Challenges of an Annotation Task for Open Information Extraction in Portuguese

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Abstract. Open information extraction (Open IE) is a task of extracting facts from a plain text without limiting the analysis to a predefined set of relationships. Although a significant number of studies have focused on this problem in the last years, there is a lack of available linguistic resources for languages other than English. An essential resource for the evaluation of Open IE methods is notably an annotated corpus. In this work, we present the challenges involved in the creation of a golden set corpus for the Open IE task in the Portuguese language. We describe our methodology, an annotation tool to support the task and our results on performing this annotation task in a small validation corpus.

Keywords: Open information extraction · Portuguese · Corpora Annotation

1 Introduction

While the quantity and diversity of textual contents on the Web are continually growing, traditional Information Extraction (IE) tools are designed to identify a fixed set of information types, thus having low coverage regarding all possible information obtained and processed from the Web. To solve this problem, Banko et al. [4] proposed the Open IE task, which aims to extract facts from sentences without predefining a set of target relationships to be analyzed.

Although Open IE has undoubtedly gained importance in the area in the last decade, most systems and methods available in the literature are still focused on the English language [25]. Considering those systems focused on Open IE in Portuguese language, only a few of them have been proposed in the last five years.

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The creation of an annotated corpora is a crucial step for fostering the development of new methods and the evaluation of existing ones in Natural Language Processing (NLP). Thus, we believe that the construction of such a resource for Open IE in Portuguese can have a considerable impact in the development of systems and methods available for this language.

As such, this work describes the process of building a reference corpus for Open IE in the Portuguese language, explaining the methodology and open challenges. We present our results and discuss them, looking towards the creation of a golden dataset for Open IE. Some of our contributions are described as follows:

- Systematic mapping on Open IE for the Portuguese language;
- Definition of an annotation guide for Open IE for the Portuguese language;
- Development of a support tool for the annotation task (OpenIEAnn);
- Analysis of our results in a small test corpus for the annotation task;

This paper is organized into sections as follows. Section 2 presents our systematic mapping for the Portuguese language. Section 3 describes our annotation guide. Section 4 presents the experimental setup and Sect. 5 presents and discusses our results. Finally, Sect. 6 concludes our work.

2 Systematic Mapping

The available resources, such as annotation tools and linguistic resources, for Open IE in Portuguese are insufficient when compared to those for the English language. Aiming to identify the studies and available resources in Portuguese for this task, we conducted a systematic mapping study (SMS). Our SMS follows Petersen's work [21] recommendations and the Systematic Mapping Study on Open Information Extraction [15]. In the planning step, we establish the main research question as follows: "What are the studies conducted in Portuguese Open IE area?". The search method used to find the primary studies were carried out by an automatic search in electronic databases. To recover primary studies on Portuguese, we used two keywords: *"open information extraction" + portuguese* or *"open relation extraction" + portuguese*[1]. Two databases was adopted: *Google Scholar*[2] and *dblp*[3].

Our inclusion criteria retain all studies on Open IE area focusing on the Portuguese language. We looked for studies, which contain keywords at least in title, summary, and keywords fields. *Exclusion criteria* (F–filters) for primary studies are:

- **F1:** Remove studies which have some "Open IE" terms, but are not studies on the topic (−103 entries removed).

[1] Queries was performed on March 2018.
[2] http://scholar.google.com Query 1: 172 entries and Query 2: 35 entries.
[3] https://dblp.uni-trier.de Query 1: 2 entries and Query 2: no matches.

- **F2:** Remove studies not published in journals or conferences (−33 entries removed).
- **F3:** Remove surveys or review papers (−10 entries removed).
- **F4:** Remove studies which do not extract facts from texts written in Portuguese (−11 entries removed).
- **Duplicated:** Remove one of the duplicate occurrences (−36 entries removed).

Table 1 presents the summary of the studies published in Portuguese Open IE area. As far as we know, only three studies made the datasets public during their research. To this point, we consider as public, the dataset indexed by some URL available on the Web and presented in the paper. The authors in [11] published a single dataset of sentences for Open IE evaluation systems to Portuguese[4].

Table 1. Summary of the studies published in Portuguese Open IE area. The sources were conferences and journals, for the last one, we used the italic font. R.Group is the research group or institute. Input indicates the NLP tasks combined with the proposed method. The approach indicates whether it is rule-based (Rules), machine learning (Data) or both (Mixed) and machine translate. ML indicates whether the system is multilingual and PD stands for Public Dataset.

Study	System	Year	Source	R.Group	Type	Input	Approach	ML	PD
[13]	DepOE	2012	ROBUS-UNSUP	CITIUS	Proposal	DP	Rules	✓	
[10]		2013	ENIAC	UFC/UNIFOR	Proposal	POS	Rules		
[14]	DepOE+	2014	*SEPLN*	CITIUS	Proposal	DP, Coreference	Rules	✓	
[26]		2014	*Linguamática*	FORMAS	Proposal	POS, Chunker	Mixed		
[7]		2014	IBERAMIA	PUC-RS	Proposal	POS, Parser	Data		
[11]	ArgOE	2015	EPIA	CITIUS	Proposal	DP	Rules	✓	✓
[9]		2015	HLT-NAACL	CMU/GOOGLE	Proposal	OLLIE [24]	Translate	✓	✓
[20]	Report	2015	STIL	UNIFOR	Proposal	POS, Chunker	Rules		
[6]		2016	PROPOR	PUC-RS	Proposal	POS, Parser	Rules		
[23]	RAPPORT	2016	PROPOR	CISUC	Application				
[12]	LinguaKit	2017	*Linguamática*	CITIUS	Application				
[1]		2017	*Knowledge Organization*	PUC-RS	Proposal	POS, Parser	Data		
[5]		2017	STIL	FORMAS	Proposal	POS, Chunker	Data		
[25]		2017	ICEIS	FORMAS	Proposal	POS, Chunker	Mixed		
[18]	DependentIE	2017	ENIAC	FORMAS	Proposal	DP	Rules		
[27]	SGS	2018	*J.UCS*	FORMAS	Proposal	POS, Chunker	Mixed		✓

[4] Download at http://gramatica.usc.es/~gamallo/prototypes/ArgOE-beta.tar.gz.

We believe that the resource is limited in size (103 sentences) and it is not domain independent (texts on ecological issues). The second study was presented by the authors in [9][5] whose dataset has not been revised by humans. Finally, the authors in [27] published their datasets in PostgreSQL's *dump* format[6]. This last dataset was manually annotated and it is composed of 582 facts extracted from sentences from the *CETENFolha* corpus[7]. We are unable to find the methodology applied in the annotation task, and thus it is hard to judge the quality of their result.

3 Annotation Guide

Our annotation guide is strongly based on the guidelines proposed by Hovy and Lavid [16]. We performed the task in five steps as shown in Fig. 1. The first step is the definition of the task that is based on the definition proposed by the authors in [28]: "An open information extractor is a function from a document, d, to a set of triples, $\{\langle arg_1, rel, arg_2\rangle\}$, where the $args$ are noun phrases and rel is a textual fragment indicating an implicit, semantic relation between the two noun phrases.".

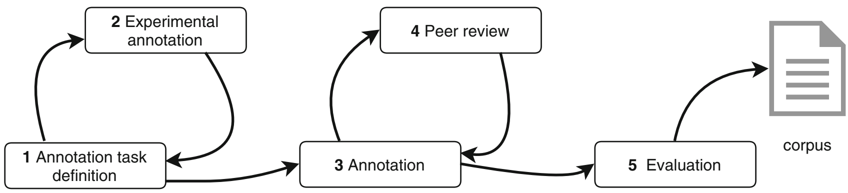

Fig. 1. Our flow to Portuguese Open IE annotation task.

The proposed definition by the authors in [28] is general, and it can lead to many differences among the annotators. In an interactive process between steps 1 and 2, we define a set of constraints to be applied to such general definition. This set of constraints does not indicate all possible restrictions but enables the proposed annotation task to be feasible. Therefore, the **first challenge** of this annotation is to set a threshold for an open-domain task. There is a trade-off between the feasibility of performing an evaluation of the outcome of the task and limiting the set of possible relationships from being extracted into a sentence. Our constraints are based on X-bar theory definitions published in "Novo manual de sintaxe" [17] and the set of constraints (C) for this study is as follows:

[5] Download at https://console.cloud.google.com/storage/browser/wikipedia_multilingual_relations_v1/multilingual_relations_data/auto/extractions/.
[6] Download at http://formas.ufba.br/page/downloads.
[7] http://www.linguateca.pt/cetenfolha/.

C1. When there is a word chain through a preposition forming a noun phrase (NP), we first select the fragment that is composed of a noun, proper noun or pronoun, its respective determinants and direct modifiers (articles, numerals, adjectives and some pronouns). For example:

– Adjectives: HIGH players/NEW students
– Articles: THE boy/A girl
– Numerals: TWO hamburgers
– Pronouns: MY shoes/SOME people

C2. When a sentence has an transitive verb with preposition (indirect mode), the preposition will be attached to the fragment *rel*. For example, given the sentence “David travels to another country.” one fact could be {*David, travels to, another country*}.

C3. We call minimal fact (minimal) any extracted fact having as arguments NPs composed only of a noun, proper noun or pronoun with its determinants and direct modifiers. For example, in the sentence “Senator Barack Obama of Illinois was elected president of the United States over Senator John McCain of Arizona.”, one minimal fact could be {*Senator Barack Obama, was elected president of, the United States*}, but {*Senator Barack Obama of Illinois, was elected president of, the United States*} is not minimal. It is, however, considered as a valid extraction.

C4. If there are fragments with a noun function (preposition chain) that modify arguments in minimal facts, new facts (not minimal) must be added by the annotator (see C3 second triple example).

C5. A fact must only be extracted from a sentence if it contains a proper noun or pronoun in, at least, one of the arguments.

C6. For n–ary facts, if there is no significant loss of information, the annotator must extract multiple binary facts. In the example presented by the authors in [2] “Elvis moved to Memphis in 1948.”, two extracted facts {*Elvis, moved to, Memphis*} and {*Elvis, moved in, 1948*} are valid and minimal.

C7. The coordinating conjunctions with additive function can generate multiple extracted facts and also a fact with the coordinated conjunction. In the example “The newspaper is published in London and Madrid.” there are at least three facts {*The newspaper, is published in, London*}, {*The newspaper, is published in, Madrid*} and {*The newspaper, is published in, London and Madrid*}.

C8. Relations and arguments in the extracted facts must agree in number. For example, in the sentence “Two of the world’s main cities are London and Madrid.”, the subject and the verb of the sentence are plurals. Thus the only possible extraction is {*Two of the world’s main cities, are, London and Madrid*}, despite the coordinating conjunction.

The third step in this guide is the annotation task, and each annotator performed the task individually. This step is interactive with a fourth step evaluation. All annotators present their questions and then perform a new round of annotation to increase the agreement among participants. The last step is to evaluate all extracted facts among all annotators. Annotators evaluate all facts carried out among all annotators. The final version of the corpus is the set of all extracted facts with the evaluation by each annotator.

3.1 Proposed Tool

OpenIEAnn tool was developed to support the proposed annotation task. Figure 2 presents the main form of this tool. Two primary functions of this tool are to support the user in identifying and extracting facts in sentences and calculating the agreement among the raters of the annotation task. The tool was built using *brat rapid annotation tool*[8] version 1.3, *CoreNLP* version 3.9.1[9] for POS tagger and DP, *CoGrOO*[10] version 4.0 for Chunker, DKPro Statistics[11] version 2.1.0 for agreements, and *Universal Dependencies*[12] version 2.0 for CoreNLP models[13]. The tool, as well as all the models and resources are available in review version link[14]. Other functions available in OpenIEAnn are: (i) import raw text file with sentences to annotation format and (ii) export only sentences with the extracted facts.

Fig. 2. Main form of the OpenIEAnn annotation tool.

[8] http://brat.nlplab.org/.
[9] https://stanfordnlp.github.io/CoreNLP/.
[10] http://cogroo.sourceforge.net/download/current.html.
[11] https://dkpro.github.io/dkpro-statistics/.
[12] http://universaldependencies.org/.
[13] The Brazilian Portuguese Universal Dependencies is converted from the Google Universal Dependency Treebanks version 2.0.
[14] http://formas.ufba.br/.

4 Experimental Setup

We carried out the annotation task on a small corpus. We randomly selected sentences from five different sources and domains. From each source, we recovered five sentences and built a corpus with 25 sentences as follows:

- 5 Wikipedia sentences - source in Portuguese Wikipedia version https://pt.wikipedia.org/wiki/
- 5 CETENFolha sentences - source by CETENFolha corpus https://www.linguateca.pt/cetenfolha
- 5 WEB sentences - source by Bing API
- 5 Adoro Cinema sentences - source by crawler in website http://www.adorocinema.com/
- 5 Europarl sentences - source by Europarl corpus v7.0 http://www.statmt.org/europarl/

Five Brazilian Portuguese natives participated in this experiment identified as rater 1, 2, 3, 4 and 5. Each rater was invited to perform two tasks. The first one was the Open IE task performed within the set of sentences considering our constraints. The second task was performed after extracting all the facts from the five raters. All those extracted facts were unified and the second task was to classify those extracted facts manually as valid or invalid.

Free-marginal multi-rater kappa (Randolph's kappa [22]) was set to calculate the agreement among the raters. The agreement of the second task is trivial. All raters evaluated the same extracted facts in a binary classification. For the first task, the divergence starts when each rater performs Open IE extractions different from other raters. The label is nominal, and each extracted fact must have a label given by a rater and if other raters have also performed the same extraction, thus the same label is assigned among them. Otherwise, random and different labels from other raters are given. The comparison of the extracted facts among raters was done in three ways: (i) full – that compares the arguments, relationship, and minimal property separately, (ii) partial – that does not evaluate the minimal property, and (iii) text – that concatenates the arguments with the relationship forming a single string.

5 Results

There are two rounds between the third and fourth step of our annotation task (Fig. 1). The degree of agreement among the raters in the first round was presented in Table 2. Generally, the agreement is low when we remember the small set of sentences in this step. The **second challenge** is to unify the understanding about the task performed. We believe that constraints should be followed by a relevant example set to fix the task rules.

In the first task, we performed two rounds to evaluate the behavior of raters between steps 3 and 4. In Table 3, we present the results of agreement for the second round of the first task. After an alignment meeting about the rules of

Table 2. Degree of agreement among raters in the 1st round of manual annotation.

Measure	Mode	1–2	1–3	1–4	1–5	2–3	2–4	2–5	3–4	3–5	4–5	All raters
Kappa	Full	0.0874	0.1795	0.1306	0.1547	0.0715	0.0911	0.0937	0.1313	0.0916	0.1212	0.0570
	Partial	0.1745	0.2164	0.1722	0.2294	0.1050	0.1183	0.1238	0.1760	0.1288	0.1517	0.0805
	Text	0.2142	0.2571	0.2007	0.2741	0.1321	0.1488	0.1796	0.1807	0.1577	0.1960	0.1013
#Fact	Full	189	198	226	165	231	247	187	263	213	227	435
	Partial	175	192	218	155	224	241	182	253	206	221	406
	Text	166	185	212	148	216	232	170	252	200	212	376
#Exact fact	Full	17	36	30	26	17	23	18	35	20	28	5
	Partial	31	42	38	36	24	29	23	45	27	34	12
	Text	36	48	43	41	29	35	31	46	32	42	17

the task, the agreement increased. The high agreement between raters 1–4 and 4–5 in both rounds contributed to achieving our results. However, there was a low agreement between raters 1–2. The **third challenge** is to solve the trade-off between the dedicated time to the task and the result of agreement expected for the generate corpus. As it is expected, a high amount of raters can decrease the agreement and require a high amount of rounds for the task. One suggestion is to eliminate the worst rater as done by the authors in [19].

Table 3. The degree of agreement among raters in the 2nd round of manual annotation.

Measure	Mode	1–2	1–3	1–4	1–5	2–3	2–4	2–5	3–4	3–5	4–5	All raters
Kappa	Full	0.0821	0.2315	0.2799	0.1130	0.0640	0.1001	0.0781	0.1662	0.1091	0.2233	0.0791
	Partial	0.1556	0.2480	0.3288	0.1630	0.0952	0.1240	0.1109	0.1870	0.1397	0.2615	0.1018
	Text	0.2081	0.2837	0.3607	0.1967	0.1360	0.1676	0.1545	0.2093	0.1818	0.2776	0.1252
#Fact	Full	189	227	245	279	211	235	237	286	298	298	471
	Partial	177	224	236	267	205	230	230	281	290	289	441
	Text	166	217	229	257	195	218	217	275	278	283	411
#Exact fact	Full	16	53	69	32	14	24	19	48	33	67	8
	Partial	28	56	78	44	20	29	26	53	41	76	14
	Text	35	62	83	51	27	37	34	58	51	79	22

In the second task before generating the corpus, all raters were invited to evaluate all extracted facts from the twenty-five sentences. In this task, we observed in Table 4 a higher agreement between the raters, thus making explicit the worst rater (or the most divergent).

Table 4. Degree of agreement among raters in the evaluation of 442 extracted facts.

Measure	1–2	1–3	1–4	1–5	2–3	2–4	2–5	3–4	3–5	4–5	All raters
Kappa	0.1176	0.7285	0.4705	0.3619	0.1719	0.1945	0.2036	0.6244	0.6063	0.7466	0.4226
#Exact fact	247	382	325	301	259	264	266	359	355	386	176

Low values for the agreement in the first task hide other challenges during the task. To identify these challenges, we consult the raters on the sources of disagreement. The list was extracted from the "inter–rater–agreement–tutorial" at dkpro.github website[15]. In Table 5 the results of the survey are presented. Two questions were unanimity and alert us to two challenges. The **fourth challenge** is to solve the"Hard or debatable cases" which is the first unanimity. Nevertheless, the second unanimity is the **fifth challenge** that introduces "Personal opinions or values". We believe that difficult cases can greatly increase the bias and use of personal values. When we increase the number of constraints to solve difficult cases, we are limiting the extraction of our relationships. On the other hand, if we do not do it, difficult/hard cases are even more biased. How the problem will be handled depends on the cause. However, an important issue related to these problems is the agreement measure.

Table 5. Survey results to identify the difficulties during the tasks.

Sources of disagreement	**Rater 1**	**Rater 2**	**Rater 3**	**Rater 4**	**Rater 5**
Insecurity in deciding on a category		✓	✓		
Hard or debatable cases	✓	✓	✓	✓	✓
Carelessness				✓	✓
Difficulties or differences in comprehending instructions		✓		✓	
Openness for distractions					✓
Tendency to relax performance standard when tired	✓	✓		✓	✓
Personal opinions or values	✓	✓	✓	✓	✓

Studies such as the one proposed by the authors in [8] discuss the problems of bias and prevalence for kappa measures that are widely used. The authors in [3] suggest that in cases of detection of these problems coefficients like α and π are performed. We opted for a variation of kappa that solves these problems. While careful with the choice of agreement measure, we believe that this has not determined the low agreement values. The sentence set is small, but more than 400 facts have been extracted from all the raters. There is a difficulty in standardizing the triple arguments which can generate much duplicate information. Simple example such "David is a PhD student in Computer Science" can generates triples such {*"David", is, a PhD student in Computer Science*} and {*"David", is a PhD student in, Computer Science*}. Although the two facts contain the same information, we recognize it as relations between different concepts.

[15] https://dkpro.github.io/dkpro-statistics/dkpro-agreement-tutorial.pdf.

6 Conclusions

In this work, we draw up a set of constraints and conduct an annotation task for Open IE using a small set of sentences from Portuguese. Although the small set (hard to generalize), we consider that some of the main challenges of this task have been experienced. A large number of extracted facts in comparison to the initial set of sentences indicates a great difficulty in standardizing the task. This fact leads us to the most significant result of this study which is the low agreement between the rates. The Open IE task proved challenging to define a standard concept, and annotator bias an ever-present variable. The experience of performing the task in a small corpus enables the improvement of OpenIEAnn annotation tool, thus identifying some challenges and proposing some insights to mitigate these challenges.

The next steps of this research are (i) add more sentences into the corpus, (ii) evaluate the annotator bias through more sentences and (iii) add support for different languages in the OpenIEAnn tool.

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