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SemEval-2016 Task 5: Aspect Based Sentiment Analysis

Maria Pontiki[*1], **Dimitrios Galanis**[1], **Haris Papageorgiou**[1], **Ion Androutsopoulos**[1,2], **Suresh Manandhar**[3], **Mohammad AL-Smadi**[4], **Mahmoud Al-Ayyoub**[4], **Yanyan Zhao**[5], **Bing Qin**[5], **Orphée De Clercq**[6], **Véronique Hoste**[6], **Marianna Apidianaki**[7], **Xavier Tannier**[7], **Natalia Loukachevitch**[8], **Evgeny Kotelnikov**[9], **Nuria Bel**[10], **Salud María Jiménez-Zafra**[11], **Gülşen Eryiğit**[12]

[1]Institute for Language and Speech Processing, Athena R.C., Athens, Greece,
[2]Dept. of Informatics, Athens University of Economics and Business, Greece,
[3]Dept. of Computer Science, University of York, UK,
[4]Computer Science Dept., Jordan University of Science and Technology Irbid, Jordan,
[5]Harbin Institute of Technology, Harbin, Heilongjiang, P.R. China,
[6]LT3, Ghent University, Ghent, Belgium,
[7]LIMSI, CNRS, Univ. Paris-Sud, Université Paris-Saclay, Orsay, France,
[8]Lomonosov Moscow State University, Moscow, Russian Federation,
[9]Vyatka State University, Kirov, Russian Federation,
[10]Universitat Pompeu Fabra, Barcelona, Spain,
[11]Dept. of Computer Science, Universidad de Jaén, Spain,
[12]Dept. of Computer Engineering, Istanbul Technical University, Turkey

Abstract

This paper describes the SemEval 2016 shared task on Aspect Based Sentiment Analysis (ABSA), a continuation of the respective tasks of 2014 and 2015. In its third year, the task provided 19 training and 20 testing datasets for 8 languages and 7 domains, as well as a common evaluation procedure. From these datasets, 25 were for sentence-level and 14 for text-level ABSA; the latter was introduced for the first time as a subtask in SemEval. The task attracted 245 submissions from 29 teams.

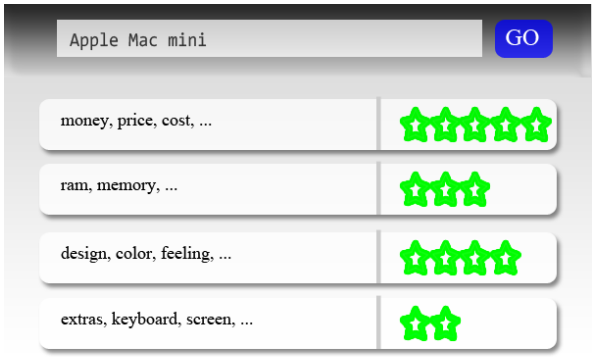

Figure 1: Table summarizing the average sentiment for each aspect of an entity.

1 Introduction

Many consumers use the Web to share their experiences about products, services or travel destinations (Yoo and Gretzel, 2008). Online opinionated texts (e.g., reviews, tweets) are important for consumer decision making (Chevalier and Mayzlin, 2006) and constitute a source of valuable customer feedback that can help companies to measure satisfaction and improve their products or services. In this setting, Aspect Based Sentiment Analysis (ABSA) - i.e., mining opinions from text about specific entities and their aspects (Liu, 2012) - can provide valuable insights to both consumers and businesses. An ABSA method can analyze large amounts of unstructured texts and extract (coarse- or fine-grained) information not included in the user ratings that are available in some review sites (e.g., Fig. 1).

Sentiment Analysis (SA) touches every aspect (e.g., entity recognition, coreference resolution, negation handling) of Natural Language Processing (Liu, 2012) and as Cambria et al. (2013) mention "*it requires a deep understanding of the explicit and implicit, regular and irregular, and syntactic and semantic language rules*". Within the last few years several SA-related shared tasks have been organized in the context of workshops and conferences focus-

*Corresponding author: mpontiki@ilsp.gr.

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ing on somewhat different research problems (Seki et al., 2007; Seki et al., 2008; Seki et al., 2010; Mitchell, 2013; Nakov et al., 2013; Rosenthal et al., 2014; Pontiki et al., 2014; Rosenthal et al., 2015; Ghosh et al., 2015; Pontiki et al., 2015; Mohammad et al., 2016; Recupero and Cambria, 2014; Ruppenhofer et al., 2014; Loukachevitch et al., 2015). Such competitions provide training datasets and the opportunity for direct comparison of different approaches on common test sets.

Currently, most of the available SA-related datasets, whether released in the context of shared tasks or not (Socher et al., 2013; Ganu et al., 2009), are monolingual and usually focus on English texts. Multilingual datasets (Klinger and Cimiano, 2014; Jiménez-Zafra et al., 2015) provide additional benefits enabling the development and testing of cross-lingual methods (Lambert, 2015). Following this direction, this year the SemEval ABSA task provided datasets in a variety of languages.

ABSA was introduced as a shared task for the first time in the context of SemEval in 2014; SemEval-2014 Task 4[1] (SE-ABSA14) provided datasets of English reviews annotated at the sentence level with aspect terms (e.g., "mouse", "pizza") and their polarity for the laptop and restaurant domains, as well as coarser aspect categories (e.g., "FOOD") and their polarity only for restaurants (Pontiki et al., 2014). SemEval-2015 Task 12[2] (SE-ABSA15) built upon SE-ABSA14 and consolidated its subtasks into a unified framework in which all the identified constituents of the expressed opinions (i.e., aspects, opinion target expressions and sentiment polarities) meet a set of guidelines and are linked to each other within sentence-level tuples (Pontiki et al., 2015). These tuples are important since they indicate the part of text within which a specific opinion is expressed. However, a user might also be interested in the overall rating of the text towards a particular aspect. Such ratings can be used to estimate the mean sentiment per aspect from multiple reviews (McAuley et al., 2012). Therefore, in addition to sentence-level annotations, SE-ABSA16[3] accommodated also text-level ABSA annotations and provided the respective training and testing data. Furthermore, the SE-ABSA15 annotation framework was extended to new domains and applied to languages other than English (Arabic, Chinese, Dutch, French, Russian, Spanish, and Turkish).

The remainder of this paper is organized as follows: the task set-up is described in Section 2. Section 3 provides information about the datasets and the annotation process, while Section 4 presents the evaluation measures and the baselines. General information about participation in the task is provided in Section 5. The evaluation scores of the participating systems are presented and discussed in Section 6. The paper concludes with an overall assessment of the task.

2 Task Description

The SE-ABSA16 task consisted of the following subtasks and slots. Participants were free to choose the subtasks, slots, domains and languages they wished to participate in.

Subtask 1 (SB1): Sentence-level ABSA. Given an opinionated text about a target entity, identify all the opinion tuples with the following types (tuple slots) of information:

- **Slot1: Aspect Category**. Identification of the entity E and attribute A pairs towards which an opinion is expressed in a given sentence. E and A should be chosen from predefined inventories[4] of entity types (e.g., "RESTAURANT", "FOOD") and attribute labels (e.g., "PRICE", "QUALITY").

- **Slot2: Opinion Target Expression (OTE)**. Extraction of the linguistic expression used in the given text to refer to the reviewed entity E of each E#A pair. The OTE is defined by its starting and ending offsets. When there is no explicit mention of the entity, the slot takes the value "NULL". The identification of Slot2 values was required only in the restaurants, hotels, museums and telecommunications domains.

- **Slot3: Sentiment Polarity**. Each identified E#A pair has to be assigned one of the following polarity labels: "positive", "negative", "neutral" (mildly positive or mildly negative).

[1] http://alt.qcri.org/semeval2014/task4/

[2] http://alt.qcri.org/semeval2015/task12/

[3] http://alt.qcri.org/semeval2016/task5/

[4] The full inventories of the aspect category labels for each domain are provided in Appendix A.

Lang.	Domain	Subtask	Train			Test		
			#Texts	#Sent.	#Tuples	#Texts	#Sent.	#Tuples
EN	REST	SB1	350	2000	2507	90	676	859
EN	REST	SB2	335	1950	1435	90	676	404
EN	LAPT	SB1	450	2500	2909	80	808	801
EN	LAPT	SB2	395	2375	2082	80	808	545
AR	HOTE	SB1	1839	4802	10509	452	1227	2604
AR	HOTE	SB2	1839	4802	8757	452	1227	2158
CH	PHNS	SB1	140	6330	1333	60	3191	529
CH	CAME	SB1	140	5784	1259	60	2256	481
DU	REST	SB1	300	1711	1860	100	575	613
DU	REST	SB2	300	1711	1247	100	575	381
DU	PHNS	SB1	200	1389	1393	70	308	396
FR	REST	SB1	335	1733	2530	120	696	954
FR	MUSE	SB3	-	-	-	162	686	891
RU	REST	SB1	302	3490	4022	103	1209	1300
RU	REST	SB2	302	3490	1545	103	1209	500
ES	REST	SB1	627	2070	2720	286	881	1072
ES	REST	SB2	627	2070	2121	286	881	881
TU	REST	SB1	300	1104	1535	39	144	159
TU	REST	SB2	300	1104	972	39	144	108
TU	TELC	SB1	-	3000	4082	-	310	336

Table 1: Datasets provided for SE-ABSA16.

An example of opinion tuples with Slot1-3 values from the restaurants domain is shown below: *"Their sake list was extensive, but we were looking for Purple Haze, which wasn't listed but made for us upon request!"* → {cat: "DRINKS#STYLE_OPTIONS", trg: "sake list", fr: "6", to: "15", pol: "positive"}, {cat: "SERVICE#GENERAL", trg: "NULL", fr: "0", to: "0", pol: "positive"}. The variable cat indicates the aspect category (Slot1), pol the polarity (Slot3), and trg the OTE (Slot2); fr, to are the starting/ending offsets of OTE.

Subtask 2 (SB2): Text-level ABSA. Given a customer review about a target entity, the goal was to identify a set of {cat, pol} tuples that summarize the opinions expressed in the review. cat can be assigned the same values as in SB1 (E#A tuple), while pol can be set to "positive", "negative", "neutral", or "conflict". For example, for the review text "*The So called laptop Runs to Slow and I hate it! Do not buy it! It is the worst laptop ever* ", a system should return the following opinion tuples: {cat: "LAPTOP#GENERAL", pol: "negative"}, {cat: "LAPTOP#OPERATION_PERFORMANCE", pol: "negative"} .

Subtask 3 (SB3): Out-of-domain ABSA. In SB3 participants had the opportunity to test their systems in domains for which no training data was made available; the domains remained unknown until the start of the evaluation period. Test data for SB3 were provided only for the museums domain in French.

3 Datasets

3.1 Data Collection and Annotation

A total of 39 datasets were provided in the context of the SE-ABSA16 task; 19 for training and 20 for testing. The texts were from 7 domains and 8 languages; English (EN), Arabic (AR), Chinese (CH), Dutch (DU), French (FR), Russian (RU), Spanish (ES) and Turkish (TU). The datasets for the domains of restaurants (REST), laptops (LAPT), mobile phones (PHNS), digital cameras (CAME), hotels (HOTE) and museums (MUSE) consist of customer reviews, whilst the telecommunication domain (TELC) data consists of tweets. A total of 70790 manually annotated ABSA tuples were provided for training and testing; 47654 sentence-level annotations (SB1) in 8 languages for 7 domains, and 23136 text-level annotations (SB2) in 6 languages for 3 domains. Table 1 provides more information on the distribution of texts, sentences and annotated tuples per dataset.

The REST, HOTE, and LAPT datasets were annotated

at the sentence-level (SB1) following the respective annotation schemas of SE-ABSA15 (Pontiki et al., 2015). Below are examples[5] of annotated sentences for the aspect category "SERVICE#GENERAL" in EN (1), DU (2), FR (3), RU (4), ES (5), and TU (6) for the REST domain and in AR (7) for the HOTE domain:

1. Service was slow, but the people were friendly. → {trg: "Service", pol: "negative"}, {trg: "people", pol: "positive"}
2. Snelle bediening en vriendelijk personeel moet ook gemeld worden!! → {trg: "bediening", pol: "positive"}, {trg: "personeel", pol: "positive"}
3. Le service est impeccable, personnel agréable. → {trg: "service" , pol: "positive"}, {trg: "personnel", pol: "positive"}
4. Про сервис ничего негативного не скажешь-быстро подходят, все улыбаются, подходят спрашивают, всё ли нравится. → {trg: "сервис", pol: "neutral" }
5. También la rapidez en el servicio. → {trg: "servicio", pol: "positive" }
6. Servisi hızlı valesi var. → {trg: "Servisi", pol: "positive"}
7. .. الخدمة جيدة جدا و سريعة → {trg: "الخدمة" , pol: "positive"}

The LAPT annotation schema was extended to two other domains of consumer electronics, CAME and PHNS. Examples of annotated sentences in the LAPT (EN), PHNS (DU and CH) and CAME (CH) domains are shown below:

1. It is extremely portable and easily connects to WIFI at the library and elsewhere. → {cat: "LAPTOP#PORTABILITY", pol: "positive"} , {cat: "LAPTOP#CONNECTIVITY", pol: "positive"}
2. Apps starten snel op en werken vlot, internet gaat prima. → {cat: "SOFTWARE#OPERATION_PERFORMANCE", pol: "positive"}, {cat: "PHONE#CONNECTIVITY", pol: "positive"}
3. 当然屏幕这么好 →{cat: "DISPLAY#QUALITY", pol: "positive"}
4. 更 轻 便 的 机 身 也 便 于 携 带。→ {cat: "CAMERA# PORTABILITY", pol: "positive"}

In addition, the SE-ABSA15 framework was extended to two new domains for which annotation guidelines were compiled: TELC for TU and MUSE for FR. Below are two examples:

1. #Internet kopuyor sürekli :(@turkcell → {cat: "INTERNET#COVERAGE", trg: "Internet", pol: "positive"}
2. 5€ pour les étudiants, ça vaut le coup. → {cat: "MUSEUM#PRICES", "NULL", "positive"}

The text-level (SB2) annotation task was based on the sentence-level annotations; given a customer review about a target entity (e.g., a restaurant) that included sentence-level annotations of ABSA tuples, the goal was to identify a set of $\{cat, pol\}$ tuples that summarize the opinions expressed in it. This was not a simple summation/aggregation of the sentence-level annotations since an aspect may be discussed with different sentiment in different parts of the review. In such cases the dominant sentiment had to be identified. In case of conflicting opinions where the dominant sentiment was not clear, the "conflict" label was assigned. In addition, each review was assigned an overall sentiment label about the target entity (e.g., "RESTAURANT#GENERAL", "LAPTOP#GENERAL"), even if it was not included in the sentence-level annotations.

3.2 Annotation Process

All datasets for each language were prepared by one or more research groups as shown in Table 2. The EN, DU, FR, RU and ES datasets were annotated using BRAT (Stenetorp et al., 2012), a web-based annotation tool, which was configured appropriately for the needs of the task. The TU datasets were annotated using a customized version of TURKSENT (Eryigit et al., 2013), a sentiment annotation tool for social media. For the AR and the CH data in-house tools[6] were used.

[5] The offsets of the opinion target expressions are omitted.

[6] The AR annotation tool was developed by the technical team of the Advanced Arabic Text Mining group at Jordan University of Science and Technology. The CH tool was developed by the Research Center for Social Computing and Information Retrieval at Harbin Institute of Technology.

Lang.	Research team(s)
English	Institute for Language and Speech Processing, Athena R.C., Athens, Greece Dept. of Informatics, Athens University of Economics and Business, Greece
Arabic	Computer Science Dept., Jordan University of Science and Technology Irbid, Jordan
Chinese	Harbin Institute of Technology, Harbin, Heilongjiang, P.R. China
Dutch	LT3, Ghent University, Ghent, Belgium
French	LIMSI, CNRS, Univ. Paris-Sud, Université Paris-Saclay, Orsay, France
Russian	Lomonosov Moscow State University, Moscow, Russian Federation Vyatka State University, Kirov, Russian Federation
Spanish	Universitat Pompeu Fabra, Barcelona, Spain SINAI, Universidad de Jaén, Spain
Turkish	Dept. of Computer Engineering, Istanbul Technical University, Turkey Turkcell Global Bilgi, Turkey

Table 2: Research teams that contributed to the creation of the datasets for each language.

Below are some further details about the annotation process for each language.

English. The SE-ABSA15 (Pontiki et al., 2015) training and test datasets (with some minor corrections) were merged and provided for training (REST and LAPT domains). New data was collected and annotated from scratch for testing. In a first phase, the REST test data was annotated by an experienced[7] linguist (annotator A), and the LAPT data by 5 undergraduate computer science students. The resulting annotations for both domains were then inspected and corrected (if needed) by a second expert linguist, one of the task organizers (annotator B). Borderline cases were resolved collaboratively by annotators A and B.

Arabic. The HOTE dataset was annotated in repeated cycles. In a first phase, the data was annotated by three native Arabic speakers, all with a computer science background; then the output was validated by a senior researcher, one of the task organizers. If needed (e.g. when inconsistencies were found) they were given back to the annotators.

Chinese. The datasets presented by Zhao et al. (2015) were re-annotated by three native Chinese speakers according to the SE-ABSA16 annotation schema and were provided for training and testing (PHNS and CAME domains).

Dutch. The REST and PHNS datasets (De Clercq and Hoste, 2016) were initially annotated by a trained linguist, native speaker of Dutch. Then, the output was verified by another Dutch linguist and disagreements were resolved between them. Finally, the task organizers inspected collaboratively all the annotated data and corrections were made when needed.

French. The train (REST) and test (REST, MUSE) datasets were annotated from scratch by a linguist, native speaker of French. When the annotator was not confident, a decision was made collaboratively with the organizers. In a second phase, the task organizers checked all the annotations for mistakes and inconsistencies and corrected them, when necessary. For more information on the French datasets consult Apidianaki et al. (2016).

Russian. The REST datasets of the SentiRuEval-2015 task (Loukachevitch et al., 2015) were automatically converted to the SE-ABSA16 annotation schema; then a linguist, native speaker of Russian, checked them and added missing information. Finally, the datasets were inspected by a second linguist annotator (also native speaker of Russian) for mistakes and inconsistencies, which were resolved along with one of the task organizers.

Spanish. Initially, 50 texts (134 sentences) from the whole available data were annotated by 4 annotators. The inter-anotator agreement (IAA) in terms of F-1 was 91% for the identification of OTE, 88% for the aspect category detection (E#A pair), and 80% for opinion tuples extraction (E#A, OTE, polarity). Provided that the IAA was substantially high for all slots, the rest of the data was divided into 4 parts and each one was annotated by a different native Spanish speakers (2 linguists and 2 software engineers). Subsequently, the resulting annotations were validated and corrected (if needed) by the task organizers.

[7] Also annotator for SE-ABSA14 and 15.

Turkish. The TELC dataset was based on the data used in (Yıldırım et al., 2015), while the REST dataset was created from scratch. Both datasets were annotated simultaneously by two linguists. Then, one of the organizers validated/inspected the resulting annotations and corrected them when needed.

3.3 Datasets Format and Availability

Similarly to SE-ABSA14 and SE-ABSA15, the datasets[8] of SE-ABSA16 were provided in an XML format and they are available under specific license terms through META-SHARE[9], a repository devoted to the sharing and dissemination of language resources (Piperidis, 2012).

4 Evaluation Measures and Baselines

The evaluation ran in two phases. In the first phase (Phase A), the participants were asked to return separately the aspect categories (Slot1), the OTEs (Slot2), and the {Slot1, Slot2} tuples for SB1. For SB2 the respective text-level categories had to be identified. In the second phase (Phase B), the gold annotations for the test sets of Phase A were provided and participants had to return the respective sentiment polarity values (Slot3). Similarly to SE-ABSA15, F-1 scores were calculated for Slot1, Slot2 and {Slot1, Slot2} tuples, by comparing the annotations that a system returned to the gold annotations (using micro-averaging). For Slot1 evaluation, duplicate occurrences of categories were ignored in both SB1 and SB2. For Slot2, the calculation for each sentence considered only distinct targets and discarded "NULL" targets, since they do not correspond to explicit mentions. To evaluate sentiment polarity classification (Slot3) in Phase B, we calculated the accuracy of each system, defined as the number of correctly predicted polarity labels of the (gold) aspect categories, divided by the total number of the gold aspect categories. Furthermore, we implemented and provided baselines for all slots of SB1 and SB2. In particular, the SE-ABSA15 baselines that were implemented for the English language (Pontiki et al., 2015), were adapted for the other languages by using appropriate stopword lists and tokenization functions. The baselines are briefly discussed below:

SB1-Slot1: For category (E#A) extraction, a Support Vector Machine (SVM) with a linear kernel is trained. In particular, *n* unigram features are extracted from the respective sentence of each tuple that is encountered in the training data. The category value (e.g., "SERVICE#GENERAL") of the tuple is used as the correct label of the feature vector. Similarly, for each test sentence *s*, a feature vector is built and the trained SVM is used to predict the probabilities of assigning each possible category to *s* (e.g., {"SERVICE#GENERAL", 0.2}, {"RESTAURANT#GENERAL", 0.4}. Then, a threshold[10] *t* is used to decide which of the categories will be assigned[11] to *s*. As features, we use the 1,000 most frequent unigrams of the training data excluding stopwords.

SB1-Slot2: The baseline uses the training reviews to create for each category *c* (e.g., "SERVICE#GENERAL") a list of OTEs (e.g., "SERVICE#GENERAL" → {"staff", "waiter"}). These are extracted from the (training) opinion tuples whose category value is *c* . Then, given a test sentence *s* and an assigned category *c*, the baseline finds in *s* the first occurrence of each OTE of *c*'s list. The OTE slot is filled with the first of the target occurrences found in *s*. If no target occurrences are found, the slot is assigned the value "NULL".

SB1-Slot3: For polarity prediction we trained a SVM classifier with a linear kernel. Again, as in Slot1, *n* unigram features are extracted from the respective sentence of each tuple of the training data. In addition, an integer-valued feature[12] that indicates the category of the tuple is used. The correct label for the extracted training feature vector is the corresponding polarity value (e.g., "positive"). Then, for each tuple {category, OTE} of a test sentence *s*, a feature vector is built and classified using the trained SVM.

SB2-Slot1: The sentence-level tuples returned by the SB1 baseline are copied to the text level and duplicates are removed.

[8] The data are available at: `http://metashare.ilsp.gr:8080/repository/search/?q=semeval+2016`

[9] META-SHARE (`http://www.metashare.org/`) was implemented in the framework of the META-NET Network of Excellence (`http://www.meta-net.eu/`).

[10] The threshold *t* was set to 0.2 for all datasets.

[11] We use the –b 1 option of LibSVM to obtain probabilities.

[12] Each E#A pair has been assigned a distinct integer value.

Lang./ Dom.	Slot1 F-1	Slot2 F-1	{Slot1,Slot2} F-1	Slot3 Acc.
EN/ REST	NLANG./U/73.031	NLANG./U/72.34	NLANG./U/52.607	XRCE/C/88.126
	NileT./U/72.886	AUEB-./U/70.441	XRCE/C/48.891	IIT-T./U/86.729
	BUTkn./U/72.396	UWB/U/67.089	NLANG./C/45.724	NileT./U/85.448
	AUEB-./U/71.537	UWB/C/66.906	TGB/C/43.081*	IHS-R./U/83.935
	BUTkn./C/71.494	GTI/U/66.553	bunji/U/41.113	ECNU/U/83.586
	SYSU/U/70.869	Senti./C/66.545	UWB/C/41.108	AUEB-./U/83.236
	XRCE/C/68.701	bunji/U/64.882	UWB/U/41.088	INSIG./U/82.072
	UWB/U/68.203	NLANG./C/63.861	DMIS/U/39.796	UWB/C/81.839
	INSIG./U/68.108	DMIS/C/63.495	DMIS/C/38.976	UWB/U/81.723
	ESI/U/67.979	XRCE/C/61.98	**basel**./C/37.795	SeemGo/C/81.141
	UWB/C/67.817	AUEB-./C/61.552	IHS-R./U/35.608	bunji/U/81.024
	GTI/U/67.714	UWate./U/57.067	IHS-R./U/34.864	TGB/C/80.908*
	AUEB-./C/67.35	KnowC./U/56.816*	UWate./U/34.536	ECNU/C/80.559
	NLANG./C/65.563	TGB/C/55.054*	SeemGo/U/30.667	UWate./U/80.326
	LeeHu./C/65.455	BUAP/U/50.253	BUAP/U/18.428	INSIG./C/80.21
	TGB/C/63.919*	**basel**./C/44.071		DMIS/C/79.977
	IIT-T./U/63.051	IHS-R./U/43.808		DMIS/U/79.627
	DMIS/U/62.583	IIT-T./U/42.603		IHS-R./U/78.696
	DMIS/C/61.754	SeemGo/U/34.332		Senti./U/78.114
	IIT-T./C/61.227			LeeHu./C/78.114
	bunji/U/60.145			**basel**./C/76.484
	basel./C/59.928			bunji/C/76.251
	UFAL/U/59.3			SeemGo/U/72.992
	INSIG./C/58.303			AKTSKI/U/71.711
	IHS-R./U/55.034			COMMI./C/70.547
	IHS-R./U/53.149			SNLP/U/69.965
	SeemGo/U/50.737			GTI/U/69.965
	UWate./U/49.73			CENNL./C/63.912
	CENNL./C/40.578			BUAP/U/60.885
	BUAP/U/37.29			

Table 3: English REST results for SB1.

SB2-Slot3: For each text-level aspect category *c* the baseline traverses the predicted sentence-level tuples of the same category returned by the respective SB1 baseline and counts the polarity labels (positive, negative, neutral). Finally, the polarity label with the highest frequency is assigned to the text-level category *c*. If there are no sentence-level tuples for the same *c*, the polarity label is determined based on all tuples regardless of *c*.

The baseline systems and evaluation scripts are implemented in Java and are available for download from the SE-ABSA16 website[13]. The LibSVM package[14] (Chang and Lin, 2011) is used for SVM training and prediction. The scores of the baselines in the test datasets are presented in Section 6 along with the system scores.

5 Participation

The task attracted in total 245 submissions from 29 teams. The majority of the submissions (216 runs) were for SB1. The newly introduced SB2 attracted 29 submissions from 5 teams in 2 languages (EN and SP). Most of the submissions (168) were runs for the REST domain. This was expected, mainly for two reasons; first, the REST classification schema is less fine-grained (complex) compared to the other domains (e.g., LAPT). Secondly, this domain was supported for 6 languages enabling also multilingual or language-agnostic approaches. The remaining submissions were distributed as follows: 54 in LAPT, 12 in PHNS, 7 in CAME and 4 in HOTE.

[13] http://alt.qcri.org/semeval2016/task5/index.php?id=data-and-tools

[14] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

Lang./ Dom.	Slot1 F-1	Slot2 F-1	{Slot1,Slot2} F-1	Slot3 Acc.
ES/ REST	GTI/U/70.588 GTI/C/70.027 TGB/C/63.551* UWB/C/61.968 INSIG./C/61.37 IIT-T./U/59.899 IIT-T./C/59.062 UFAL/U/58.81 **basel**./C/54.686	GTI/C/68.515 GTI/U/68.387 IIT-T./U/64.338 TGB/C/55.764* **basel**./C/51.914	TGB/C/41.219* **basel**./C/36.379	IIT-T./U/83.582 TGB/C/82.09* UWB/C/81.343 INSIG./C/79.571 **basel**./C/77.799
FR/ REST	XRCE/C/61.207 IIT-T./U/57.875 IIT-T./C/57.033 INSIG./C/53.592 **basel**./C/52.609 UFAL/U/49.928	IIT-T./U/66.667 XRCE/C/65.316 **basel**./C/45.455	XRCE/C/47.721 **basel**./C/33.017	XRCE/C/78.826 UWB/C/75.262 UWB/C/74.319 INSIG./C/73.166 IIT-T./U/72.222 **basel**./C/67.4
RU/ REST	UFAL/U/64.825 INSIG./C/62.802 IIT-T./C/62.689 IIT-T./C/58.196 **basel**./C/55.882 Danii./C/39.601 Danii./U/38.692	**basel**./C/49.308 Danii./U/33.472 Danii./C/30.618	**basel**./C/39.441 Danii./U/22.591 Danii./C/22.107	MayAnd/U/77.923 INSIG./C/75.077 IIT-T./U/73.615 Danii./U/73.308 Danii./C/72.538 **basel**./C/71
DU/ REST	TGB/C/60.153* INSIG./C/56 IIT-T./U/55.247 IIT-T./C/54.98 UFAL/U/53.876 **basel**./C/42.816	IIT-T./U/56.986 TGB/C/51.775* **basel**./C/50.64	TGB/C/45.167* **basel**./C/30.916	TGB/C/77.814* IIT-T./U/76.998 INSIG./C/75.041 **basel**./C/69.331
TU/ REST	UFAL/U/61.029 **basel**./C/58.896 IIT-T./U/56.627 IIT-T./C/55.728 INSIG./C/49.123	**basel**./C/41.86	**basel**./C/28.152	IIT-T./U/84.277 INSIG./C/74.214 **basel**./C/72.327
AR/ HOTE	INSIG./C/52.114 UFAL/U/47.302 **basel**./C/40.336	**basel**./C/30.978	**basel**./C/18.806	INSIG./C/82.719 IIT-T./U/81.72 **basel**./C/76.421

Table 4: REST and HOTE results for SB1.

An interesting observation is that, unlike SE-ABSA15, Slot1 (aspect category detection) attracted significantly more submissions than Slot2 (OTE extraction); this may indicate a shift towards concept-level approaches. Regarding participation per language, the majority of the submissions (156/245) were for EN; see more information in Table 5. Most teams (20) submitted results only for one language (18 for EN and 2 for RU). Of the remaining teams, 3 submitted results for 2 languages, 5 teams submitted results for 3-7 languages, while only one team participated in all languages.

6 Evaluation Results

The evaluation results are presented in Tables 3 (SB1: REST-EN), 4 (SB1: REST-ES, FR, RU, DU, TU & HOTE-AR), 6 (SB1: LAPT, CAME, PHNS), and 7 (SB2)[15]. Each participating team was allowed to submit up to two runs per slot and domain in each phase; one constrained (C), where only the provided training data could be used, and one unconstrained (U), where other resources (e.g., publicly available

[15]No submissions were made for SB3-MUSE-FR & SB1-TELC-TU.

Language	Teams	Submissions
English	27	156
Arabic	3	4
Chinese	3	14
Dutch	4	16
French	5	13
Russian	5	15
Spanish	6	21
Turkish	3	6
All	29	245

Table 5: Number of participating teams and submitted runs per language.

lexica) and additional data of any kind could be used for training. In the latter case, the teams had to report the resources used. Delayed submissions (i.e., runs submitted after the deadline and the release of the gold annotations) are marked with "*".

As revealed by the results, in both SB1 and SB2 the majority of the systems surpassed the baseline by a small or large margin and, as expected, the unconstrained systems achieved better results than the constrained ones. In SB1, the teams with the highest scores for Slot1 and Slot2 achieved similar F-1 scores (see Table 3) in most cases (e.g., EN/REST, ES/REST, DU/REST, FR/REST), which shows that the two slots have a similar level of difficulty. However, as expected, the {Slot1, Slot2} scores were significantly lower since the linking of the target expressions to the corresponding aspects is also required. The highest scores in SB1 for all slots (Slot1, Slot2, {Slot1, Slot2}, Slot3) were achieved in the EN/REST; this is probably due to the high participation and to the lower complexity of the REST annotation schema compared to the other domains. If we compare the results for SB1 and SB2, we notice that the SB2 scores for Slot1 are significantly higher (e.g., EN/LAPT, EN/REST, ES/REST) even though the respective annotations are for the same (or almost the same) set of texts. This is due to the fact that it is easier to identify whether a whole text discusses an aspect *c* than finding all the sentences in the text discussing *c* . On the other hand, for Slot3, the SB2 scores are lower (e.g., EN/REST, ES/REST, RU/REST, EN/LAPT) than the respective SB1 scores. This is mainly because an aspect may be discussed at different points in a text and often with different sentiment. In such cases a system has to identify the dominant sentiment, which usually is not trivial.

Lang./ Dom.	Slot1 F-1	Slot3 Acc.
EN/ LAPT	NLANG./U/51.937	IIT-T./U/82.772
	AUEB-./U/49.105	INSIG./U/78.402
	SYSU/U/49.076	ECNU/U/78.152
	BUTkn./U/48.396	IHS-R./U/77.903
	UWB/C/47.891	NileT./U/77.403
	BUTkn./C/47.527	AUEB-./U/76.904
	UWB/U/47.258	LeeHu./C/75.905
	NileT./U/47.196	Senti./U/74.282
	NLANG./C/46.728	INSIG./C/74.282
	INSIG./U/45.863	UWB/C/73.783
	AUEB-./C/45.629	UWB/U/73.783
	IIT-T./U/43.913	SeemGo/C/72.16
	LeeHu./C/43.754	UWate./U/71.286
	IIT-T./C/42.609	bunji/C/70.287
	SeemGo/U/41.499	bunji/U/70.162
	INSIG./C/41.458	ECNU/C/70.037
	bunji/U/39.586	**basel**./C/70.037
	IHS-R./U/39.024	COMMI./C/67.541
	basel./C/37.481	GTI/U/67.291
	UFAL/U/26.984	BUAP/U/62.797
	CENNL./C/26.908	CENNL./C/59.925
	BUAP/U/26.787	SeemGo/U/40.824
CH/ CAME	UWB/C/36.345	SeemGo/C/80.457
	INSIG./C/25.581	INSIG./C/78.17
	basel./C/18.434	UWB/C/77.755
	SeemGo/U/17.757	**basel**./C/74.428
		SeemGo/U/73.181
CH/ PHNS	UWB/C/22.548	SeemGo/C/73.346
	basel./C/17.03	INSIG./C/72.401
	INSIG./C/16.286	UWB/C/72.023
	SeemGo/U/10.43	**basel**./C/70.132
		SeemGo/U/65.406
DU/ PHNS	INSIG./C/45.551	INSIG./C/83.333
	IIT-T./U/45.443	IIT-T./U/82.576
	IIT-T./C/45.047	**basel**./C/80.808
	basel./C/33.55	

Table 6: LAPT, CAME, and PHNS results for SB1.

7 Conclusions

In its third year, the SemEval ABSA task provided 19 training and 20 testing datasets, from 7 domains and 8 languages, attracting 245 submissions from 29 teams. The use of the same annotation guidelines for domains addressed in different languages gives the opportunity to experiment also with cross-lingual or language-agnostic approaches. In addition, SE-ABSA16 included for the first time a text-

Lang./ Dom.	Slot1 F-1	Slot3 Acc.
EN/ REST	GTI/U/83.995 UWB/C/80.965 UWB/U/80.163 bunji/U/79.777 **basel**./C/78.711 SYSU/U/68.841 SYSU/U/68.841	UWB/U/81.931 ECNU/U/81.436 UWB/C/80.941 ECNU/C/78.713 **basel**./C/74.257 bunji/U/70.545 bunji/C/66.584 GTI/U/64.109
ES/ REST	GTI/C/84.192 GTI/U/84.044 **basel**./C/74.548 UWB/C/73.657	UWB/C/77.185 **basel**./C/74.548
RU/ REST	**basel**./C/84.792	**basel**./C/70.6
RU/ REST	**basel**./C/84.792	**basel**./C/70.6
DU/ REST	**basel**./C/70.323	**basel**./C/73.228
TU/ REST	**basel**./C/72.642	**basel**./C/57.407
AR/ HOTE	**basel**./C/42.757	**basel**./C/73.216
EN/ LAPT	UWB/C/60.45 UWB/U/59.721 bunji/U/54.723 **basel**./C/52.685 SYSU/U/48.889 SYSU/U/48.889	ECNU/U/75.046 UWB/U/75.046 UWB/C/74.495 **basel**./C/73.028 ECNU/C/67.523 bunji/C/62.202 bunji/U/60 GTI/U/58.349

Table 7: Results for SB2.

level subtask. Future work will address the creation of datasets in more languages and domains and the enrichment of the annotation schemas with other types of SA-related information like topics, events and figures of speech (e.g., irony, metaphor).

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Appendix A. Aspect inventories for all domains

Entity Labels
LAPTOP, DISPLAY, KEYBOARD, MOUSE, MOTHERBOARD, CPU, FANS_COOLING, PORTS, MEMORY, POWER_SUPPLY OPTICAL_DRIVES, BATTERY, GRAPHICS, HARD_DISK, MULTIMEDIA_DEVICES, HARDWARE, SOFTWARE, OS, WARRANTY, SHIPPING, SUPPORT, COMPANY
Attribute Labels
GENERAL, PRICE, QUALITY, DESIGN_FEATURES, OPERATION_PERFORMANCE, USABILITY, PORTABILITY, CONNECTIVITY, MISCELLANEOUS

Table 8: Laptops.

Entity Labels
PHONE, DISPLAY, KEYBOARD, CPU, PORTS, MEMORY, POWER_SUPPLY, HARD_DISK, MULTIMEDIA_DEVICES, BATTERY, HARDWARE, SOFTWARE, OS, WARRANTY, SHIPPING, SUPPORT, COMPANY
Attribute Labels
Same as in Laptops (Table 8) with the exception of PORTABILITY that is included in the DESIGN_FEATURES label and does not apply as a separate attribute type.

Table 9: Mobile Phones.

Entity Labels
CAMERA, DISPLAY, KEYBOARD, CPU, PORTS, MEMORY, POWER_SUPPLY, BATTERY, MULTIMEDIA_DEVICES, HARDWARE, SOFTWARE, OS, WARRANTY, SHIPPING, SUPPORT, COMPANY, LENS, PHOTO, FOCUS
Attribute Labels
Same as in Laptops (Table 8).

Table 10: Digital Cameras.

Entity Labels
RESTAURANT, FOOD, DRINKS, AMBIENCE, SERVICE, LOCATION
Attribute Labels
GENERAL, PRICES, QUALITY, STYLE_OPTIONS, MISCELLANEOUS

Table 11: Restaurants.

Entity Labels
HOTEL, ROOMS, FACILITIES, ROOM_AMENITIES, SERVICE, LOCATION, FOOD_DRINKS
Attribute Labels
GENERAL, PRICE, COMFORT, CLEANLINESS, QUALITY, STYLE_OPTIONS, DESIGN_FEATURES, MISCELLANEOUS

Table 12: Hotels.

Entity Labels
TELECOM OPERATOR, DEVICE, INTERNET, CUSTOMER_SERVICES, APPLICATION_SERVICE
Attribute Labels
GENERAL, PRICE_INVOICE, COVERAGE, SPEED, CAMPAIGN_ADVERTISEMENT, MISCELLANEOUS

Table 13: Telecommunications.

Entity Labels
MUSEUM, COLLECTIONS, FACILITIES, SERVICE, TOUR_GUIDING, LOCATION
Attribute Labels
GENERAL, PRICES, COMFORT, ACTIVITIES, ARCHITECTURE, INTEREST, SET UP, MISCELLANEOUS

Table 14: Museums.

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