here, we investigate an alternative strategy where we explore using the PMI scores as weights to scale up the loss of a pair with related labels (which should keep the fine-grained emoji classes separate). Hence, we set \( w_{yi,ya} = 1 + Sim(yi, ya) \) where \( Sim(yi, ya) = max(0, npm_i(yi, ya)) \). We train RoBERTa on 5M random samples with the overall loss function in Eq. 6, one time using this new weighting method and another time using the weighting method used in all our reported models so far: \( w_{yi,ya} = 1 − Sim(yi, ya) \). Given these two ways to acquire \( w_{yi,ya} \) in Eq. 4, we fine-tune the trained model on the 16 Twitter tasks. Our results in Table 10 show the penalizing strategy to perform lower than our original clustering strategy reported in all experiments in this paper. We also present
their performance on each dataset in Table 12.

| Method     | Average |
|------------|---------|
| PMI        | 77.70   |
| EC-Emb     | 77.53   |
|              | 1 − Sim(yi, ya) |
| PMI        | 77.39   |
| EC-Emb     | 77.36   |

Table 10: Comparing different weighting strategies and methods of measuring inter-class similarity.

Can we use the emoji class embedding (EC-Emb) for corpus-level weighting? We experiment with using the embedding of the emoji class (EC-Emb) as an alternative weighting method in place of PMI. Namely, we train RoBERTa on surrogate label prediction (using our 31M using our TweetEmoji-En dataset) for three epochs with a standard cross-entropy loss. We then extract weights of the last classification layer and use these weights as class embeddings, \( E = \{e_1, e_2, \ldots, e_C\} \), where \( e_i \in \mathbb{R}^d \), \( d \) is hidden dimension (i.e., 768), and \( |C| \) is the size of classes (i.e., 1, 067). The correlation of each pair of emojis is computed using cosine similarity, i.e.,

\[
Sim(y_i, y_a) = \frac{e_i^\top e_a}{\|e_i\| \cdot \|e_a\|} \quad 23
\]

As Table 10 and 12 shows, using PMI scores performs slightly better than using class embeddings in both the clustering and penalizing strategies mentioned previously in the current section. For more intuition, we hand-pick three query emojis and manually compare the quality of similarity measures produced by both PMI and class embeddings for these. As Table 11 shows, both PMI and EC-Emb are capable of capturing sensible correlations between emojis (although the embedding approach includes a few semantically distant emojis, such as the emoji ‘😄’ being highly related to ‘😊’).

**F.2 Qualitative Analysis**

We provide a qualitative visualization analysis of our model representation. For this purpose, we use our Info-DCL-RoBERTa to obtain representations of samples in the TweetEmoji’s Dev set (‘[CLS]’ token from the last encoder layer) then average the representations of all tweets with the same surrogate label (emoji). We then project these emoji embeddings into a two-dimensional space using t-SNE. As Fig. 3 shows, we can observe a number of distinguishable clusters. For instance, a cluster of love and marriage is grouped in the left region, unhappy and angry faces are in the right side, and food at the bottom. We can also observe sensible relations between clusters. For instance, the cluster of love and marriage is close to the cluster of smiling faces but is far away from the cluster of unhappy faces. In addition, the cluster of aquatic animals (middle bottom) is close to terrestrial animals while each of these is still visually distinguishable. This indicates that our InfoDCL model has meticulously captured the relations between the emoji surrogate labels.

| Q meth | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|--------|---|---|---|---|---|---|---|---|---|----|
| PMI    | .11| .10| .10| .10| .10| .10| .09| .09| .09| .07|
| E-em   | .34| .32| .31| .31| .30| .28| .27| .27| .27| .26|
| PMI    | .67| .66| .66| .62| .62| .61| .55| .54| .46|    |
| E-em   | .36| .36| .36| .36| .35| .35| .34| .34| .34| .33|
| PMI    | .05| .03| .02| .02| .01| .01| .00| .00| .00| .00|
| E-em   | .36| .34| .34| .34| .34| .32| .32| .32| .32| .32|

Table 11: Ranking of emoji similarity by different methods. PMI is normalized point-wise mutual information. E-em: EC-Emb is the cosine similarity between class embeddings. Emojis are ranked by the similarity scores (under emojis) between them and the query. Q: Query emoji, meth: Method.

| Q meth | 1 − Sim(yi, ya) | 1 + Sim(yi, ya) |
|--------|----------------|----------------|
| Method     | CLS-emb | PMI | CLS-emb | PMI |
| Crisis2000 | 95.95 | 95.93 | 95.88 | 95.95 |
| Emo94-2000 | 81.03 | 81.30 | 81.00 | 80.43 |
| Hate2000   | 57.26 | 57.16 | 57.35 | 57.26 |
| Hate2001   | 76.07 | 77.42 | 76.95 | 76.59 |
| Hate2008   | 51.86 | 50.47 | 52.04 | 51.68 |
| Human2017  | 93.77 | 93.66 | 93.65 | 93.53 |
| Irony2007A | 75.39 | 73.95 | 74.09 | 74.32 |
| Irony2008B | 57.02 | 55.50 | 56.99 | 55.10 |
| Offensive2000 | 89.29 | 80.89 | 81.08 | 80.81 |
| Offensive2001 | 76.73 | 75.90 | 72.45 | 74.64 |
| Offensive2002 | 96.01 | 95.98 | 95.99 | 95.73 |
| Offensive2003 | 86.81 | 86.28 | 86.22 | 86.13 |
| Offensive2004 | 81.40 | 81.02 | 81.18 | 80.48 |
| Offensive2005 | 91.30 | 91.64 | 91.45 | 91.95 |
| Offensive2006 | 57.02 | 55.50 | 56.99 | 55.10 |
| Offensive2007 | 75.39 | 73.95 | 74.09 | 74.32 |
| Offensive2008 | 70.69 | 71.60 | 69.91 | 71.57 |

Table 12: Comparing different weighting strategies and methods of measuring inter-class similarity.

23Self-similarity is set to 0.
24We only include monochronic emoji in this figure.
| Task          | InfoDCL | A    | B    | C    | D    | E    | F    | G    | H    |
|--------------|---------|------|------|------|------|------|------|------|------|
| CrisiOltea   | 95.93   | 95.88| 95.90| 95.86| 95.93| 95.96| 95.81| 95.91| 95.88|
| EmOmah       | 81.03   | 79.96| 80.64| 81.49| 79.04| 81.26| 80.56| 80.50| 80.43|
| HatCra       | 57.26   | 57.25| 57.60| 57.25| 57.05| 57.05| 57.17| 57.29| 57.07|
| HatBasu      | 76.07   | 77.83| 78.00| 76.56| 76.97| 77.30| 76.39| 77.65| 77.84|
| HatCrau      | 51.86   | 51.71| 51.55| 52.40| 50.43| 51.31| 50.44| 49.39| 51.25|
| HumorMoo     | 93.77   | 93.38| 92.98| 93.50| 93.60| 93.14| 93.76| 93.50| 93.78|
| IronYtee-A   | 75.39   | 74.08| 73.32| 72.82| 75.37| 73.77| 73.75| 75.31| 75.31|
| IronYtee-B   | 57.02   | 56.26| 56.06| 56.18| 53.95| 55.66| 56.00| 57.52| 57.52|
| OffensEzamp  | 80.29   | 79.61| 79.91| 80.68| 80.21| 79.58| 80.59| 80.44| 80.25|
| SarCShoef    | 76.73   | 71.40| 72.39| 72.12| 70.23| 71.61| 73.12| 73.87| 75.37|
| SarCPhreo    | 96.01   | 95.90| 95.87| 96.02| 95.86| 96.10| 96.00| 95.86| 95.91|
| SarCRejal    | 86.81   | 87.10| 86.76| 86.76| 86.23| 87.19| 86.59| 86.22| 87.03|
| SarCBaum     | 81.40   | 80.27| 80.09| 80.57| 80.06| 81.26| 81.00| 80.15| 81.16|
| SentIRosen   | 91.30   | 91.56| 90.87| 91.66| 89.87| 90.17| 91.31| 90.96| 91.13|
| SentIThele   | 71.72   | 71.68| 71.64| 72.22| 71.71| 71.68| 71.63| 71.74| 71.38|
| StanceMoham  | 70.69   | 70.35| 70.84| 70.32| 69.56| 70.35| 70.04| 69.43| 70.31|
| Average      | 77.70   | 77.14| 77.15| 77.32| 76.58| 77.45| 77.12| 77.04| 77.60|

Table 13: Full results of ablation study. A: wo LCL, B: wo CCL, C: wo LCL & CCL, D: wo SLP, E: wo MLM, F: wo epoch-wise re-pairing, G: w additional weighting model, H: InfoDCL+Self data augmentation.

| Percentage | 1  | 5  | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|------------|----|----|----|----|----|----|----|----|----|----|----|-----|
| In-Domain  |    |    |    |    |    |    |    |    |    |    |    |     |
| RoBERTa    | 46.96 | 62.70 | 66.41 | 71.96 | 73.54 | 74.34 | 75.09 | 74.99 | 75.37 | 75.95 | 76.27 | 76.24 |
| BERTweet   | 46.87 | 60.46 | 64.75 | 69.08 | 74.96 | 75.88 | 76.35 | 76.70 | 77.12 | 77.39 | 77.92 | 77.81 |
| Sim-D      | 56.23 | 65.43 | 70.19 | 73.70 | 75.24 | 75.45 | 76.08 | 76.32 | 76.79 | 77.01 | 77.35 | 77.81 |
| InfoDCL-RB | 59.78 | 68.45 | 73.19 | 74.85 | 75.82 | 75.98 | 76.81 | 76.93 | 77.37 | 77.35 | 77.67 | 78.17 |
| InfoDCL-BTw | 56.06 | 65.54 | 70.24 | 74.54 | 75.84 | 76.10 | 76.68 | 76.99 | 77.42 | 77.77 | 78.11 | 78.58 |

| Out-of-Domain |    |    |    |    |    |    |    |    |    |    |    |     |
| RoBERTa      | 32.62 | 50.10 | 52.38 | 67.80 | 71.41 | 72.64 | 73.44 | 73.89 | 74.16 | 74.13 | 74.53 | 74.53 |
| BERTweet     | 33.33 | 48.69 | 52.01 | 58.68 | 62.52 | 69.81 | 70.67 | 71.74 | 72.32 | 73.08 | 73.48 | 73.96 |
| Sim-D        | 45.96 | 55.74 | 61.32 | 69.05 | 70.74 | 72.01 | 72.80 | 73.03 | 73.94 | 74.22 | 74.36 | 74.48 |
| InfoDCL-RB   | 48.85 | 62.06 | 67.10 | 70.75 | 72.28 | 73.45 | 74.17 | 74.44 | 74.95 | 75.22 | 75.28 | 75.54 |
| InfoDCL-BTw  | 45.59 | 54.15 | 59.42 | 67.43 | 70.61 | 71.50 | 72.33 | 72.50 | 73.12 | 73.63 | 74.15 | 74.32 |

Table 14: Few-shot learning on downstream tasks where we use varying percentages of Train sets. We report the averaged Test macro-$F_1$ score across 16 in-domain tasks and eight out-of-domain tasks, respectively. Sim-D: SimCSE-Distant, RB: RoBERTa, BTw: BERTweet.

Figure 3: Visualizing emojis in two-dimensional space using t-SNE. We can clearly observe some clusters of similar emojis, such as love and marriage (left middle), music (left bottom), money (middle bottom), unhappiness (right middle).
### Table 15: Full result of few-shot learning on Baseline (1), fine-tuning RoBERTa.

|                          | # of Training Samples |
|--------------------------|-----------------------|
|                          | 20  | 100  | 500  | 1000 |
|                          |     |      |      |      |
| **Percentage**            |     |      |      |      |
|                          | 1   | 5    | 10   | 20   |
|                           | 93.47  | 95.07  | 95.42  | 95.40  | 95.53  | 95.55  | 95.59  | 95.79  | 95.63  | 95.76  | 95.68  | 95.76  | 95.76  | 95.76  | 95.76  |
|                           | 12.73  | 42.06  | 43.51  | 45.58  | 50.99  | 70.92  | 72.48  | 73.99  | 74.53  | 75.08  | 75.63  | 76.18  | 76.63  | 77.12  | 77.57  | 78.02  |
|                           | 94.08  | 34.73  | 43.92  | 62.99  | 63.02  | 66.13  | 66.64  | 67.67  | 67.43  | 67.69  | 68.78  | 69.59  | 70.09  | 70.73  | 71.09  | 71.45  |
|                           | 45.46  | 53.56  | 48.87  | 74.87  | 75.47  | 75.19  | 76.55  | 77.27  | 77.02  | 77.40  | 77.07  | 76.92  | 76.89  | 76.82  | 76.78  | 76.70  |
|                           | 44.08  | 85.83  | 97.02  | 87.98  | 88.52  | 88.30  | 88.13  | 88.84  | 89.29  | 89.31  | 89.10  | 89.00  | 89.00  | 89.00  | 89.00  | 89.00  |
|                           | 40.90  | 40.48  | 49.87  | 78.67  | 82.88  | 90.19  | 89.47  | 89.92  | 89.42  | 89.59  | 88.96  | 90.22  | 49.92  | 53.74  | 65.94  | 69.24  |
|                           | 8.87  | 45.89  | 50.01  | 52.26  | 52.57  | 53.37  | 54.00  | 54.51  | 54.94  | 58.41  | 59.46  | 59.46  | 47.26  | 52.33  | 71.80  | 75.48  |
|                          |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| **Average**               |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
|                           |     |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
|                           | 32.62  | 50.10  | 52.38  | 67.80  | 70.41  | 71.24  | 73.44  | 73.89  | 74.16  | 74.13  | 75.43  | 75.43  | 27.67  | 41.12  | 69.26  | 71.42  |

### Table 16: Full result of few-shot learning on Baseline (11), fine-tuning BERTweet.

|                          | # of Training Samples |
|--------------------------|-----------------------|
|                          | 20  | 100  | 500  | 1000 |
|                          |     |      |      |      |
| **Percentage**            |     |      |      |      |
|                          | 1   | 5    | 10   | 20   |
|                           | 8.44  | 8.78  | 7.76  | 17.85  | 31.73  | 42.57  | 51.52  | 56.03  | 58.17  | 61.24  | 62.31  | 64.48  | 6.25  | 7.86  | 55.09  | 62.94  |
|                           | 1.74  | 22.10  | 9.35  | 43.88  | 46.79  | 47.06  | 49.02  | 49.61  | 51.02  | 54.21  | 58.39  | 53.33  | 1.27  | 1.48  | 4.41  | 20.92  |
|                           | 44.46  | 49.15  | 52.05  | 60.70  | 64.68  | 65.06  | 65.05  | 66.16  | 66.17  | 67.48  | 67.57  | 67.27  | 49.57  | 53.74  | 65.94  | 69.24  |
|                           | 48.93  | 59.61  | 57.33  | 75.14  | 75.32  | 76.06  | 76.05  | 76.70  | 76.04  | 77.04  | 77.63  | 77.33  | 40.55  | 64.86  | 70.63  | 78.76  |
|                           | 48.58  | 84.79  | 86.21  | 86.57  | 87.36  | 87.98  | 87.77  | 87.25  | 88.02  | 88.05  | 88.13  | 87.94  | 45.38  | 59.23  | 85.45  | 86.68  |
|                           | 48.07  | 46.96  | 43.87  | 43.05  | 50.87  | 90.74  | 91.20  | 91.77  | 91.94  | 92.05  | 91.93  | 92.25  | 14.34  | 12.86  | 32.28  | 46.22  |
|                           | 14.15  | 28.93  | 45.48  | 50.25  | 51.58  | 52.82  | 52.79  | 53.32  | 54.24  | 56.42  | 58.74  | 57.48  | 46.12  | 70.62  | 89.23  | 91.08  |
|                           | 52.28  | 89.19  | 85.41  | 91.96  | 92.31  | 99.91  | 90.34  | 92.91  | 93.08  | 94.34  | 94.32  | 94.48  | 30.89  | 34.90  | 62.52  | 68.22  |

|                          |     |      |      |      |
| **Average**               |     |      |      |      |
|                           |     |      |      |      |
|                           | 46.87  | 60.46  | 64.75  | 59.08  |
|                           | 9.48  | 7.76  | 7.58  | 7.40  | 7.30  | 7.21  | 7.14  | 7.14  | 7.14  | 7.14  |
|                           | 19.34  | 28.32  | 37.58  | 46.75  | 56.08  | 65.81  | 75.64  | 85.48  | 95.32  | 95.32  | 95.32  |
|                           | 47.26  | 52.33  | 57.44  | 62.31  | 64.48  | 66.35  | 68.71  | 71.44  | 74.08  | 74.08  | 74.08  |
|                           | 27.59  | 34.79  | 59.08  | 67.43  | 71.24  | 73.44  | 73.89  | 74.16  | 74.13  | 75.43  | 75.43  |
|                           | 39.14  | 38.23  | 68.35  | 73.50  |

**Table 16:** Full result of few-shot learning on Baseline (11), fine-tuning BERTweet.
### Table 17: Full result of few-shot learning on SimCSE-Distant.

| Method | Percentage | # of Training Samples |
|--------|------------|-----------------------|
| SST-5  | 62.87      | 100                   |
| SST-2  | 62.20      | 500                   |
| SST-1  | 61.79      | 1000                  |
| Emo-Biq | 61.01      | 1                      |
| Emo-MR-RO | 60.84 | 10                      |
| Emo-Biq | 61.01      | 50                      |
| Emo-MR-RO | 60.84 | 100                     |
| Emo-Biq | 61.01      | 500                     |
| Emo-MR-RO | 60.84 | 1000                    |

Table 18: Full result of few-shot learning on InfoDCL-RoBERTa.

| Method | Percentage | # of Training Samples |
|--------|------------|-----------------------|
| SST-5  | 61.08      | 100                   |
| SST-2  | 61.34      | 500                   |
| SST-1  | 61.60      | 1000                  |
| Emo-Biq | 61.47      | 1                      |
| Emo-MR-RO | 61.31 | 10                      |
| Emo-Biq | 61.47      | 50                      |
| Emo-MR-RO | 61.31 | 100                     |
| Emo-Biq | 61.47      | 500                     |
| Emo-MR-RO | 61.31 | 1000                    |

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### Table 18: Full result of few-shot learning on InfoDCL-RoBERTa.

| Method | Percentage | # of Training Samples |
|--------|------------|-----------------------|
| SST-5  | 61.80      | 100                   |
| SST-2  | 62.06      | 500                   |
| SST-1  | 62.38      | 1000                  |
| Emo-Biq | 62.34      | 1                      |
| Emo-MR-RO | 62.20 | 10                      |
| Emo-Biq | 62.34      | 50                      |
| Emo-MR-RO | 62.20 | 100                     |
| Emo-Biq | 62.34      | 500                     |
| Emo-MR-RO | 62.20 | 1000                    |
| Percentage | # of Training Samples |
|------------|-----------------------|
| 1 5 10 20 30 40 50 60 70 80 90 100 | 20 100 500 1000 |
| Crisis      | 94.09 95.07 95.29 95.70 95.60 95.83 95.79 95.86 95.84 95.84 95.84 95.84 57.68 89.00 94.13 94.79 |
| Emotional   | 29.53 34.42 74.42 77.04 77.55 77.83 79.56 80.06 80.66 80.04 81.96 52.02 49.49 51.08 52.60 |
| Hate        | 32.42 69.28 74.02 75.12 76.59 76.15 76.77 77.05 77.23 77.40 77.77 78.72 54.94 63.05 72.41 74.13 |
| Hate       | 51.79 51.63 49.59 52.39 53.50 52.64 53.08 52.50 53.38 54.20 55.84 53.95 52.07 88.45 91.22 92.71 |
| Humor       | 58.84 67.69 71.74 72.94 73.57 75.46 77.06 76.00 76.59 77.90 78.77 78.72 59.42 31.47 60.75 68.86 |
| Irony       | 21.92 32.05 36.96 46.94 50.06 50.79 52.74 53.28 56.22 55.36 58.12 59.15 23.50 39.78 49.35 |
| Irony      | 55.61 74.56 77.48 78.14 79.31 79.64 79.68 80.47 79.96 80.91 80.26 79.83 53.79 52.02 73.74 76.39 |
| Offense_Rep | 56.77 54.25 53.80 79.73 79.83 79.47 78.91 78.66 79.29 78.14 80.52 55.84 52.23 78.41 79.21 |
| Sentiment   | 85.54 87.98 89.01 90.47 91.32 92.31 93.00 93.77 94.37 95.14 95.77 96.67 62.96 66.66 84.86 85.91 |
| Sentiment   | 80.56 82.99 83.82 84.98 86.12 86.07 86.12 86.34 86.10 86.78 86.42 87.20 48.97 48.55 80.24 81.42 |
| Sentiment   | 71.96 78.74 79.64 81.03 80.94 81.84 82.25 81.96 82.42 82.88 83.11 83.20 54.47 67.95 77.88 79.86 |
| Sentiment   | 51.13 67.15 80.51 87.87 88.24 88.69 88.92 89.22 89.49 89.95 89.63 90.41 62.97 78.22 89.73 90.35 |
| Sentiment   | 65.32 69.46 69.76 70.62 71.07 71.31 71.22 71.65 71.71 71.45 72.09 71.98 26.79 28.37 64.63 67.71 |
| Stance      | 31.67 40.06 48.05 56.54 61.17 61.10 64.04 65.38 66.12 66.08 67.19 68.22 29.90 33.94 55.87 61.30 |
| Average     | 56.66 65.54 70.24 74.54 75.84 76.10 76.88 76.99 77.42 77.77 78.11 78.58 45.29 52.64 71.31 74.03 |
| Emotion_Rep | 12.31 14.81 27.45 44.30 54.18 57.67 60.11 59.24 62.41 64.31 65.20 65.81 13.00 29.74 61.28 65.57 |
| Emotion_Rep | 4.39 26.17 36.93 45.15 48.75 50.02 50.85 51.32 52.58 53.59 53.77 54.99 3.30 3.01 13.11 23.36 |
| Sentiment   | 47.12 50.30 54.64 56.70 62.89 62.29 64.76 65.53 65.84 65.57 67.73 67.70 46.91 51.50 65.01 67.89 |
| Sentiment   | 49.18 68.42 68.51 70.88 74.05 74.78 75.17 75.85 75.40 76.33 77.27 76.88 49.69 67.78 76.81 76.70 |
| Sentiment   | 82.95 86.37 87.16 87.16 88.30 88.30 88.37 88.11 88.19 88.58 88.82 88.21 55.86 83.00 85.77 86.90 |
| Sentiment   | 56.44 59.69 59.46 90.81 91.02 92.04 92.13 92.06 92.35 92.23 92.36 92.41 64.98 44.15 92.22 92.07 |
| SST-5       | 23.14 38.42 49.67 52.45 52.98 54.06 54.09 54.45 54.84 55.01 55.13 55.93 17.84 21.24 40.02 49.84 |
| SST-2       | 89.22 91.04 91.52 91.85 92.72 92.84 93.16 93.43 93.33 94.43 94.32 93.73 58.17 90.51 90.88 91.69 |
| Average     | 45.59 54.15 59.42 67.43 70.61 71.50 72.33 72.50 73.12 73.63 74.15 74.38 38.72 48.87 65.64 69.25 |

Table 19: Full result of few-shot learning on Info-DCL-BERTweet.