SemEval-2020 Task 12: Multilingual Offensive Language Identification in Social Media (OffensEval 2020)

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Abstract

We present the results and main findings of SemEval-2020 Task 12 on Multilingual Offensive Language Identification in Social Media (OffensEval 2020). The task involves three subtasks corresponding to the hierarchical taxonomy of the OLID schema (Zampieri et al., 2019a) from OffensEval 2019. The task featured five languages: English, Arabic, Danish, Greek, and Turkish for Subtask A. In addition, English also featured Subtasks B and C. OffensEval 2020 was one of the most popular tasks at SemEval-2020 attracting a large number of participants across all subtasks and also across all languages. A total of 528 teams signed up to participate in the task, 145 teams submitted systems during the evaluation period, and 70 submitted system description papers.

1 Introduction

Given the multitude of terms and definitions used in the literature, a few recent studies have investigated the common aspects of different abusive language detection subtasks (Waseem et al., 2017; Wiegand et al., 2018). The precursor to this shared task, SemEval-2019 Task 6: OffensEval (Zampieri et al., 2019b) is one such example. OffensEval 2019 used the Offensive Language Identification Dataset (OLID) (Zampieri et al., 2019a), which contains over 14,000 English tweets annotated using a hierarchical three-level annotation schema that takes both the target and the type of offensive content into account. The assumption behind this annotation schema is that the target of offensive messages is an important variable that allows us to discriminate between, for example, hate speech, which often consists of insults targeted toward a group and cyberbullying which is typically targeted toward an individual. A number of related shared tasks feature subtasks corresponding to similar hierarchical models have been recently organized. Examples include HASOC 2019 (Mandl et al., 2019) for English, German, and Hindi, HatEval 2019 (Basile et al., 2019) for English and Spanish, GermEval 2019 for German (Struß et al., 2019), and TRAC 2020 (Kumar et al., 2018b) for Bengali, Hindi, and English.

OffensEval 2019 attracted nearly 800 teams and received 115 submissions evidencing the interest of the community in this topic. Therefore, we organized OffensEval 2020 (SemEval-2020 Task 12), described in this report to build off the success of the prior task with several improvements. We use the same aforementioned three-level taxonomy to annotate new datasets.

Each level in the taxonomy corresponds to a subtask in the competition:

- subtask A: Offensive language identification;
- subtask B: Automatic categorization of offense types;
- subtask C: Offense target identification.

Our new contributions are as follows:

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We provided the participants with a large-scale semi-supervised training dataset containing over 9 million English tweets (Rosenthal et al., 2020).

We use larger datasets for all subtasks during the evaluation period.

We introduce shared tasks and multilingual datasets in four new languages for sub-task A: Arabic (Mubarak et al., 2020b), Danish (Sigurbergsson and Derczynski, 2020), Greek (Pitenis et al., 2020), and Turkish (Coltekin, 2020). This opens the possibility for cross-lingual training and analysis.

OffensEval 2020 has been an extremely successful task. The significant interest continued from last year, with 528 teams participating in the task and 145 of them submitting results. Furthermore, OffensEval 2020 received 70 system description papers, an all-time record for a SemEval task.

The remainder of this paper is organized as follows: Section 2 describes the annotation schema and 3 presents the five datasets that were used in the competition. Sections 4-9 present the results and analysis of the five languages included in the competition. Finally, Section 10 concludes this paper and presents avenues for related work.

2 Annotation Schema

OLID’s annotation schema proposes a hierarchical modeling of offensive language. It classifies each example using the following three-level hierarchy:

- **Level A - Offensive Language Detection**
  Is a text is offensive (OFF) or not (NOT)?
  - NOT: content that is neither offensive, nor profane;
  - OFF: content containing inappropriate language, insults, or threats.

- **Level B - Categorization of Offensive Language**
  Is the offensive text targeted (TIN) or untargeted (UNT)?
  - TIN: targeted insult or threat towards a group or an individual;
  - UNT: text containing untargeted profanity or swearing.

- **Level C - Offensive Language Target Identification**
  Who or what is the target of the offensive content?
  - IND: the target is an individual explicitly or implicitly mentioned in the conversation;
  - GRP: hate speech, targeting group of people based on ethnicity, gender, sexual orientation, religious belief, or other common characteristic;
  - OTH: targets that do not fall into any of the previous categories, e.g., organizations, events, and issues.

3 Data

In this section, we describe our datasets for the five languages: English, Arabic, Danish, Greek, and Turkish.

All of the languages follow the OLID annotation schema and all the dataset have been pre-processed using the same methods, for example, all user mentions were substituted to @USER for anonymization. The introduction of new languages using a standardised schema with the purpose of detecting offensive and targeted speech should improve dataset consistency. This strategy is in line with current best practices in abusive language data collection (Vidgen and Derczynski, 2020). All languages contain data for Subtask A, and only English contains data for task B and C. The distribution of the data for all languages for Subtask A is shown in Table 1 and for English B and C is shown in Table 2 and 3 respectively. Examples of the labels for each dataset are shown in Table 4.
Table 1: Distribution of label combinations for Task A in the data.

| Language | Training | Test |
|----------|----------|------|
|          | OFF      | NOT  | Total |
|          | 1,448,861 | 7,640,279 | 9,089,140 |
| English  | 1,090    | 2,807 | 3,897  |
| Arabic   | 1,589    | 6,411 | 8,000  |
| Danish   | 384      | 2,577 | 2,961  |
| Greek    | 2,486    | 6,257 | 8,743  |
| Turkish  | 6,131    | 25,625 | 31,756 |

Table 2: Distribution of label combinations for Task B in the data.

| Language | Training | Test |
|----------|----------|------|
|          | TIN      | UNT  | Total |
|          | 149,550  | 39,424 | 188,974 |
| English  | 850      | 1,072 | 1,922  |

Table 3: Distribution of label combinations for Task C in the data.

| Language | Training | Test |
|----------|----------|------|
|          | IND      | GRP  | OTH  | Total |
|          | 120,330  | 22,176 | 7,043 | 149,549 |
| English  | 580      | 190   | 80   | 850 |

Table 4: Tweet examples from the dataset, with their corresponding labels for each subtask of the annotation schema.

| Language | Tweet | A | B | C |
|----------|-------|---|---|---|
| English  | This account owner asks for people to think rationally. | NOT | —  | —  |
| Arabic   | لعنة الله عليك يا ساءك يا حيان يا ابن الكلب. | OFF | —  | —  |
| Danish   | Du glemmer Østeuropaer som er de værste | OFF | —  | —  |
| Greek    | Παραδέξου το, είσαι αγάμητη εδώ και καιρό... | OFF | —  | —  |
| Turkish  | Bøyie devam et seni gerizekahi | OFF | —  | —  |
| English  | this job got me all the way fucked up real shit | OFF | UNT | —  |
| English  | wtf ari her ass tooo big | OFF | TIN | IND |
| English  | @USER We are a country of morons | OFF | TIN | GRP |

**English**  The English dataset provided to the OffensEval 2020 participants is the Semi-Supervised Offensive Language Identification Dataset (SOLID). SOLID contains over nine million English tweets, and it is, to the best of our knowledge, the largest dataset of its kind. The data in SOLID was collected from Twitter using the 20 most common English stopwords such as the, of, and, to, etc. to ensure that random tweets were collected. SOLID was then labeled in a semi-supervised manner using democratic co-training and OLID as a seed dataset. Four models with different inductive biases were used: PMI (Turney and Littman, 2003), FastText (Joulin et al., 2016), LSTM (Hochreiter and Schmidhuber, 1997), and BERT (Devlin et al., 2019). The OFF tweets for the test set were selected using the semi-supervised process and then annotated manually for all subtasks. 2,500 NOT tweets were included using this process without being annotated. Inter-Annotator Agreement (IAA) was computed on a small subset of instances that were predicted to be OFF. IAA is 0.988 for Level A (almost perfect agreement), 0.818 for Level B (substantial agreement), and 0.630 for Level C (moderate agreement). Agreement in Level C is more challenging to achieve because of its 3-way annotation and because a tweet may target more than one label, but only one label can be chosen in the
annotation. More details about the dataset can be found in [Rosenthal et al. (2020)].

**Arabic** The Arabic dataset consists of 10,000 tweets that were manually annotated by a native speaker who is familiar with several Arabic dialects. To increase the chance of having offensive content, only tweets having two or more vocative particles (“yA” in Arabic) were considered for annotation. This increased offensive tweets in the final dataset to 20%. The vocative particle is used mainly to direct the speech to a person or a group (similar to “O” in English), and it’s widely observed in offensive communications in almost all Arabic dialects. The IAA was 0.92 (using Fleiss’ \( \kappa \) coefficient). More details can be found in [Mubarak et al., 2020b].

**Danish** The Danish dataset consisted of 3,600 comments drawn from Facebook, Reddit, and comments in a local newspaper, Ekstra Bladet[^3]. Collection of the dataset was partially seeded from abusive terms gathered during a crowd-sourced lexicon compilation; this seeding was limited to half the data, to ensure sufficient data diversity. The data is not divided into distinct train and development splits, but rather, system builders are encouraged to perform cross-validation, in an attempt to reduce the artefacts that standard splits can introduce [Gorman and Bedrick, 2019]. Annotation was performed at the individual post level by males aged 25-40. A full description of the dataset and an accompanying data statement [Bender and Friedman, 2018] is in Sigurbergsson and Derczynski (2020).

**Greek** The Offensive Greek Twitter Dataset (OGTD) used in this task is a compilation of 10,287 tweets. The tweets were sampled using popular and trending hashtags, including television programs such as series, reality and entertainment shows, along with some politically related tweets. Another portion of the dataset was fetched using pejorative terms and “you are” as keywords. This particular strategy was adopted with the hypothesis that TV and politics would gather a handful of offensive posts, along with tweets containing vulgar language for further investigation. A team of volunteer annotators participated in the annotation process, with each tweet being judged by three annotators. In cases of disagreement, labels with majority agreement above 66% were selected as the actual tweet labels. The IAA was 0.78 (using Fleiss’ \( \kappa \) coefficient). A full description of the dataset collection and annotation is detailed in [Pitenis et al. (2020)].

**Turkish** The Turkish dataset consists of over 35,000 tweets sampled uniformly from the Twitter stream filtered by a list of most frequent words in the language, as identified by Twitter. The tweets were annotated by volunteers. Most tweets are annotated by a single annotator. The annotation agreement calculated with 5,000 doubly-annotated tweets is 92.3% (Cohen’s \( \kappa = 0.761 \)). An interesting aspect of this data set is its sampling, which did not include any specific method for spotting offensive language, e.g., filtering by offensive words, or following usual targets of offensive language. As a result, the distribution closely resembles the actual offensive language use on Twitter and contains more non-offensive tweets than offensive tweets (approximately 4:1). The details of the sampling and the annotation process can be found in [Çöltekin (2020)].

### 4 Task Participation

A total of 528 teams signed up to participate in the task, and 145 of them submitted results across the five languages. Of the latter, a total of 6 teams made submissions for all five languages, 19 did so for four languages, 11 worked on three languages, 13 on two languages, and 96 focused on just one language. Tables [13][14] and [15] show a summary of which team participated in which task. A total of 70 teams submitted system description papers, and Table [12] provides links to these papers for the teams that submitted one. Below, we analyze the representation and models used for all language tracks.

**Representation** The vast majority of teams used some pre-trained embeddings, including context-ualized BERT-style Transformers [Vaswani et al., 2017] or ELMo [Peters et al., 2018], or context-independent embeddings from word2vec [Mikolov et al., 2013] or GloVe [Pennington et al., 2014], including language-specific embeddings such as Mazajak [Farha and Magdy, 2019] in Arabic. Some
teams used other techniques: word n-grams character n-grams lexicons for sentiment analysis and lexicon of offensive words Other representations included emoji priors extracted from the weakly supervised dataset, and sentiment analysis using NLTK (Bird et al., 2009), Vader (Hutto and Gilbert, 2014) and FLAIR (Akbik et al., 2018). While most teams used a transformer-based word embedding, with BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and mBERT (Devlin et al., 2019) being popular, the latter is known to have problems processing some Danish characters, e.g., the ð/aa mapping (Strømberg-Derczynski et al., 2020).

Machine learning models In terms of learning models, most teams used some kind of pre-trained Transformers: typically BERT, but some other models were also tried such as RoBERTa, XLM-RoBERTa (Conneau et al., 2019) Albert (Lan et al., 2019), and GPT-2 (Radford et al., 2019). Other popular models included CNNs (Fukushima, 1980), RNNs (Rumelhart et al., 1986), and GRUs (Cho et al., 2014). Older models such as SVMs (Cortes and Vapnik, 1995), fell out of fashion, but were still used by many teams, typically as part of ensembles that also used Transformers. Ensembles were also very popular.

5 English Track

A total of 87 teams made submissions for the English subtasks (23 of them participated in the 2019 edition of the task): 27 teams participated in all three English subtasks, 18 teams participated in two English subtasks, and 42 focused on one English subtask only.

Pre-processing and normalization Most teams performed some kind of pre-processing (67 teams) or text normalization (26 teams), which are typical steps when working with tweets. Text normalization included various text transformations such as converting emojis to plain text, segmenting hashtags, general tweet text normalization (Satapathy et al., 2019), abbreviation expansion, bad word replacement, error correction, lowercasing, stemming, and/or lemmatization. Other techniques included the removal of @user mentions, URLs, hashtags, emojis, emails, dates, numbers, punctuation, consecutive character repetitions, offensive words, and/or stop words.

Additional data Most teams found the weakly supervised SOLID dataset useful, and 58 teams ended up using it in their systems. Another six teams gave it a try, but could not benefit from it, and the remaining teams only used the manually annotated training data. Some teams used additional datasets from HASOC 2019 (Mandl et al., 2019), the Kaggle competitions on Detecting Insults in Social Commentary and Toxic Comment Classification, TRAC 2018 shared task on Aggression Identification (Kumar et al., 2018a; Kumar et al., 2018c), Wikipedia Detox dataset (Wulczyn et al., 2017), and the datasets from (Davidson et al., 2017) and (Wulczyn et al., 2017), as well as some lexicons such as HurtLex (Bassignana et al., 2018), and Hatebase. Finally, one team created their own dataset.

5.1 Subtask A

A total of 82 teams made submissions for Subtask A, and the results can be seen in Table 5. This was the most popular subtask among all subtasks and across all languages. The best team UHH-LT achieved an F1 score of 0.9204 using an ensemble of ALBERT models of different sizes. The second team was UHH-LT with an F1 score of 0.9204, and it used RoBERTa-large that was fine-tuned on the SOLID dataset in an unsupervised way, i.e., using the MLM objective. The third team, Galileo, achieved an F1 score of 0.9198, using an ensemble that combined XLM-RoBERTa-base and XLM-RoBERTa-large trained on the subtask A data for all languages. The top-10 teams used BERT, RoBERTa or XLM-RoBERTa, sometimes as part of ensembles that also included CNNs and LSTMs (Hochreiter and Schmidhuber, 1997). Overall, the competition for this subtask was very strong, and the scores are very close: the teams ranked 2–16

http://github.com/carpedm20/emoji
http://github.com/grantjenks/python-wordsegment
http://www.kaggle.com/c/detecting-insults-in-social-commentary
http://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge
http://hatebase.org/
are within one point in the third decimal place, and those ranked 2–59 are within two absolute points in
the second decimal place from the winner. All but one team beat the majority baseline (we expect the
team flipped the labels).

| #  | Team               | Score  |
|----|--------------------|--------|
| 1  | UHH-LT             | 0.9204 |
| 2  | Galileo            | 0.9198 |
| 3  | Rouges             | 0.9187 |
| 4  | GUR                | 0.9166 |
| 5  | KS@LTH             | 0.9162 |
| 6  | kungfupanda        | 0.9151 |
| 7  | TysonYU            | 0.9146 |
| 8  | AlexU-BackTranslation-TL | 0.9139 |
| 9  | SpurthiAH          | 0.9136 |
| 10 | amsqr              | 0.9135 |
| 11 | m20170548          | 0.9134 |
| 12 | Coffee_Latte       | 0.9132 |
| 13 | wac81              | 0.9129 |
| 14 | hwijeen            | 0.9129 |
| 15 | UJNLP              | 0.9128 |
| 16 | ARA                | 0.9119 |
| 17 | Ferryman           | 0.9115 |
| 18 | ALT                | 0.9114 |
| 19 | SINAI              | 0.9105 |
| 20 | MindCoders         | 0.9105 |
| 21 | IRLab.AIICICT      | 0.9104 |
| 22 | erfan              | 0.9103 |
| 23 | Light              | 0.9103 |
| 24 | KAFK               | 0.9099 |
| 25 | PALI               | 0.9098 |
| 26 | PRHLT-UPV          | 0.9097 |
| 27 | YNU_oxz            | 0.9097 |
| 28 | IITP-AINLPML       | 0.9094 |

| #  | Team               | Score  |
|----|--------------------|--------|
| 29 | UTFPR              | 0.9094 |
| 30 | IU-UM@LING         | 0.9094 |
| 31 | talhaanwar         | 0.9093 |
| 32 | SSN_NLP            | 0.9092 |
| 33 | Hitachi            | 0.9091 |
| 34 | kathrync           | 0.9091 |
| 35 | XD                 | 0.9090 |
| 36 | UoB                | 0.9090 |
| 37 | PAI-NLP            | 0.9089 |
| 38 | PingANPAI          | 0.9089 |
| 39 | VerifiedXiaoPAI    | 0.9089 |
| 40 | nlpUP              | 0.9089 |
| 41 | NLP_Passau         | 0.9088 |
| 42 | TheNorth           | 0.9087 |
| 43 | problemConquero    | 0.9085 |
| 44 | Lee                | 0.9084 |
| 45 | Wu427              | 0.9081 |
| 46 | ITNLTP             | 0.9078 |
| 47 | Better Place       | 0.9077 |
| 48 | IITG-ADBU          | 0.9075 |
| 49 | *doxaAI            | 0.9075 |
| 50 | NTU_NLP            | 0.9067 |
| 51 | FERMI              | 0.9065 |
| 52 | mdherath           | 0.9063 |
| 53 | INGEOTEC           | 0.9061 |
| 54 | PGSG               | 0.9060 |
| 55 | SRIB2020           | 0.9048 |
| 56 | tcaselli           | 0.9036 |
| 57 | OffensSzeged       | 0.9032 |
| 58 | aprosio            | 0.9032 |
| 59 | RGCL               | 0.9006 |
| 60 | byteam             | 0.8994 |
| 61 | jpmerez            | 0.8990 |
| 62 | PUM                | 0.8973 |
| 63 | shardul007         | 0.8927 |
| 64 | 12C                | 0.8919 |
| 65 | sonal.kumari       | 0.8900 |
| 66 | JIS                | 0.8887 |
| 67 | IR3218             | 0.8843 |
| 68 | TeamKGP            | 0.8822 |
| 69 | UNT Linguistics    | 0.8820 |
| 70 | janecek1           | 0.8744 |
| 71 | Team Oulu          | 0.8655 |
| 72 | TECHSSN            | 0.8655 |
| 73 | KDELAB             | 0.8653 |
| 74 | HateLab            | 0.8617 |
| 75 | IASBS              | 0.8577 |
| 76 | IUST               | 0.8288 |
| 77 | Duluth             | 0.7714 |
| 78 | RTNLU              | 0.7665 |
| 79 | KarthikaS          | 0.6351 |
| 80 | Bodensee           | 0.4954 |
| 81 | Majority Baseline  | 0.4193 |
| 82 | IRLab@IITV         | 0.0728 |

Table 5: Results for English Subtask A. Teams are ranked in decreasing order of macro-averaged F1.

### 5.2 Subtask B

A total of 41 teams made submissions for Subtask B, and the results can be seen in Table 6. The winner
is Galileo (which were third on subtask A), whose ensemble model achieved an F1 score of 0.7462. The
second place team, PGSG, used a complex teacher-student architecture built on top of a BERT-LSTM
model, which was fine-tuned on the SOLID dataset in an unsupervised way, i.e., optimizing for the MLM
objective. NTU_NLP ranked 3rd with an F1 score of 0.69063. They solved Subtasks A, B, and C as part
of a multi-task BERT-based model. The differences in the scores for subtask B are much larger than A.
For example, the 4th team is two points behind the third one and seven points behind the 1st one. The
top ranking teams is again dominated by BERT-based Transformer models. All but four teams beat the
majority baseline.

### 5.3 Subtask C

A total of 37 teams made submissions for Subtask C and the results are available in Table 7. The best team is once again Galileo with an F1 score of 0.7145. LT@Helsinki is in second place with an F1 score of 0.6700. They used fine-tuned BERT with oversampling to improve class imbalance. The third best system is PRHLT-UPV with an F1 score of 0.6692, which combines BERT with hand-crafted features; it is followed very closely by LT2 at rank 4, which achieved an F1 score of 0.6683. This subtask is also dominated by BERT-based models. All teams beat the majority baseline. The absolute
| # | Team                  | Score | # | Team                  | Score | # | Team                  | Score |
|---|----------------------|-------|---|----------------------|-------|---|----------------------|-------|
| 1 | Galileo              | 0.7462| 15| Wu427                | 0.6208| 29| PALI                 | 0.5533|
| 2 | PGSвлек              | 0.7362| 16| UNT Linguistics      | 0.6174| 30| HoangDung            | 0.5524|
| 3 | NTU_NLP              | 0.6906| 17| I2C                  | 0.6012| 31| KAFK                 | 0.5518|
| 4 | UoB                  | 0.6734| 18| PRHLT-UPV            | 0.5987| 32| PAI-NLP              | 0.5451|
| 5 | TysonYU              | 0.6687| 19| SRIB2020             | 0.5805| 33| VerifiedXiaoPAI      | 0.5451|
| 6 | GUIR                 | 0.6650| 20| FERMI                | 0.5804| 34| Duluth               | 0.5382|
| 7 | UHH-LT               | 0.6598| 21| IU-UM@LING           | 0.5746| 35| Bodensee             | 0.4926|
| 8 | Ferryman             | 0.6576| 22| PingANPAI            | 0.5687| 36| TECHSSN              | 0.3894|
| 9 | IITG-ADBU            | 0.6528| 23| nlpUP                | 0.5678| 37| KarthikaS            | 0.3741|
| 10| kathrync             | 0.6445| 24| Team Oulu            | 0.5676|    | Majority Baseline    | 0.3741|
| 11| IRLab_DAIICT         | 0.6412| 25| KDELAB               | 0.5638| 38| IRLab@IITV          | 0.2950|
| 12| INGEOTEC             | 0.6321| 26| wac81                | 0.5627| 39| SSN_NLP              | 0.2912|
| 13| HateLab              | 0.6303| 27| IITP-AINLPML         | 0.5569| 40| IJS                  | 0.2841|
| 14| AlexU-BackTranslation-TL | 0.6300| 28| problemConquero      | 0.5569| 41| KEIS@JUST            | 0.2777|

Table 6: Results for English Subtask B.

| # | Team                  | Score | # | Team                  | Score |
|---|----------------------|-------|---|----------------------|-------|
| 1 | Galileo              | 0.7145| 14| KAFK                 | 0.6168|
| 2 | LT@Helsinki          | 0.6700| 15| ssn_nlp              | 0.6116|
| 3 | PRHLT-UPV            | 0.6692| 16| IJS                  | 0.6094|
| 4 | UHH-LT               | 0.6683| 17| PALI                 | 0.6015|
| 5 | ITNLP                | 0.6543| 18| FERMI                | 0.5882|
| 6 | wac81                | 0.6489| 19| problemConquero      | 0.5871|
| 7 | PUM                  | 0.6473| 20| Ferryman             | 0.5809|
| 8 | PingANPAI            | 0.6394| 21| AlexU-BackTranslation-TL | 0.5761|
| 9 | IITP-AINLPML         | 0.6388| 22| IITG-ADBU            | 0.5756|
| 10| PAI-NLP              | 0.6347| 23| Duluth               | 0.5744|
| 11| GUIR                 | 0.6319| 24| KDELAB               | 0.5720|
| 12| IU-UM@LING           | 0.6265| 25| NTU_NLP              | 0.5695|
| 13| mdherath             | 0.6232| 26| INGEOTEC             | 0.5626|

Table 7: Results for English Subtask C.

F1-scores obtained by the best teams in English Subtasks A and C are substantially higher than the scores obtained by the best teams in OffensEval 2019: 0.9223 against 0.829 in A and 0.7145 against 0.6600 in C. This suggests that the much larger English dataset made available in OffensEval 2020 (SOLID [Rosenthal et al., 2020]) helps the models making more accurate predictions.

Furthermore, it confirms that the weakly supervised method used to compile and annotate SOLID is a viable alternative to popular manual annotation approaches. A more detailed analysis of the systems’ performances will be carried out to determine the impact of this large dataset in the results.

5.4 Best Systems

We provide some more details about the approaches used by the top teams for each subtask. We use sub-indices to show their rank for each subtask. Additional summaries of some of the best teams can be found in the Appendix [A]

Galileo (A:3,B:1,C:1) This team was ranked 3rd, 1st, and 1st on the English Subtasks A, B, and C, respectively. This is also the only team ranked among the top-3 across all languages. For Subtask A, they used multi-lingual pre-trained Transformers based on XLM-RoBERTa, followed by multi-lingual fine-tuning using the OffensEval data. Ultimately, they submitted an ensemble that combined XLM-RoBERTa-base and XLM-RoBERTa-large, achieving an F1 score of 0.9198. For Subtasks B and C, they used knowledge distillation in a teacher-student framework, using Transformers such as ALBERT.
and ERNIE 2.0 (Sun et al., 2019) as teacher models, achieving an F1 score of 0.7462 and 0.7145, for Subtasks B and C respectively.

**LT2** (A:1) This team was ranked 1st on Subtask A with an F1 score of 0.9223. They fine-tuned different Transformer models on the OLID training data, and then combined them into an ensemble. They experimented with BERT-base and BERT-large (uncased), RoBERTa-base and RoBERTa-large, XLM-RoBERTa, and four different ALBERT models (large-v1, large-v2, xxlarge-v1, and xxlarge-v2). In their official submission, they submitted an ensemble using only the ALBERT models. They did not use the labels of the SOLID dataset, but found the tweets it contained nevertheless useful for unsupervised fine-tuning (i.e., using the MLM objective) of the pre-trained Transformers.

## 6 Arabic Track

The total number of users registered for the Arabic track was 108. Ultimately, 53 teams entered the competition with at least one valid submission. Among them, 10 teams participated only in the Arabic track while the rest participated in other languages in addition to Arabic. This is the second shared task for Arabic after the one at the 4th workshop on Open-Source Arabic Corpora and Processing Tools (Mubarak et al., 2020a), which had different settings and few participating teams.

| #  | Team           | Score  | #  | Team           | Score  | #  | Team           | Score  |
|----|----------------|--------|----|----------------|--------|----|----------------|--------|
| 1  | ALAMIHamza     | 0.9017 | 21 | SaiSakethAluru | 0.8455 | 41 | thanirdu       | 0.7881 |
| 2  | alt            | 0.9016 | 22 | will_go        | 0.8440 | 42 | PRHLT-UPV      | 0.7868 |
| 3  | Galileo        | 0.8989 | 23 | erfan          | 0.8418 | 43 | anitasaroj     | 0.7793 |
| 4  | alisafaya      | 0.8972 | 24 | jimperez       | 0.8402 | 44 | yemen2016      | 0.7721 |
| 5  | AMR-KELEG      | 0.8958 | 25 | Bushr          | 0.8395 | 45 | saroarj        | 0.7474 |
| 6  | fte10kso       | 0.8902 | 26 | klaraling      | 0.8241 | 46 | kxkjava        | 0.7306 |
| 7  | iaf7           | 0.8778 | 27 | zohor_orabe    | 0.8221 | 47 | frankakorpel   | 0.7251 |
| 8  | sabino         | 0.8744 | 28 | mircea.tanase  | 0.8220 | 48 | COMA           | 0.5436 |
| 9  | aialharbi      | 0.8714 | 29 | machouz        | 0.8216 | 49 | JCT            | 0.4959 |
| 10 | yasserotiey    | 0.8691 | 30 | orabia         | 0.8198 | 50 | aprosio        | 0.4642 |
| 11 | SAJA           | 0.8655 | 31 | Taha           | 0.8183 | 51 | sonal.kumari   | 0.4536 |
| 12 | Ferryman       | 0.8592 | 32 | hamadanayel    | 0.8182 | 52 | sayanta95      | 0.4466 |
| 13 | SAFA           | 0.8555 | 33 | kathrync       | 0.8176 | 53 | SpurthiAH      | 0.4451 |
| 14 | hhaddad        | 0.8520 | 34 | fatemah        | 0.8147 | 54 | Majority Baseline | 0.4441 |
| 15 | talhaanwar     | 0.8519 | 35 | jberm          | 0.8125 |        |                |
| 16 | saradhiy       | 0.8500 | 36 | zahra.raj      | 0.8057 |        |                |
| 17 | lukez          | 0.8498 | 37 | 12C            | 0.8056 |        |                |
| 18 | tanvidadu      | 0.8480 | 38 | jlee24282      | 0.8024 |        |                |
| 19 | TysonYU        | 0.8474 | 39 | karishmaslaud  | 0.8021 |        |                |
| 20 | hwijeen        | 0.8455 | 40 | asking28       | 0.8002 |        |                |

Table 8: Results for Arabic Subtask A.

**Pre-processing and normalization** Most teams performed some kind of pre-processing or text normalization (e.g. Hamza shapes, Alif Maqsoura, Taa Marbouta, diacritics, non-Arabic characters, etc.), and only one team replaced emojis with their textual meanings.

### 6.1 Results

Table 8 shows the teams and their F1-scores for the Arabic Subtask A. The majority baseline score is 0.4441, assuming that all tweets are not offensive. Most teams achieved almost double the baseline score. The top team is ALAMIHamza from Université Sidi Mohamed Ben Abdellah-Fès (Morocco) which achieved an F1-score of 0.9017. The alt team from Qatar Computing Research Institute (Qatar) came in a close second place with an F1-score of 0.9016 and the Galileo team from Baidu Inc. (China) earned the third place with an F1-score of 0.8989. Note, Galileo was also the best performing team overall for the English subtasks.
The team obtained the highest F1-score using BERT to encode Arabic tweets with a sigmoid classifier and they performed translations of the meaning of emojis. A summary of the other top teams can be found in Appendix A.

7 Danish Track

The total number of users registered for the Danish track was 72. Ultimately, 39 teams entered at least one valid submission out of 72 users registered for the task. This is the first shared task with this language, and only the second time that offensive language detection has been run over it (Sigurbergsson and Derczynski (2020)).

The results are detailed in Table 9. All but one team beat the FastText baseline score of 0.5148 F1 and most reached an F1 of 0.7. Interestingly, one of the top ranked teams, JCT, used entirely non-neural methods.

**LT@Helsinki** The team used a NordicBERT-based approach, provided by BotXO, which is customised to Danish, and avoids some of the preprocessing noise and ambiguity introduced by other popular BERT implementations. On top of this, they reduced orthographic lengthening to maximum two repeated characters, converted emojis to “sentiment scores”, and counted incidences of hashtags and username references. Tuning was done with 10-fold cross validation, to find reliable results; this showed that the NordicBERT system gave them the best results of the classifiers they tried.

| #  | Team          | Score | #  | Team          | Score | #  | Team          | Score |
|----|---------------|-------|----|---------------|-------|----|---------------|-------|
| 1  | LT@Helsinki  | 0.8119| 14 | Rouges        | 0.7587| 27 | TeamKGP       | 0.6973|
| 2  | Galileo       | 0.8021| 14 | Smatgrisene   | 0.7587| 28 | Stormbreaker  | 0.6842|
| 3  | NLPDove       | 0.7923| 16 | machouz       | 0.7561| 29 | talhaanwar    | 0.6819|
| 4  | aprosio       | 0.7766| 17 | IU-UM@LING    | 0.7553| 30 | Sonal         | 0.6711|
| 5  | KS@LTH        | 0.7750| 18 | Ferryman      | 0.7525| 31 | RGCL          | 0.6556|
| 6  | JCT           | 0.7741| 19 | MindCoders    | 0.7380| 32 | PRHLT-UPV     | 0.6369|
| 7  | jmperez       | 0.7723| 20 | ARA           | 0.7267| 33 | IUST          | 0.6226|
| 8  | TysonYU       | 0.7685| 21 | INGEOTEC      | 0.7237| 34 | SRIIB2020     | 0.6127|
| 9  | FERMI         | 0.7685| 22 | KUISAIL       | 0.7231| 35 | IR3218        | 0.5736|
| 10 | NLP_Passau    | 0.7673| 23 | JAK           | 0.7086| 36 | SSN_NLP       | 0.5678|
| 11 | GruPaTo       | 0.7620| 24 | LIR           | 0.7019| 37 | Team Oulu     | 0.5587|
| 12 | KEIS@JUST     | 0.7612| 25 | MeisterMorxrc | 0.6998| 38 | IJS           | 0.4913|
| 13 | will_go       | 0.7596| 26 | problemConquero | 0.6974|

Table 9: Results for Danish Subtask A.

**Pre-processing and normalization** Many teams used the pre-processing included in the relevant embedding model (e.g. BPE (Heinzerling and Strube, 2018)). Beyond that, transformations included emoji normalisation, spelling correction, sentiment tagging, lexical and regex-based term and phrase flagging, hashtag segmentation and WordPieces.

### 7.1 Results

The results are detailed in Table 9. All but one team beat the FastText baseline score of 0.5148 F1 and most reached an F1 of 0.7. Interestingly, one of the top ranked teams, JCT, used entirely non-neural methods.

**LT@Helsinki** The team used a NordicBERT-based approach, provided by BotXO, which is customised to Danish, and avoids some of the preprocessing noise and ambiguity introduced by other popular BERT implementations. On top of this, they reduced orthographic lengthening to maximum two repeated characters, converted emojis to “sentiment scores”, and counted incidences of hashtags and username references. Tuning was done with 10-fold cross validation, to find reliable results; this showed that the NordicBERT system gave them the best results of the classifiers they tried.

8 Greek Track

The total number of users registered for the Greek track was 71. Ultimately, 37 teams entered at least one valid submission out of 72 users registered for the track. This is the first shared task for offensive language detection to include Greek. The dataset offered to OffensEval participants is an extended version of the one created and experimented on by Pitenis et al. (2020).

**Pre-processing and normalization** Most participants performed pre-processing or text normalization techniques and only one team reported emoji replacement with their textual meanings.

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9See https://github.com/botxo/nordic_bert
### Table 10: Results for Greek Subtask A.

| #  | Team            | Score | #  | Team          | Score | #  | Team          | Score |
|----|-----------------|-------|----|---------------|-------|----|---------------|-------|
| 1  | NLPDove         | 0.8522| 14 | kathrync      | 0.8147| 27 | IUST          | 0.7756|
| 2  | Galileo         | 0.8507| 15 | talhaanwar     | 0.8141| 28 | KEIS@JUST     | 0.7730|
| 3  | KS@LTH          | 0.8481| 16 | IU-UM@LING     | 0.8140| 29 | aprosio       | 0.7700|
| 4  | KUISAIL         | 0.8432| 17 | MindCoders     | 0.8137| 30 | Team Oulu     | 0.7615|
| 5  | IJS             | 0.8329| 18 | RGCL           | 0.8135| 31 | JCT           | 0.7568|
| 6  | SU-NLP          | 0.8317| 19 | problemConquer | 0.8115| 32 | IRlab@ITV     | 0.7181|
| 7  | LT@Helsinki     | 0.8258| 20 | Rouges         | 0.8030| 33 | TeamKGP       | 0.7041|
| 8  | FERMI           | 0.8231| 21 | TysonYU        | 0.8022| 34 | SSN_NLP       | 0.6779|
| 9  | Ferryman        | 0.8222| 22 | Sonal          | 0.8017| 35 | fatemah       | 0.6036|
| 10 | INGEOTEC        | 0.8197| 23 | JAK            | 0.7956| 36 | CyberTronics  | 0.4265|
| 11 | will_go         | 0.8176| 24 | ARA            | 0.7828| 37 | Stormbreaker  | 0.2688|
| 12 | jmperez         | 0.8153| 25 | machouz        | 0.7820|     |               |       |
| 13 | LIIR            | 0.8148| 26 | PRHLT-UPV      | 0.7763|     |               |       |

8.1 Results

The detailed leader board is available in Table [10]. The top team, NLPDove, achieved an F1 score of 0.852, with Galileo coming close at second place with an F1 score of 0.851. The KS@LTH team earned third place with an F1 score of 0.848. It is no surprise that the majority of high ranking submissions and participants make use of the widely-acclaimed Transformers models, BERT being the most prominent among them, along with pre-trained word embeddings in their systems.

**NLPDove (A:1)** The team achieved the highest F1 score using pre-trained word embeddings (mBERT) fine-tuned with the labels provided by the dataset. A domain specific vocabulary was generated by running the WordPiece algorithm (Schuster and Nakajima, 2012) and using embeddings for extended vocabulary to pre-train and fine-tune the model.

9 Turkish Track

The total number of users registered for the Turkish track was 86. Ultimately, 46 teams entered at least one valid submission. All teams except for one participated in at least one other OffensEval subtask. This is the first shared track on detecting Turkish offensive language.

9.1 Results

The overview of the macro-averaged F1 scores are presented in Table [11]. The team Galileo obtained the best macro-averaged F1 score 0.8258, followed by SU-NLP and KUI-SAIL with F1 scores of 0.8167 and 0.8141 respectively. The second and third place teams are from Turkey, suggesting that some language specific resources and tuning may be effective. All teams except two score higher than the majority class baseline (an F1 score of 0.44), most results lie in the interval 0.70 to 0.80.

**Galileo (A:1)** The first team in Turkish Subtask A was Galileo, who also obtained top results in other subtasks. The system used is language agnostic, and it is based an ensemble of pre-trained multilingual models further trained on the multi-lingual OffensEval data.

10 Conclusion

We present the results of OffensEval 2020, which featured datasets in five languages (English, Arabic, Danish, Greek, and Turkish). English consists of the three Subtasks (A, B, and C) representing each level of the OLID hierarchy. The other four languages consist only of Subtask A. The competition attracted a total of 528 teams and 145 teams submitted results across all languages and subtasks. Finally, 70 teams submitted system description papers. To the best of our knowledge, OffensEval 2020 is the most popular SemEval task of all times in terms of the number of system description papers.
| #  | Team            | Score | #  | Team             | Score | #  | Team               | Score |
|----|-----------------|-------|----|------------------|-------|----|--------------------|-------|
| 1  | Galileo         | 0.8258| 18 | LT@Helsinki      | 0.7719| 35 | PRHLT-UPV          | 0.7127|
| 2  | SU-NLP          | 0.8167| 19 | NLP_Passau       | 0.7676| 36 | SRIB2020           | 0.6993|
| 3  | KUISAIL         | 0.8141| 20 | will_go          | 0.7653| 37 | Team Oulu          | 0.6868|
| 4  | KS@LTTH        | 0.8101| 21 | FERMI            | 0.7578| 38 | ARA                | 0.6381|
| 5  | NLPDove        | 0.7967| 22 | problemConquero  | 0.7553| 39 | aprosio            | 0.6268|
| 6  | TysonYU        | 0.7933| 23 | pin_code_        | 0.7496| 40 | f_shahaby         | 0.5730|
| 7  | RGCL            | 0.7859| 24 | talhaanwar       | 0.7477| 41 | CyberTronics       | 0.5420|
| 8  | Rouges          | 0.7815| 25 | IUST             | 0.7476| 42 | IASBS              | 0.5362|
| 9  | tcaselli        | 0.7790| 26 | alaeddin         | 0.7473| 43 | JCT                | 0.5099|
| 10 | Mind Coders     | 0.7789| 27 | fatemah          | 0.7469| 44 | machouz            | 0.4518|
| 11 | INGEOTEC        | 0.7758| 28 | kathrync         | 0.7461| 45 | jooyeon Lee        | 0.4435|
| 12 | Ferryman        | 0.7737| 29 | Sonal            | 0.7422| 46 | Stormbreaker       | 0.3109|
| 13 | ANDES           | 0.7737| 30 | MeisterMorxrc    | 0.7398|     |                    |       |
| 14 | I2C             | 0.7735| 31 | JAK              | 0.7334|     |                    |       |
| 15 | IU-UM@LING      | 0.7729| 32 | KEIS@JUST        | 0.7330|     |                    |       |
| 16 | IJS             | 0.7724| 33 | TeamKGP          | 0.7301|     |                    |       |
| 17 | LIIR            | 0.7720| 34 | TOBB ETU         | 0.7154|     |                    |       |

Table 11: Results for Turkish Subtask A.

The participation and response OffensEval 2020 received confirm the interest of the community in this topic and allowed us to compare a variety of different methods on different languages and datasets. We received a large number of submissions in all five language tracks ranging from 37 teams in the Greek track to 81 teams in the English track Subtask A. We observed that 96 teams of the 145 teams chose to participate in only one of the languages while only 6 teams submitted results for all languages. 43 teams participated in 2-4 language tracks. We observed similar trends to OffensEval 2019, particularly that the best teams in all languages and subtasks used models with pre-trained contextual embeddings, most notably BERT.

OffensEval 2020 provides us with several avenues for future work. We would like to have Subtasks B and C organized for all languages as well as additional languages which are typically under-represented. Another interesting aspect to explore is code-mixed datasets, for example, Arabic written in both Arabic and Latin script.

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A Top Teams

Below is a description of additional top teams for all subtasks and languages.

**LT2 (EN A:2)** This team was ranked 2nd on subtask A with an F1 score of 0.9204. It uses RoBERTa-large that was fine-tuned on the SOLID dataset in an unsupervised way i.e., using the MLM objective.

**PGSG (EN B:2)** The team was ranked 2nd on Subtask B with an F1 score of 0.73623. They first fine-tuned the BERT-Large, Uncased (Whole Word Masking) checkpoint using the tweets from SOLID, but ignoring their labels. For this, they optimized for the MLM objective only, without the Next Sentence Prediction loss in BERT. Then, they built a BERT-LSTM model using this fine-tuned BERT, and adding LSTM layers on top of it, together with the [CLS] token. Finally, they used this architecture to train a Noisy Student model using the SOLID data.

**NTU_NLP (EN B:3)** The team is 3rd on subtask B with an F1 score of 0.69063. They proposed a hierarchical multi-task learning approach that solves Subtasks A, B, and C simultaneously, following the hierarchical structure of the annotation schema of the OLID dataset. Their architecture has three layers. The input of the first layer is the output of BERT, and its output (D1-OUT) is directly connected to the output layer for Subtask A. The second layer’s input is the BERT output concatenated with D1-OUT, and its output (D2-OUT) is directly connected to the output layer for Subtask B. The third layer’s input is the BERT output concatenated with D2-OUT, and its output is directly connected to the output layer for Subtask C.

**LT@Helsinki (EN C:2)** The team was ranked 2nd on English Subtask C with an F1 score of 0.6700. They used a very simple approach: over-sample the training data to overcome the class imbalance, and then fine-tune BERT-base-uncased.

**PRHLT-UPV (EN C:3)** The team was ranked 3rd on English Subtask C with an F1 score of 0.6692. They used a combination of BERT and hand-crafted features, which were concatenated to the [CLS] representation from BERT. The features include the length of the tweets, the number of misspelled words, and the use of punctuation marks, emoticons, and noun phrases.

**alt (AR A:2)** The ‘alt’ team was second place for Arabic subtask A. They used ensemble of SVM, CNN-BiLSTM and Multilingual BERT. The SVMs used character n-grams + word n-grams + word embeddings as features. CNN-BiLSTM used learned character embeddings and pretrained word embeddings as features.

**Galileo (AR A:3, GR: A:2)** The Galileo team was in third place for Arabic and second place for Greek. They used multi-lingual fine-tuning with multi-lingual unsupervised models from Transformers (e.g., BERT, GPT-2, ALBERT). They were also the top performing team overall for English as described previously.

**KS@LTH (GR: A:3)** The KS@LTH team used Monolingual BERT, showing a slight gap in performance between the Multilingual and the Monolingual models compared to the second place team.
### B Participants

| Team                  | System Description Paper                      | Team                  | System Description Paper                      |
|-----------------------|-----------------------------------------------|-----------------------|-----------------------------------------------|
| AdelaideCyC           | (Herath et al., 2020)                         | LISAC FSDM-USMBA      | (Alani et al., 2020)                         |
| AlexU-BackTranslation-TL | (Ibrahim et al., 2020)                      | LT@Helsinki          | (Pâumes et al., 2020)                        |
| ALT                   | (Hassan et al., 2020)                        | LT2                  | (Wiedemann et al., 2020)                     |
| anmsgr                | (Mosquera, 2020)                             | NAYEL                | (Nayel, 2020)                                |
| ANDES                 | (Arango et al., 2020)                        | NLP_Passau           | (Hussein et al., 2020)                       |
| BhamNLP               | (Alharbi and Lee, 2020)                      | NLPDove              | (Ahn et al., 2020)                           |
| BIU-JCT               | (Uzan and HaCohen-Kerner, 2020)              | snlpUP               | (Hamdy et al., 2020)                         |
| BRUMS                 | (Ranasinghe and Hettiarachchi, 2020)         | Nova-Wang            | (Wang and Marinho, 2020)                     |
| CoLi @ UdS            | (Chapman et al., 2020)                       | NTU_NLP              | (Chen et al., 2020)                          |
| CyberTronics          | (Sayanta et al., 2020)                       | NUIG                 | (Suryawanshi et al., 2020)                   |
| DoTheMath             | (Orabe et al., 2020)                         | Oulu                 | (Jahan and Oussalah, 2020)                   |
| Duluth                | (Pedersen, 2020)                             | PGSF                 | (Pham-Hong and Choksi, 2020)                 |
| FBK-DH                | (Casula et al., 2020)                        | pin_colo             | (Arslan, 2020)                               |
| Ferryman              | (Weilong et al., 2020)                       | PRHLT-UPV            | (De la Peña Sarracén and Rosso, 2020)        |
| Galileo               | (Wang et al., 2020)                          | problemConquero      | (Laud et al., 2020)                          |
| Garain                | (Garain, 2020)                               | PUM                  | (Janiszewski et al., 2020)                   |
| GnuPaTo               | (Colla et al., 2020)                         | Rouges               | (Dadu and Pant, 2020)                        |
| GUIR                  | (Sotudeh et al., 2020)                       | SalamNET             | (Husain et al., 2020)                        |
| Hitachi               | (Ravikiran et al., 2020)                     | SINAI                | (Plaza-del Arco et al., 2020)                |
| I2C                   | (Alvarez et al., 2020)                       | Smatgrisene          | (Henrichsen and Rathje, 2020)                |
| iCompass              | (Messaoudi et al., 2020)                     | Sonal.kumari         | (Kumari, 2020)                               |
| IITG-ADBU              | (Barua et al., 2020)                         | SSN_NLP_MLRG         | (Kalanav and Thenmozhi, 2020)                |
| IITP-AINLPM           | (Chosh et al., 2020)                         | SU-NLP               | (Ozdemir and Yemteri, 2020)                  |
| INGEOotec              | (Miranda-Jiménez et al., 2020)               | TAC                  | (Anwar and Bang, 2020)                       |
| IR3218-UI             | (Kurniawan et al., 2020)                     | TECHSSN              | (Srivastava et al., 2020)                    |
| IRLab@IITV            | (Saroj et al., 2020)                         | TheNorth             | (Alonso, 2020)                               |
| IRLab_DAICT            | (Parikh et al., 2020)                        | UJNLP                | (Yao et al., 2020)                           |
| KAFK                  | (Das et al., 2020)                           | UNT                  | (Fromknecht and Palmer, 2020)                |
| KDELAB                | (Hanahata and Aono, 2020)                    | UiB                  | (Lim and Madabushi, 2020)                    |
| KEIS@JUST             | (Tawabeh et al., 2020)                       | UPB                  | (Tanase et al., 2020)                        |
| KS@LTH                | (Sohil, 2020)                                | UTFPR                | (Borjioa and Paetzold, 2020)                 |
| KUISAIL               | (Safaya et al., 2020)                        | WOLI                 | (Oinly et al., 2020)                         |
| Kangfupanda           | (Zia et al., 2020)                           | XD                   | (Dong and Cui, 2020)                         |
| Lee                   | (Junyi et al., 2020)                         | YNU_pzx              | (Qi et al., 2020)                            |
| LIIR                  | (Chadery and Moens, 2020)                    |                      |                                               |

Table 12: The teams that participated in OffensEval-2020 and submitted system description papers with the corresponding reference thereof.
| Team                           | A-Arabic | A-Danish | A-Greek | A-Turkish | A-English | B-English | C-English |
|-------------------------------|----------|----------|---------|-----------|-----------|-----------|-----------|
| AlexU-BackTranslation-TL      | ✓        |          |         |           | ✓         | ✓         | ✓         |
| ALT                           |          | ✓        |         |           |           |           |           |
| aialharbi                     |          |          | ✓       |           |           |           |           |
| alaeddin                      |          |          |         |           |           |           |           |
| ALAMIHamza                    |           |          |         |           |           |           |           |
| alisafaya                     |          |          |         |           |           |           |           |
| AMR-KELEG                     |          |          |         |           |           |           |           |
| amsqqr                        |          |          |         |           |           |           | ✓         |
| ANDIES                        |          |          |         |           |           |           | ✓         |
| anitasaroj                    |          |          |         |           |           |           |           |
| aprosio                       |          |          |         |           |           |           |           |
| ARA                           |          |          |         |           |           |           |           |
| asking28                      |          |          |         |           |           |           |           |
| Better Place                  |          |          |         |           |           |           |           |
| Bodensee                      |          |          |         |           |           |           |           |
| Bushr                         |          |          |         |           |           |           |           |
| byteam                        |          |          |         |           |           |           |           |
| Coffee_Latte                  |          |          |         |           |           |           |           |
| COMA                          |          |          |         |           |           |           |           |
| CyberTronics                  |          |          |         |           |           |           |           |
| doxaAI                        |          |          |         |           |           |           |           |
| Duluth                        |          |          |         |           |           |           |           |
| erfan                         | ✓        |          |         |           |           |           |           |
| shahaby                       |          |          |         |           |           |           |           |
| fatemah                       |          |          |         |           |           |           |           |
| FERMI                         |          |          |         |           |           |           |           |
| Ferryman                      |          |          |         |           |           |           |           |
| frankakorpel                  |          |          |         |           |           |           |           |
| fte10kso                      |          |          |         |           |           |           |           |
| Galileo                       |          |          |         |           |           |           |           |
| GruPaTo                       |          |          |         |           |           |           |           |
| GUIR                          |          |          |         |           |           |           |           |
| hamadanayel                   |          |          |         |           |           |           |           |
| HateLab                       |          |          |         |           |           |           |           |
| hhaddad                       |          |          |         |           |           |           |           |
| Hitachi                       |          |          |         |           |           |           |           |
| HoangDung                     |          |          |         |           |           |           |           |
| hwijeen                       |          |          |         |           |           |           |           |
| I2C                           |          |          |         |           |           |           |           |
| iaf7                          |          |          |         |           |           |           |           |
| IASBS                         |          |          |         |           |           |           |           |
| HITG-ABDU                     |          |          |         |           |           |           |           |
| IITP-AINLPML                  |          |          |         |           |           |           |           |
| IJS                           |          |          |         |           |           |           |           |
| INGEOTEC                      |          |          |         |           |           |           |           |
| IR3218                        |          |          |         |           |           |           |           |
| IRlab@IITV                    |          |          |         |           |           |           |           |
| IRLab2DAIICT                  |          |          |         |           |           |           |           |
| IS                            |          |          |         |           |           |           |           |
| ITNLP                         |          |          |         |           |           |           |           |
| IU-UM@LING                    |          |          |         |           |           |           |           |
| IUST                          |          |          |         |           |           |           |           |
| JAK                           |          |          |         |           |           |           |           |
| janecek1                      |          |          |         |           |           |           |           |
| jbern                         |          |          |         |           |           |           |           |
| JCT                           |          |          |         |           |           |           |           |
| jlee24282                     |          |          |         |           |           |           |           |
| jmperez                       |          |          |         |           |           |           |           |
| jooyeon Lee                   |          |          |         |           |           |           |           |
| KAFK                          |          |          |         |           |           |           |           |
| karishmaslaud                 |          |          |         |           |           |           |           |
| KarthikaS                     |          |          |         |           |           |           |           |
| kathyrc                      |          |          |         |           |           |           |           |
| KDELAB                        |          |          |         |           |           |           |           |
| KEIS@JUST                     |          |          |         |           |           |           |           |

Table 13: Overview of team participation in the subtasks (part 1).
| Team                  | A-Arabic | A-Danish | A-Greek | A-Turkish | A-English | B-English | C-English |
|-----------------------|----------|----------|---------|-----------|-----------|-----------|-----------|
| klaralang             | ✓        |          |         |           |           |           |           |
| KS@LTH                |          | ✓        | ✓       |           |           |           |           |
| KUISAIL               |          |          |         | ✓         |           |           |           |
| kungfupanda           |          |          |         |           |           |           |           |
| kxkjava                | ✓        |          |         |           |           |           |           |
| Lee                   |          |          |         |           |           |           |           |
| Light                 |          |          |         |           |           |           |           |
| LIIR                  |          |          |         |           |           |           |           |
| LT@Helsinki           |          | ✓        | ✓       | ✓         |           |           |           |
| LT2                   |          |          |         |           |           |           |           |
| lukez                 |          |          |         |           |           |           |           |
| m20170548             |          |          |         |           |           |           |           |
| machouz               |          |          |         |           |           |           |           |
| mdherath              |          |          |         |           |           |           |           |
| MeisterMorxrc         |          | ✓        | ✓       |           |           |           |           |
| MindCoders            |          |          |         |           |           |           |           |
| mircea.tanase         |          |          |         |           |           |           |           |
| NLP_Passau            |          |          |         |           |           |           |           |
| NLP_Dove              |          |          |         |           |           |           |           |
| nlpUP                 |          |          |         |           |           |           |           |
| NTU_NLP               |          |          |         |           |           |           |           |
| OffensSzeged          |          |          |         |           |           |           |           |
| orabia                |          |          |         |           |           |           |           |
| Oulu                  |          |          |         |           |           |           |           |
| PAI-NLP               |          |          |         |           |           |           |           |
| PALI                  |          |          |         |           |           |           |           |
| PSG                   |          |          |         |           |           |           |           |
| pin_codL              |          |          |         |           |           |           |           |
| PingANPAI             |          |          |         |           |           |           |           |
| PRHLT-UPV             |          |          |         |           |           |           |           |
| problemConquero       | ✓        | ✓        | ✓       |           |           |           |           |
| PUM                   |          |          |         |           |           |           |           |
| RGCL                  |          |          |         |           |           |           |           |
| Rouges                |          |          |         |           |           |           |           |
| RTNLU                 |          |          |         |           |           |           |           |
| sabino                |          |          |         |           |           |           |           |
| SAFA                  |          |          |         |           |           |           |           |
| SaiSakethAluru        |          |          |         |           |           |           |           |
| SAJA                  |          |          |         |           |           |           |           |
| saradhix              |          |          |         |           |           |           |           |
| saroarj               |          |          |         |           |           |           |           |
| sayanta95             |          |          |         |           |           |           |           |
| shardul007            |          |          |         |           |           |           |           |
| SINAI                 |          |          |         |           |           |           |           |
| Smatgrisene           |          |          |         |           |           |           |           |
| Sonal                 |          |          |         |           |           |           |           |
| sonal.kumari          |          |          |         |           |           |           |           |
| SpurthiAH             |          |          |         |           |           |           |           |
| SRIB2020              |          |          |         |           |           |           |           |
| SSN_NLP               |          |          |         |           |           |           |           |
| Stormbreaker          |          |          |         |           |           |           |           |
| SU-NLP                |          |          |         |           |           |           |           |
| Taha                  |          |          |         |           |           |           |           |
| talhaanwar            |          |          |         |           |           |           |           |
| tanvidadu             |          |          |         |           |           |           |           |
| tcaselli              |          |          |         |           |           |           |           |
| Team Oulu             |          |          |         |           |           |           |           |
| TeamKGP               |          |          |         |           |           |           |           |
| TECHSSN               |          |          |         |           |           |           |           |
| tharindu              |          |          |         |           |           |           |           |
| TheNorth              |          |          |         |           |           |           |           |
| TOBB ETU              |          |          |         |           |           |           |           |
| TysonYU               |          |          |         |           |           |           |           |
| UJNLP                 |          |          |         |           |           |           |           |

Table 14: Overview of team participation in the subtasks (part 2).
| Team                  | A-Arabic | A-Danish | A-Greek | A-Turkish | A-English | B-English | C-English |
|-----------------------|----------|----------|---------|-----------|-----------|-----------|-----------|
| ultraviolet           | ✓        |          |         |           |           |           | ✓         |
| UNT Linguistics       | ✓        |          |         |           |           |           |           |
| UoB                   | ✓        |          |         |           |           |           |           |
| UTFPR                 | ✓        |          |         |           |           |           |           |
| VerifiedXiaoPAI        | ✓        |          |         |           |           | ✓         |           |
| wac81                 | ✓        | ✓        |         |           |           |           | ✓         |
| will.go               | ✓        | ✓        | ✓        | ✓         | ✓         | ✓         |           |
| KUISAIL               | ✓        |          |         |           |           |           |           |
| Wu427                 | ✓        |          |         |           |           |           |           |
| XD                    | ✓        |          |         |           |           |           |           |
| yasserotiefy          | ✓        |          |         |           |           |           |           |
| yemen2016             | ✓        |          |         |           |           |           |           |
| YNUoxz                | ✓        |          |         |           |           |           |           |
| zahra.raj             | ✓        |          |         |           |           |           |           |
| zoher_orabe           | ✓        |          |         |           |           |           |           |

Table 15: Overview of team participation in the subtasks (part 3).