DWIE: an entity-centric dataset for multi-task document-level information extraction.

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Abstract
This paper presents DWIE, the ‘Deutsche Welle corpus for Information Extraction’, a newly created multi-task dataset that combines four main Information Extraction (IE) annotation sub-tasks: (i) Named Entity Recognition (NER), (ii) Coreference Resolution, (iii) Relation Extraction (RE), and (iv) Entity Linking. DWIE is conceived as an entity-centric dataset that describes interactions and properties of conceptual entities on the level of the complete document. This contrasts with currently dominant mention-driven approaches that start from the detection and classification of named entity mentions in individual sentences. Further, DWIE presented two main challenges when building and evaluating IE models for it. First, the use of traditional mention-level evaluation metrics for NER and RE tasks on entity-centric DWIE dataset can result in measurements dominated by predictions on more frequently mentioned entities. We tackle this issue by proposing a new entity-driven metric that takes into account the number of mentions that compose each of the predicted and ground truth entities. Second, the document-level multi-task annotations require the models to transfer information between entity mentions located in different parts of the document, as well as between different tasks, in a joint learning setting. To realize this, we propose to use graph-based neural message passing techniques between document-level mention spans. Our experiments show an improvement of up to 5.5 F\textsubscript{1} percentage points when incorporating neural graph propagation into our joint model. This demonstrates DWIE’s potential to stimulate further research in graph neural networks for representation learning in multi-task IE. We make DWIE publicly available at [https://github.com/klimzaporojets/DWIE](https://github.com/klimzaporojets/DWIE).

Keywords: Named Entity Recognition, Entity Linking, Relation Extraction, Coreference Resolution, Joint Models, Graph Neural Networks

1. Introduction
The last decade has produced a growing interest in using multi-task information extraction (IE) datasets, building joint models that aim to take advantage of the inter-relation between tasks, thus trying to address two or more of them simultaneously ([Bekoulis et al., 2018b; Fei et al., 2020; Lee et al., 2017, 2018; Luan et al., 2019]). However, the currently widely used IE datasets to build such models exhibit three major limitations. First, the annotation schema adopted in most of these datasets is mention-driven, focusing on annotating elements (e.g., relations, entity types) that involve specific entity mentions explicitly mentioned in the text. This produces very localized annotations (e.g., sentence-based relations between entity mentions) that do not take into account a more general document-level meaning. Second, the annotation of currently widely used IE datasets is driven by either relying on a priori defined annotation schemas ([Augenstein et al., 2017]

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Figure 1: An example from the DWIE dataset with entity mentions underlined. We show 8 of the 29 entities in the graph on the right. It illustrates the relations that can be derived from the content of the article. The relations that are explicitly mentioned in the text (trigger-based) are depicted by solid arrows. Conversely, the relations that are implicit and/or need the whole document context (document-based) to be derived are represented by dashed arrows.

Doddington et al., 2004; Hendrickx et al., 2010; Song et al., 2015; Walker et al., 2006; Zhang et al., 2017b) or on distantly supervised labeling techniques (Han et al., 2018; Peng et al., 2017; Quirk & Poon, 2017; Riedel et al., 2010; Yao et al., 2019). In consequence, the resulting annotations are not necessarily representative of the actual information contained in the annotated corpus. Finally, the number of annotated extraction tasks in most of the IE datasets is rather limited. Most of them focus on a single or at most a few different tasks. Furthermore, some other datasets, including the well-known TAC-KBPs (Ellis et al., 2015, 2014; Ji et al., 2010, 2015, 2017), use different non-overlapping corpora for each of the tracks that group a few related tasks. Consequently, current models addressing multiple IE tasks together often use multi-tasking (with different datasets per task) rather than really joint modeling approaches.

In this work, we tackle the aforementioned limitations of IE datasets by introducing a new dataset named DWIE. It consists of 802 general news articles in English, selected randomly from a corpus collected from Deutsche Welle\(^1\) between 2002 and 2018, as part of the CPN project\(^2\). We focus on annotating four main IE tasks: (i) Named Entity Recognition (NER), (ii) Coreference Resolution, (iii) Relation Extraction (RE), and (iv) Entity Linking.\(^3\) Figure 1 shows an example snippet from the DWIE corpus. We adopt an entity-centric approach where all annotations are made on the entity level. Each of the entities is composed by the coreferenced entity mentions from the entire document (e.g., the entity Meghan in Fig. 1 clusters the entity mentions “Meghan Markle” and “Meghan” across the whole document). This allows us to make annotations on a document-level, derived not only from the information explicitly mentioned, but also implicitly present in the document (e.g., the relation citizen_of(William, Britain) for the article in Fig. 1). This entity-centric approach contrasts with mention-driven annotations in widely used IE datasets (Doddington et al., 2004; Han et al., 2018; Hendrickx et al., 2010; Ji et al., 2015; Luan et al., 2018; Song et al., 2015; Zhang et al., 2017b) where the annotation process is biased towards considering only local explicit textual evidence to annotate elements such as relations and entity types. Additionally, we use a bottom-up, data-driven annotation approach where we manually define our annotations (e.g., in terms of the entity and relation types) to maximally reflect the information of the corpus at hand. We achieve this by following a three-pass annotation procedure where we use the first exploratory annotation pass to derive the main annotation types (annotation schema) from the corpus, and the next two passes to perform schema-driven

\(^1\)https://www.dw.com

\(^2\)https://www.projectcpn.eu

\(^3\)The linking is done to Wikipedia version 20181115.

\(^4\)Also referred to as entity cluster or just cluster.
annotations and refine them by carrying out an additional parallel annotation of the corpus for fixing errors inferred from inter-annotator inconsistencies. Such bottom-up, data-driven annotation differs from currently dominant distant supervision and top-down annotation approaches driven by an a priori defined annotation schema (which is typically relatively limited in terms of distinct entity and relation types).

Besides the dataset itself, we also contribute empirical modeling results to address the aforementioned IE tasks. More specifically, our proposed dataset opens up the possibility to study two main phenomena. The first phenomenon consists in a long-range contextual information sharing between entity mentions in different parts of the document. For example, in Fig. 1 the contextual information involving the entities Ministry of Defense and Harry in sentence 7 can be combined with the information in the sentence 2 involving the entities Britain and Harry to extract a document-level relation \( \langle \text{Ministry of Defense}, \text{Britain} \rangle \).

The second phenomenon involves the joint interaction between tasks where the information obtained in one task can help to solve another task. For example, in Fig. 1 knowing the types of entities (which involves NER and coreference tasks) Britain and Kensington Palace can boost the performance of the relation extraction task by limiting the number of possible relation types between these two entities (e.g., \textit{ministry of} but not \textit{citizen of}). In order to study the impact of these two phenomena inherent to our DWIE dataset on the final results, we experiment with neural graph-based models \cite{Li2016b, Wu2020, Xu2018}. These models allow message passing between local contextual encodings, making it possible to measure the impact of local contextual information sharing both on a more general document level and across the tasks. Furthermore, previous work already has shown the positive effect of using graph-based information passing techniques on single tasks \cite{Kantor2019, Lee2018}, and between tasks \cite{Fei2020, Fu2019, Luan2019, Wadden2019} on mention-driven datasets. We expand this work even further by extending these models to be used on the entity-centric, document-level DWIE dataset.

In summary, the main objective that we address in the current paper is to introduce an entity-centric multi-task IE dataset that covers different related tasks on a document level. Furthermore, we aim to explore how neural graph-based models can boost the performance by enabling local contextual information propagation across the document (single-task models) and between different tasks (joint models). The results presented in this paper suggest that, while challenging, DWIE opens up new possibilities of research in the domain of joint entity-centric information extraction methods. The main contributions of our work are that:

1. We construct a self-contained dataset (Section 3) with joint annotations for four basic information extraction tasks (NER, entity linking, coreference resolution, and RE), that provide entity-centric document-level annotations (as opposed to typical mention-driven sentence-level annotations for, e.g., RE).

2. We introduce a data-driven, bottom-up three-pass annotation approach complemented by context-based logical rules to build such dataset (Section 3).

3. We propose a new evaluation metric for the NER and RE tasks (Section 5), in line with the entity-centric nature of DWIE.

4. We extend the competitive graph-based neural IE model DyGIE \cite{Luan2019} for the four IE tasks in DWIE (Section 4) and provide source code for NER, coreference resolution, and RE. Furthermore, we introduce a new latent attention-driven \textit{AttProp} graph propagation method and show its advantages in both single and joint model settings. The experimental results (Section 6) demonstrate the potential of such neural graph based models.
Table 1: Qualitative comparison of the datasets. We divide our comparison in five groups: (i) Core Tasks represent the main sub-tasks covered in DWIE, (ii) Doc-Based indicates whether different sub-tasks are annotated on the document-level, (iii) Entity-Centric indicates which annotations are done with respect to entity clusters (√) as opposed to individual mentions (×), (iv) Unaided specifies whether the annotation process was completely manual (√) or with some form of distant supervision (×), and (v) Open indicates whether the dataset is freely available.

| Dataset          | Core Tasks | Doc-Based | Entity-Centric | Unaided |
|------------------|------------|-----------|----------------|---------|
| DWIE             | **NER**    | [ ]       | [ ]            | [ ]     |
| TAC-KBP          | **NER**    | [ ]       | [ ]            | [ ]     |
| MUC-7            | **NER**    | [ ]       | [ ]            | [ ]     |
| SciERC           | **NER**    | [ ]       | [ ]            | [ ]     |
| DocRED           | **NER**    | [ ]       | [ ]            | [ ]     |
| Rich ERE         | **NER**    | [ ]       | [ ]            | [ ]     |
| OntoNotes 3.0    | **NER**    | [ ]       | [ ]            | [ ]     |
| ScienceIE        | **NER**    | [ ]       | [ ]            | [ ]     |
| FewRel           | **NER**    | [ ]       | [ ]            | [ ]     |
| GENIA            | **NER**    | [ ]       | [ ]            | [ ]     |
| AIDA CONLL-YAGO  | **NER**    | [ ]       | [ ]            | [ ]     |
| SemEval 2010 TS | **NER**    | [ ]       | [ ]            | [ ]     |
| NYT              | **NER**    | [ ]       | [ ]            | [ ]     |
| ACEtoWiki        | **NER**    | [ ]       | [ ]            | [ ]     |
| WNUT 2017        | **NER**    | [ ]       | [ ]            | [ ]     |
| TACRED           | **NER**    | [ ]       | [ ]            | [ ]     |

2. Related Work

This section summarizes the overview of related datasets (Section 2.1), and explores the differences between our newly created DWIE and other similar datasets widely used by the scientific community (listed in Tables 1 and 2). Next, we describe the current trends in IE to solve the tasks included in DWIE, and compare them to our proposed approach (Section 2.2). Finally, we discuss currently used metrics to evaluate model performance on IE datasets and introduce some challenges in applying them to measuring the performance on DWIE (Section 2.3).

2.1. Related Datasets

Most of IE datasets have focused on a single task, making it very challenging to develop systems that jointly train for different annotation sub-tasks on a single corpus. Well-known single-task datasets include (i) for NER: CoNLL-2003 (Sang & De Meulder, 2003) and WNUT 2017 (Derczynski et al., 2017), (ii) for relation extraction: SemEval-2010 TS (Hendrickx et al., 2010), TACRED (Zhang et al., 2017), and FewRel (Han et al., 2018), (iii) for entity linking: IITB (Kulkarni et al., 2009), CoNLL-YAGO (Hofart et al., 2011), and WikilinksNED (Eshel et al., 2017), and (iv) for coreference resolution: CoNLL-2012 (Pradhan et al., 2012) and GAP (Webster et al., 2018). Conversely, in this work we propose a multi-task dataset as a single corpus annotated with different information extraction layers: named entities, mention clustering in entities (i.e., coreference), relations between entity clusters of mentions, and entity linking. We further complement our dataset with additional tasks such as document classification and keyword extraction. It is worth noting that our coreference annotations differ from the widely adopted CoNLL-2012 (Pradhan et al., 2012) scheme in two aspects: (i) we retain singleton entities composed by only one mention as a valid entity cluster, (ii) we only cluster proper nouns, leaving out nominal and anaphoric expressions.
Table 2: Numerical comparison of DWIE and well-known IE datasets. Note that some datasets (including DWIE) use an entity-centric approach, organizing entity mentions in entity clusters, and annotating entities, relations, and linking on the cluster level. Hence, we provide both mention-level as well as cluster-level (if a particular dataset supports it) statistics.

| Dataset     | # Tokens | # Mentions | # Entity clusters | # Entity types | # Relation mentions | # Relation clusters | # Relation types | Linking |
|-------------|----------|------------|-------------------|----------------|---------------------|---------------------|------------------|---------|
| NYT         | 5,765,332| 1,388,982  | -                 | -              | 142,823             | -                   | 52               | 1,388,982|
| TACRED      | 3,866,863| -          | -                 | -              | 21,784              | -                   | 42               | -       |
| TAC-KBP 5    | 3,053,336| 6,495      | 3,750             | -              | -                   | -                   | -                | -       |
| OntoNotes 5.0 | 1,037,333| 114,213    | 112,000           | 6              | 155,535             | 50,503              | 96               | -       |
| MUC-4        | 717,798  | 14,196     | 13                | -              | -                   | -                   | -                | -       |
| GENIA        | 554,346  | 56,743     | 10,728            | 5              | 2,337               | -                   | 2                | -       |
| DWIE         | 501,095  | 43,373     | 23,130            | 311            | 317,204             | 21,749              | 65               | 28,482  |
| BC5CDR      | 343,175  | 29,271     | 10,326            | 2              | 47,813              | 3,116               | 1                | 29,562  |
| CoNLL-YAGO  | 301,418  | 34,929     | -                 | -              | -                   | -                   | -                | -       |
| ACE 2005     | 259,899  | 54,824     | 37,622            | 51             | 8,419               | 7,786               | 18               | -       |
| ACEtoWiki 7  | 259,899  | -          | -                 | -              | -                   | -                   | -                | -       |
| SEval 2010 T8 | 207,307  | 21,434     | -                 | -              | 6,674               | -                   | 9                | -       |
| ACE 2004     | 185,696  | 29,271     | 12,507            | 43             | 5,976               | 5,525               | 24               | -       |
| WNUT 2017    | 101,857  | 3,890      | -                 | 6              | -                   | -                   | -                | -       |
| ScienceIE    | 99,580   | 9,946      | 9,536             | 3              | 638                 | -                   | 1                | -       |
| SciERC       | 65,334   | 8,094      | 1,015             | 6              | 2,687               | -                   | 7                | -       |

Furthermore, most prominent efforts to produce jointly annotated datasets have focused on using a top-down annotation approach. This method involves an a priori defined annotation schema that drives the process of selection and labeling of the corpus. The de facto datasets used in most of the joint learning baselines such as ACE 2005 (Doddington et al., 2004; Walker et al., 2006), TAC-KBP 2010-2014 (Ellis et al., 2015, 2014; Ji et al., 2010, 2015, 2017) and Rich ERE (Song et al., 2015) use this annotation approach. More specifically, during the creation of the ACE 2005 dataset, the annotators initially tagged candidate documents as “good” or “bad” depending on the estimated number and types of entities present in each one. In subsequent annotation stages, only “good” documents were fully annotated and included in the final dataset. Similarly, during the creation of the TAC-KBP datasets, the annotators focused on producing annotations evenly distributed among three entity types (PERs, ORGs, and GPEs) by annotating only the documents that contained a minimum number of entities related to event types. In the case of Rich ERE, the documents to tag were prioritized by the event trigger word density calculated per 1,000 tokens, thus focusing only on content with a high number of previously defined key event-related tokens. Furthermore, other IE-related datasets (Augenstein et al., 2017; Han et al., 2018; Hendrickx et al., 2010; Yao et al., 2019; Zhang et al., 2017b) use similar pre-filtering techniques in order to select the text to be annotated. As a consequence, the corpus and annotations in these datasets tend to be biased and likely not representative of the language used in the different input domains. Conversely, we adopt a radically different bottom-up approach where we derive the annotations (e.g., entity classification types, relation types) from the data itself. This bottom-up data-driven procedure guarantees that the annotations in DWIE are representative of the document corpus information and reflects the particularities of the language used in its journalistic domain. Furthermore, it better represents the properties that are inherently present in written corpora, e.g., the long-tail distribution of different annotation types.

Finally, from the perspective of the necessary evidence to annotate a particular entity type or relation, we propose to make a distinction for the currently existing datasets between trigger-based and document-based annotations (see Doc-Based comparison group in Table 1). The trigger-based datasets require that a

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5 The EDL track only of TAC-KBP 2010.
6 Numbers based on publicly available train and development sets.
particular relation or entity type should only be annotated if it is supported by an explicit reference in a text. For example, in Fig. 1 there is a concrete reference of the relation between “Meghan” and “Harry” in form of triggers such as “gets engaged” in sentence 1 and “The wedding” in sentence 2. Most of the traditionally used jointly annotated datasets such as ACE 2005 (Doddington et al., 2004; Walker et al., 2006), TAC-KBP (Ellis et al., 2015, 2014; Ji et al., 2010, 2015, 2017) and Rich ERE (Song et al., 2015), as well as others, including FewRel (Han et al., 2018), OntoNotes (Hovy et al., 2006; Weischedel et al., 2013), TACRED (Zhang et al., 2017b), SemEval 2010 Task 8 (Hendrickx et al., 2010) and SciERC (Luan et al., 2015), are trigger-based. The disadvantage of such an approach is that it only captures the most simple cases of relations and entity types that are explicitly mentioned in the text. As a general rule, this also limits the datasets to cover only the relations between entity mentions (i.e., the annotation process is mention-driven) that appear within a single or at most a few adjacent sentences where the relation trigger occurs (see Fig. 2 in Section 4 for a more detailed illustration of this phenomenon). However, as we move to a broader document-based interpretation, it is common to find relations that are not explicitly mentioned in text. Thus, in our example of Fig. 1 the relation between “Ministry of Defence” and “Britain” is not explicitly indicated in the text. However, after reading the whole article we can infer relations such as ministry_of_agency_of and based_in between these two entities. This document-level reasoning makes it essential to adopt an entity-centric approach (see Entity-Centric comparison group in Table 1) where each entity comprises one or more entity mentions, and the annotations (i.e., relations, entity tags and entity linking in DWIE) are made on the entity level, thus abstracting from specific mention-driven triggers.

2.2. Recent advances in Information Extraction

In the last couple of years, the advances in joint modeling have been accompanied by an ever increasing interest in the use of graph-based neural networks (Li et al., 2016b; Wu et al., 2020; Xu et al., 2018). Initially, this approach has been applied to improve the performance of the single coreference resolution task by transferring document-level contextual information between coreferenced entity mention spans (Kantor & Globerson, 2019; Lee et al., 2018). Most recently, these graph propagation techniques have been successfully used in a joint setting (Fei et al., 2020; Fu et al., 2019; Luan et al., 2019; Wadden et al., 2019) by performing graph message passing updates between the shared spans across different tasks. However, while successful on mention-driven datasets such as ACE 2005 (Walker et al., 2006) and NYT (Riedel et al., 2010), as far as we are aware, the advantages of these techniques have not yet been investigated in an entity-centric document-level setting. We fill this gap by extending the neural graph-based model initially proposed by Luan et al. (2019) to be used on DWIE (see Section 4). More specifically, we explore the effect of performing document-level coreference (CorefProp) (Lee et al., 2018; Luan et al., 2019) and relation-driven (RelProp) (Luan et al., 2019) graph message passing updates between the spans. Additionally, we introduce a new latent attention-based graph propagation method (AttProp) and compare it to previously proposed task-driven graph propagation methods (CorefProp and RelProp).

2.3. Metrics and evaluation

Current dominant IE systems consider mention-level scoring of NER as well as RE components when reporting on datasets such as CoNLL-2003 (Akbik et al., 2019, 2018; Baevski et al., 2019; Chiu & Nichols, 2016; Lample et al., 2016), OntoNotes (Chiu & Nichols, 2016; Clark et al., 2018; Strubell et al., 2017), ACE 2004 (Bekoulis et al., 2018a; Li & Ji, 2014; Zhang et al., 2017a), ACE 2005 (Fei et al., 2020; Luan et al., 2019; Zhang et al., 2017b), TACRED (Soares et al., 2019; Zhang et al., 2018, 2017b), and SciEval 2010-Task 8 (Guo et al., 2019; Hu et al., 2020; Peters et al., 2019) among others. In contrast, the DWIE dataset is entity-centric where all the annotations are done on the entity cluster level. Consequently, adopting a purely mention-based evaluation approach can lead to a dominance of the score by predictions on entities composed by many mentions as opposed to entities composed by only few ones. Conversely, a purely cluster-level evaluation would be overly strict, requiring correct prediction of relation/entity types as well as an exact match of the predicted entity clusters. To tackle this problem, we propose a new scoring method that combines entity mention-level and cluster-level evaluation, while avoiding the pitfalls of either method alone (see Section 5).
3. Annotation process

In this work we introduce our bottom-up data-driven annotation approach. Our main goal is to get an annotation schema that reflects the types of entities and relations that are effectively mentioned throughout the corpus to maximally capture the information it contains. Therefore, we derive the annotation schema from the corpus itself, adopting three annotation passes that are detailed next: (i) exploratory pass, (ii) schema-driven pass, and (iii) inter-annotator refinement.

3.1. Exploratory pass

The first annotation pass aims to discover the annotation structure (i.e., annotation schema) to be used on the corpus. Three annotators are involved in this step: one expert annotator and two paid students. However, no parallel annotation is done and the role of the expert annotator is to annotate part of the corpus, as well as instructing and supervising the paid annotators. No a priori fixed schema is followed, but we ask the annotators to be as consistent as possible during the process. More specifically, the annotators are free to define their own entity and relation types for the NER and RE tasks that reflect the contents of the articles. This way, we ensure that our annotations are representative of the actual information contained in the annotated corpus.

3.2. Schema-driven pass

The main goal of this step is to create a consistent annotation schema for (i) named entity types and (ii) relation types based on the annotations made in the exploratory pass. As a first step, we identify the classification tags to be assigned to entities. We divide these tags in five main categories: type, topic, ipte, slot, and gender (see Table A.4). Furthermore, we recognize that the entity classification is multi-label by nature and thus allow different complementary entity tags to be assigned to a particular entity. This

The average number of labels per entity is 4.0 in our DWIE dataset.
Table 3: The inter-annotation agreement Cohen’s kappa scores for all the different annotation tasks before and after the dataset refinement used to analyze and correct the discrepancies between the parallel annotations.

| Task                        | Before Refinement | After Refinement |
|-----------------------------|-------------------|------------------|
| Named Entity                | 0.8497            | 0.8703           |
| Named Entity Detection      | 0.9665            | 0.9673           |
| Named Entity Classification | 0.8812            | 0.9026           |
| Coreference                 | 0.9302            | 0.9324           |
| Entity Linking              | 0.9280            | 0.9320           |
| Relation                    | 0.6594            | 0.8729           |
| Relation Detection          | 0.7686            | 0.8727           |
| Relation Classification     | 0.8118            | 0.9666           |

For our relation annotations, we focus on annotating relations between entities themselves (cf. document-based entity-centric approach). Our adopted approach allows us to think concept-wise and come up not only with relations that are explicitly stated, but also those that can be implicitly inferred from the text. As a result, our dataset includes relations whose connected mentions are located further apart in the document. This can be seen in Fig. 2 where we compare the minimum (Min.) and maximum (Max.) distances between the mentions of the two entities connected by a relation for various mention-driven (Rich ERE\(^8\), TAC-KBP\(^9\), and ACE 2005) and entity-centric (DocRED, BC5CDR, and the final version of our DWIE dataset) RE datasets. We note how other datasets that define the relation in terms of entities (BC5CDR and DocRED) require a higher number of token and sentence spans to cover all the relations in the respective dataset: entity-centric relations very often involve mentions located in different sentences in the document that refer to those entities. This is not the case for mention-driven trigger-based relations as in the TAC-KBP, Rich ERE and ACE 2005 datasets, where the annotation bias is towards finding explicitly mentioned relations, often involving entity mentions in a single sentence.

Similarly as with entity tags, we organize our relation annotations using multi-label types (see Table A.5 for details). Additionally, we define logical rules to automatically guarantee the consistency of the relations and their types. The following is an example,

\[
\text{based}_{in2}(X, Z) \land \text{in0}(Z, Y) \implies \text{based}_{in0}(X, Y)
\]

reflecting the knowledge that if an organization \(X\) is based in a city \(Z\) (relation \(\text{based}_{in2}\)), and that this city \(Z\) is located in the country \(Y\) (relation \(\text{in0}\)), the fact that company \(X\) is also located in that country (relation \(\text{based}_{in0}\)) is valid as well. The goal of this step is mainly consistency of the annotations, but it implies that an effective predictor would need to perform some form of reasoning to correctly predict all relations in the dataset. A complete list of logical rules is provided in Appendix C.

3.3. Inter-Annotator Refinement

In order to assess and further improve the quality of our dataset we reannotate a 100 randomly selected news articles (12.5% of the articles used in the previous annotation rounds) from scratch. This work is done by a second independent expert annotator. The annotations in this pass are performed by following the already defined annotation schema based on the annotation process in the exploratory and schema-driven passes. We use this second annotated subset to measure the inter-annotator agreement and subsequently

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\(^8\) We use the Rich ERE dataset from the LDC2015E29 and LDC2015E66 catalogs.

\(^9\) We use the TAC-KBP 2017 dataset from the LDC2017E54 and LDC2017E55 catalogs.
determine the parts of the dataset that still need to be improved. Table 3 compares the kappa scores before and after this refinement pass for each of the tasks (see Appendix B for details on how the kappa score is calculated). We observe that, after the refinement, all of the kappa scores are above 0.85, which is considered a ‘strong’ (McHugh, 2012) to ‘almost perfect’ (Landis & Koch, 1977) agreement.

Note that the revisions were seeded by and evaluated on the subset of 100 re-annotated articles. However, we argue that the inter-annotator refinement improved the annotation consistency of the entire dataset, given that the reviewed entity and relation types are used in more than 99.4% of all annotations in DWIE.

4. Model Architecture

In this section we introduce the end-to-end architecture used to compare the performance of models trained on the separate tasks with the models that are trained jointly for multiple tasks on the DWIE dataset. The main component of our approach is the use of Graph Neural Networks (Li et al., 2016a; Scarselli et al., 2008; Wu et al., 2020; Xu et al., 2018), relying on propagation techniques in both single-task and joint setups. More specifically, we implement span-based graph message passing on coreference (CorefProp) (Lee et al., 2018; Luan et al., 2019) and relation levels (RelProp) (Luan et al., 2019). Additionally, we introduce a latent attentive propagation method (AttProp) which is not driven by annotations of any task in particular and, as a result, can be freely applied to any task or joint combination of tasks. The interconnection between the different components of our model architecture is depicted in Fig. 3. It is based on the span-based architecture introduced in Lee et al. (2017), which supports training on the space of all entity spans simultaneously, dynamically updating span representations by using the graph propagation approach (further detailed in Section 4.4). Recent works have shown that this idea has the potential for improved effectiveness (albeit at a higher computational cost) (Dixit & Al-Onaizan, 2019; Fei et al., 2020; Lee et al., 2018; Luan et al., 2019), compared to more traditional sequence-labeling approaches (Katiyar & Cardie, 2018; Lample et al., 2016; Luan et al., 2017; Ma & Hovy, 2016). More concretely, the use of a span-based approach where all the spans are shared between the individual task modules avoids the cascading of errors from the entity mention identification module (entity scorer in Fig. 3) to the rest of the tasks.

The most similar architecture to ours in using joint span-based neural graph IE is DyGIE (Luan et al., 2019) and its successor DyGIE++ (Wadden et al., 2019). Our model is described in detail below, but here we already list the aspects in which it differs from these models:

1. We introduce the graph propagation technique AttProp (see Section 4.4), which is not directly conditioned on a particular task and can be used in single-task (for each of the tasks) as well as joint settings.

2. We define a coreference architecture that, unlike previous work in span-based coreference resolution (Lee et al., 2017, 2018), allows to also account for singleton entities in the DWIE dataset (see Sections 4.2.2 and 4.5.2) by using an additional pruner loss, which turns out essential for the single model focusing on end-to-end coreference resolution.

3. Due to the document-level nature of DWIE, we run graph propagations on the whole document. This contrasts with a sentence-based approach adopted initially in the DyGIE/DyGIE++ architectures. It also drives some changes such as the use of a single pruner (see Section 4.1) to extract spans used in coreference and RE modules. Similarly, instead of applying the shared BiLSTM sentence by sentence as in Luan et al. (2019) and Wadden et al. (2019), we do it on the entire document, in order to allow capturing cross-sentence dependencies for document-level relations and entity clusters in DWIE.

4. We add an additional decoding step (see Section 4.3) needed to transform mention-based predictions for RE and NER tasks into entity-based ones, as required by the entity-centric nature of DWIE, and propose corresponding evaluation metrics (see Section 5).

5. Finally, we make changes in the loss and prediction components to support multi-label classification (in NER and RE) as required in DWIE.
Figure 3: Architecture of our model; the span-oriented approach makes it possible to execute coreference (Section 4.2.2) and relation (Section 4.2.3) scorers independently from entity scorer (Section 4.2.1). However, a pruning step (described in Section 4.1) is needed in order to limit the memory required to perform matrix operations on span representations involved in graph propagation (AttProp, CorefProp, RelProp) (Section 4.4) as well as in the attention, coreference and relation scorer modules. The pruned spans share the same representation with the rest of the spans (shared representation). This way, the update in span representations caused by the graph propagation modules also affects the entity scorer. Our AttProp graph propagation method runs independently from coreference, relation, and entity scorers, enabling its use in combination with any task.

4.1. Span-Based Representation

The input to our model consists of document-level annotation instances. Each document $D$ from the considered document collection $\mathcal{D}$ is represented by its sequence $T$ of tokens. These tokens are represented internally as a concatenation of GloVe (Pennington et al., 2014) and character embeddings (Ma & Hovy, 2016). We also experiment with additionally concatenating BERT (Devlin et al., 2019) contextualized embeddings. Since BERT is run on a sub-token level, to the representation of each token we only concatenate the BERT-based representation of the first sub-token, as originally proposed by Devlin et al. (2019). This input is fed into a BiLSTM layer in order to obtain the output token representations by concatenating the forward and backward LSTM hidden states. The BiLSTM outputs for the considered document $D$ are written on the token level as $e_i \in \mathbb{R}^m$ ($i = 1, \ldots, |T|$). These are converted into span representations. The set of all possible spans for $D$, up to maximum span width $w_{\text{max}}$ (which is a hyperparameter of the model),
is written as \( S = \{ s_1, \ldots, s_{|S|} \} \). The number of spans can be calculated as follows,

\[
|S| = \sum_{k=1}^{w_{\text{max}}} |T| - k + 1 = w_{\text{max}} \left( |T| - \frac{w_{\text{max}} - 1}{2} \right)
\]  

We obtain the representation \( g_i^0 \) for span \( s_i \), ranging from token \( l \) to token \( r \), by concatenating their respective BiLSTM states \( e_l \) and \( e_r \) with an embedding \( \psi_{r-l} \) for the span width \( w_i = r - l \)

\[
g_i^0 = [e_l; e_r; \psi_{r-l}]
\]  

As seen from Eq. (2), the number of possible spans scales approximately linearly with the maximum span width \( w_{\text{max}} \), as well as the document length \( |T| \) (assuming \( w_{\text{max}} \ll |T| \)). This leads to a strongly increased set of spans, as compared to previous works where \( |S| \) scales with the length of individual sentences rather than entire documents (Luan et al., 2019; Wadden et al., 2019). In order to mitigate the required memory of our model, we use a shared pruner to reduce \( S \) to a smaller set \( P \) of candidate spans to be used by the coreference and RE scorers and in the graph propagation modules (see further). The choice of using a single pruner contrasts with similar work in Luan et al. (2019) and Wadden et al. (2019) where two separate pruners are used, one for the relation task, and another for coreference. Our design choice is based on the fact that both of these tasks use the same document-level entity mentions. This contrasts with datasets used in Luan et al. (2019) and Wadden et al. (2019) where, while the coreference is defined on the document-level, the relations are sentence-based.

Finally, we use graph propagation to iteratively refine the pruned spans representations. Three graph propagation mechanisms are compared in the experiments. Our own contribution is the attention-based graph propagation method \( \text{AttProp} \), where the span representations are updated in \( \tau_A \) iterations. Alternatively, \( \tau_C \) iterations of \( \text{CorefProp} \) (Lee et al., 2018; Luan et al., 2019) can be performed, or \( \tau_R \) iterations of \( \text{RelProp} \) (Luan et al., 2019).

The span representation of a particular span \( s_i \) after iteration \( t \) is denoted as \( g_t^i \) in our notation. The details of graph propagation are explained in Section 4.4. Note that in theory several of these graph propagation techniques could be accumulated, but in our setting the benefits thereof in terms of model effectiveness were minor, at a significantly higher computational cost. Therefore, in our experiments, we only compare models without graph propagation with models applying a single form of graph propagation. To keep the sections introducing the models clear, we will write \( \tau \) to denote the number of propagations in general (which could be 0, or any of \( \tau_A, \tau_C \) or \( \tau_R \), depending on the chosen experiments and considered model components).

4.2. Joint Model for Entity Recognition, Coreference Resolution, and Relation Extraction

In this section, we present the joint model including recognition of entity mentions as belonging to \( L_T \) types (introduced as NER), the clustering of the entity mentions into entities (coreference resolution), and identifying relations between entities, all on the document level. The building blocks responsible for the three sub-tasks are discussed next, as well as the total loss of the joint model. The details of the graph propagation mechanisms are then provided further on (Section 4.4).

4.2.1. Entity Mention Module

All spans \( s_i \) (up to width \( w_{\text{max}} \)) of the considered document are scored by feeding their representation (starting from Eq. (3) and potentially updated after \( \tau \) graph propagation iterations) into the feed-forward neural network (FFNN) written as \( \mathcal{F}_{\text{mention}} \), with as many outputs as there are entity types:

\[
\Phi^\tau_{\text{mention}}(s_i) = \mathcal{F}_{\text{mention}}(g_t^i).
\]  

---

\(^{10}\)For convenience, the subscript \( D \) indicating the current document is left out in the equations of this section.
Throughout this section, we will maintain the same notation of $\mathcal{F}(\mathbf{x})$ to denote a FFNN that takes as input a vector $\mathbf{x}$ and produces a vector of scores, and $\mathcal{F}(\mathbf{x})$ to refer to a FFNN with a scalar output.

The probability of each label being valid for the considered span is modeled by component-wise application of a sigmoid ($\sigma(x) = 1/(1 + e^{-x})$) to these scores $\Phi^\tau_{\text{mention}}(s_i) \in \mathbb{R}^{L_T}$ (with $L_T$ the number of entity tags). The log probability of the ground truth mention labels for all spans of document $D$ is given by

$$\log P_{\text{mention}}(E^*|G^*) = \sum_{i=1}^{[S]} \sum_{l=1}^{L_T} I_{i,l} \log \sigma(\Phi^\tau_{\text{mention}}(s_i)_l) + (1 - I_{i,l}) \log (1 - \sigma(\Phi^\tau_{\text{mention}}(s_i)_l)), \quad (5)$$

in which $E^*$ represents the set of ground truth mention labels for all spans in the document, and $I_{i,l} \in \{0,1\}$ is the ground truth indicator label for mention tag $l$ of span $s_i$. $G^*$ denotes the set of all considered span representations for the current document. The superscript $\tau$ reflects the fact that, in case graph propagation is applied, the subset of $|P|$ representations (for the spans retained after pruning) have been updated over $\tau$ iterations. By summing over all entity types ($l = 1, \ldots, L_T$), we account for the fact that a particular span can have multiple associated entity tags (i.e., the considered NER task is multi-label). At inference time, spans get assigned those entity types for which the corresponding score $\Phi^\tau_{\text{mention}}(s_i) > 0$. Note that not all valid entity mentions necessarily get an entity type assigned: if the relation extractor determines that a span is part of a relation, it effectively becomes an entity mention, even if none of the pre-defined types is considered applicable by the entity scorer.

### 4.2.2. Coreference Module

While the entity scoring is performed on all span representations $S$, this is not possible for the coreference and relation scorers, due to memory limitations. The latter scorers predict on pruned spans, as shown in Fig. 3. How the pruner is trained jointly with the model, is described in Section 4.2.4. In order to avoid confusion by introducing additional notations, we list the spans in the pruned set $P$ as $s_1, \ldots, s_{|P|}$, according to their original order in the text.

The module for coreference resolution is based on pairwise scoring of the pruned spans from $P$. Following ideas from Lee et al. (2017, 2018); Luan et al. (2018, 2019), for any span $s_j$, scores with respect to each of the preceding (also referred to as ‘antecedent’) spans $s_i$ ($i \leq j$) in the document are calculated with a neural network $\mathcal{F}_{\text{coref}}$:

$$\Phi^\tau_{\text{coref}}(s_i, s_j) = \mathcal{F}_{\text{coref}} ([g_i^t; g_j^t; \psi^t_i \odot \psi^t_j; \psi_{ij}]). \quad (6)$$

This expression scores the compatibility between spans $s_i$ and $s_j$, taking as input the concatenation of their respective span representations (after $\tau$ propagation iterations), their component-wise product, and an embedding $\psi_{ij}$ representing their distance in terms of the number of ordered candidate spans from $s_i$ to $s_j$.

In order to deal with non-coreferent or incorrect spans, previous work in span-based coreference (Lee et al. 2017, 2018) defines a dummy antecedent $\tau$ to which all non-coreferent or invalid spans point. While this approach is effective in datasets that do not contain singleton entity clusters, such as OntoNotes-based CoNLL-2012 (Pradhan et al., 2012), it does not allow to distinguish between valid singleton entity mentions and invalid mention spans. This makes it unsuitable to use on DWIE, since it contains singleton entity clusters, consisting of a single mention. In fact, 66.4% of the entity clusters in DWIE are singletons.

Furthermore, the current official CoNLL-2012 evaluation script[11] based on Pradhan et al. (2014) accounts for scenarios where either the dataset or the predicted mentions are singletons, which has a direct impact on the established B-CUBED (Bagga & Baldwin, 1998) and CEAFe (Luo, 2005) coreference scores. In order to tackle the singleton entity cluster detection in our coreference model, we propose to start from $\Phi^\tau_{\text{coref}}(s_i, s_j)$ as a self-coreference span score. By applying the correct target in the coreference loss, it allows indicating that either the span $s_j$ is not a valid mention, or that it is a valid mention that is not co-referenced with any antecedent span.

[11]https://github.com/conll/reference-coreference-scorers

[12]This would be replaced with $\Phi^\tau_{\text{coref}}(\tau, s_j)$ in the dummy-based formulation defined in Lee et al. (2017).
The log probability of the ground truth coreference labels of document $D$ is given by

$$\log P_{\text{coref}} (C^*|G^*) = \sum_{j=1}^{|P|} \frac{\sum_{s^* \in S_j^*} \exp (\Phi_{\text{coref}}^\tau (s^*, s_j))}{\sum_{i=1}^{|S_j|} \exp (\Phi_{\text{coref}}^\tau (s_i, s_j))}. \quad (7)$$

The set of ground truth coreference labels is indicated as $C^*$. The summation over $j$ represents the contribution to the log likelihood of the correct antecedent labels for each span $s_j$ in the pruned set $P$. The individual terms in the right-hand side correspond to the log probability of the correct antecedent labels for a particular span $s_j$. In the denominator, the summation ranges from the first span, up to span $s_j$ itself (i.e., for the self-coreference score), but not beyond it (given that only antecedents in the sorted sequence of pruned spans are considered). The numerator contains the contributions from the potentially multiple ground truth antecedents for span $s_j$. This stems from the fact that multiple antecedent mentions may belong to the same cluster as $s_j$, which all contribute to the probability of the correct antecedent labels. The set of ground truth antecedents corresponding to span $s_j$ is written $S_j^*$. At inference time, the highest scoring antecedent for span $s_j$ (including $s_j$ itself) is picked. Due to the idea of only predicting antecedents, picking any of the ground truth antecedents leads to the correct mention clusters [Durret & Klein 2013; Lee et al. 2017, 2018; Wiseman et al. 2015].

4.2.3. Relation Module

Similar to the coreference module (Eq. [9]), we score span pairs using an FFNN

$$\Phi_{\text{relation}}^\tau (s_i, s_j) = \mathcal{F}_{\text{relation}} ([\mathbf{g}_i^\tau; \mathbf{g}_j^\tau; \mathbf{g}_i^\tau \odot \mathbf{g}_j^\tau; \varphi_{i,j}]), \quad (8)$$

where $\varphi_{i,j}$ is again the distance embedding as introduced in Section 4.2.2. $\Phi_{\text{relation}}^\tau (i, j) \in \mathbb{R}^{L_R}$ is a vector representing relation span pair scores for each of the $L_R$ possible relation types between spans $s_i$ and $s_j$.

The log probability of the ground truth relation labels of document $D$ is given by

$$\log P_{\text{relation}} (R^*|G^*) = \sum_{i,j=1}^{|P|} \sum_{l=1}^{L_R} I_{i,j,l} \log \sigma(\Phi_{\text{relation}}^\tau (s_i, s_j)_l) + (1 - I_{i,j,l}) \log (1 - \sigma(\Phi_{\text{relation}}^\tau (s_i, s_j)_l)), \quad (9)$$

in which $R^*$ represents the set of ground truth relation labels for all combination of pruned span pairs in the document, and $I_{i,j,l} \in \{0, 1\}$ is the ground truth indicator label for relation type $l$ of the span pair $(s_i, s_j)$. Note that all $|P|^2$ pruned span pairs are considered, since the order of the spans in the relation matters (unlike the coreference case). By summing over all possible relation types $L_R$, we account for the fact that a particular relation between two spans can be multi-label (which is the case for more than 30% of relations, as shown in Table A.3).

Since this model is run in parallel with the coreference module, it is used to predict relations only between entity mentions and not entity clusters. During inference, candidate relations are accepted when $\Phi_{\text{relation}}^\tau (s_i, s_j)_l > 0$.

4.2.4. Span Pruner

The span pruner is an FFNN, denoted $\mathcal{F}_{\text{pruner}}$, that scores all spans $s_i$ based on their initial representation $\mathbf{g}_i^0$, after which only the highest scoring spans are retained in the pruned span set $P$. In our experiments $P$ contains the top 0.2 $|T|$ highest scoring spans, which covers more than 98% of all the ground truth mention spans in the DWIE dataset. We represent the pruner score for span $s_i$ as

$$\Phi_{\text{pruner}} (s_i) = \mathcal{F}_{\text{pruner}} (\mathbf{g}_i^0). \quad (10)$$

Several strategies can be used to train the pruner. One option is to directly optimize the probability of the pruner to detect the spans of correct entity mentions. With $S^*$ the set of spans with at least one ground
truth entity type, and $I_i \in \{0, 1\}$ an indicator for whether $s_i \in S^*$, the corresponding log likelihood can be written as

$$\log P_{\text{pruner}} (S^*|G^0) = \sum_{i=1}^{|S|} I_i \log \sigma (\Phi_{\text{pruner}}(s_i)) + (1 - I_i) \log (1 - \sigma (\Phi_{\text{pruner}}(s_i))),$$

(11)

leading to a separate pruner loss term. Alternatively, the pruner can be trained indirectly by adapting the mention score from Eq. (4), the coreference score from Eq. (6) or the relation score from Eq. (8) as follows:

$$\tilde{\Phi}_{\text{mention}}^\tau (s_i) = \Phi_{\text{mention}}^\tau (s_i) + \Phi_{\text{pruner}} (s_i)$$

(12)

$$\tilde{\Phi}_{\text{coref}}^\tau (s_i, s_j) = \Phi_{\text{coref}}^\tau (s_i, s_j) + \Phi_{\text{pruner}} (s_i)$$

(13)

$$\tilde{\Phi}_{\text{relation}}^\tau (s_i, s_j) = \Phi_{\text{relation}}^\tau (s_i, s_j) + \Phi_{\text{pruner}} (s_i)$$

(14)

for use in the expressions Eq. (5), Eq. (7) and Eq. (9), respectively. As such, higher pruner scores would directly correspond to higher mention or coreference scores, and lead to a meaningful ranking of spans according to pruner scores. All three strategies seem to work on a similar level, but for the presented joint model experiments, we use the indirect training through the coreference module, as in Eq. (13). Note that we did not experiment with training the pruner through the relation module, because it would be trained only on those spans involved in relations, which is a mere subset of all valid mentions.

4.2.5. Joint Model

We perform joint training in order to explore the degree to which the graph propagation techniques (see Section 4.4) affect related tasks in DWIE. For instance, we expect that performing a coreference propagation can have a positive impact on the NER task. We hypothesize that enriching the entity spans with broader contextual information coming from other mention spans in the cluster, can improve the effectiveness of the entity module. Furthermore, given the entity-centric nature of DWIE, the mention-based predictions for NER and RE have to be grouped in coreference clusters (see section 4.3 for details), which makes it necessary to execute these tasks jointly with the coreference task.

The joint loss for each document $D$ is a weighted sum of the individual loss functions of the sub-tasks:

$$L^\text{joint}_D = \sum_{(E^*, C^*, R^*)} \lambda_E \log P_{\text{mention}} (E^*|G^\tau) + \lambda_C \log P_{\text{coref}} (C^*|G^\tau) + \lambda_R \log P_{\text{relation}} (R^*|G^\tau)$$

(15)

in which $\lambda_E$, $\lambda_C$, and $\lambda_R$ are hyperparameters of the joint model.

4.3. Decoding and Prediction

Unlike previous datasets used in span-based predictions (Doddington et al., 2004; Kulkarni et al., 2018; Luan et al., 2018; Walker et al., 2006) where the relation and entity extraction are done on the mention-level, DWIE is an entity-centric dataset. During inference, this requires an additional decoding step to cluster the mention-based span-dependent predictions into entity-centric ones. First, the coreference clusters are predicted. Each of the predicted entity clusters is composed by one or more mention spans.

The actual entities (i.e., mention clusters) are labeled with the predicted entity types, by assigning the union of the entity types predicted for any of the members inside the cluster, to the resulting entity cluster. Subsequently, all pairwise predicted relations on the mention level between members of two different clusters, are assigned as predicted relations between the (cluster-level) entities.

4.4. Graph Propagation Mechanisms

In order to evaluate the impact of graph-based propagation of contextual information between the spans, we propose AttProp, and reimplement the CorefProp and RelProp graph propagation algorithms. Lee et al. (2018) proposed the gated graph propagation update function for use on coreference resolution, which was
where \( \phi \) and \( \Phi \) are calculated as follows:

\[
\phi(t) = \sigma \left( \mathcal{F}_x(g^t_i; u^t_i(s_i)) \right), \quad g^{t+1}_i = \theta(t) g^t_i + \left(1 - \theta(t)\right) u^t_i(s_i),
\]

where in our case \( x \in \{A, C, R\} \) denotes \( \text{AttProp}, \text{CorefProp}, \) and \( \text{RelProp} \), respectively. The \( n \)-dimensional vector \( \phi(t) \), produced by the single-layer FFNN \( \mathcal{F}_x \) can be interpreted as a gating vector that acts as a switch between the current span representations \( g^t_i \in \mathbb{R}^n \), and the update span vector \( u^t_i(s_i) \in \mathbb{R}^n \). The various graph propagation methods differ in how \( u^t_i(s_i) \) is calculated.

**CorefProp** — The coreference confidence score between span \( s_i \) and \( s_j \) for propagation iteration \( t \) is denoted as \( P^t_C(i, j) \) and calculated as follows,

\[
P^t_C(i, j) = \frac{\exp(\Phi^t_{\text{coref}}(s_i, s_j))}{\sum_{i' = 1}^j \exp(\Phi^t_{\text{coref}}(s_{i'}, s_j))},
\]

in which \( i' \in \{1, \ldots, j\} \) refers to all antecedent spans \( s_{i'} \) to span \( s_j \) in the pruned span set. Note that the coreference scores according to Eq. (13) are used. This means the confidence scores not only reflect whether the considered spans are compatible, but also whether the individual spans are likely to be retained by the pruner as potential entity mentions. In order to perform a \( \text{CorefProp} \) graph iteration, the span update vector \( u^t_C(i) \in \mathbb{R}^n \) is first calculated as a weighted average of the current representation of span \( s_j \) and all of its antecedents

\[
u^t_C(s_j) = \sum_{i=1}^j P^t_C(i, s_j) g^t_i,
\]

in which the weighting coefficients quantify the coreference compatibility of the corresponding span with \( s_j \). After that, the update equations Eq. (16) and Eq. (17) are applied.

**RelProp** — Similarly as with \( \text{CorefProp} \), a relation span update vector is calculated as formalized next,

\[
u^t_R(s_j) = \sum_{i=1}^{\left|P\right|} (A_R f(\Phi^t_{\text{relation}}(s_i, s_j))) \odot g^t_i,
\]

where \( A_R \in \mathbb{R}^{n \times \left|L_R\right|} \) is a trainable projection tensor, and \( f \) is a non-linear activation function (ReLU). Similarly as in Eq. (19), the update vector can be interpreted as a weighted sum of all span representations, with the additional expressiveness stemming from the projection matrix \( A_R \) in accounting for the relation scores.

**AttProp** — In order to measure the impact of the ‘supervised’ \( \text{CorefProp} \) and \( \text{RelProp} \) propagation techniques described by equations (18)-(20) above, we introduce a latent attentive propagation. Unlike \( \text{CorefProp} \) and \( \text{RelProp} \) that are driven by the task-specific confidence propagation scores \( \Phi^t_{\text{coref}}(s_i, s_j) \) and \( \Phi^t_{\text{relation}}(s_i, s_j) \), \( \text{AttProp} \) is influenced only by latent attention weights between all the pruned spans \( P \) calculated as follows,

\[
\Phi^t_{\text{att}}(s_i, s_j) = \mathcal{F}_\text{att} \left( \{g^t_i, g^t_j, g^t_i \odot g^t_j; \varphi_{i,j}\} \right),
\]

where \( \varphi_{i,j} \) is the distance feature embedding function between spans \( s_i \) and \( s_j \), and \( \Phi^t_{\text{att}}(s_i, s_j) \) is the attention score between these spans. This score is normalized with a softmax to get the \( P^t_A(i, j) \) confidence score

\[
P^t_A(i, j) = \frac{\exp(\Phi^t_{\text{att}}(s_i, s_j))}{\sum_{j'=1}^{\left|P\right|} \exp(\Phi^t_{\text{att}}(s_i, s_{j'}))}.
\]
The span update vector $\mathbf{u}_A(s_i) \in \mathbb{R}^n$ is calculated as a weighted sum of all the $P$ span representations as opposed to only antecedents in CorefProp

$$u_A(s_i) = \sum_{j=1}^{P} P_A(s_i, s_j) \mathbf{g}_j,$$

(23)

4.5. Single Task Models

In this section we shortly describe independent baseline models for the three individual core tasks under study in this paper, as training these models not entirely corresponds to merely minimizing the corresponding loss term from the total loss Eq. (15).

4.5.1. Single Entity Recognition Model

The single-task NER model is designed for detecting and correctly labeling the individual entity spans, and is based on Eq. (5). However, even for the single models, the graph propagation mechanism $\text{AttProp}$ may be useful, but for that the pruner needs to be jointly trained with the model. This is obtained by augmenting the mention loss $-\log P_{\text{mention}}(E^*|G^\tau)$ with the pruner loss $-\log P_{\text{pruner}}(S^*|G^0)$ according to Eq. (11).

4.5.2. Single Coreference Resolution Model

The single-task end-to-end coreference model needs to detect mentions and correctly cluster them. Here again, the standard coreference loss $-\log P_{\text{coref}}(C^*|G^\tau)$ according to Eq. (13) and Eq. (7) is extended with the pruner loss $-\log P_{\text{pruner}}(S^*|G^0)$. This turned out essential for correctly predicting the singleton clusters.

4.5.3. Single Relation Extraction Model

The single relation extraction model is trained to detect mentions as well as the correct pairwise relations between mentions (i.e., without the coreference step). In order to train the pruner as well, the standard relation score is extended as described in Eq. (14) before calculating the loss $-\log P_{\text{relation}}(R^*|G^\tau)$ based on Eq. (9).

5. Entity-Centric Metrics

Unlike the currently widespread datasets that use a mention-driven approach to annotate named entities (Bekoulis et al., 2017; Derczynski et al., 2017; Sang & De Meulder, 2003; Weischedel et al., 2011), relations (Augenstein et al., 2017; Bekoulis et al., 2017; Doddington et al., 2004; Ji et al., 2017; Kim et al., 2003; Luan et al., 2018; Song et al., 2015) and entity linking (Bentivogli et al., 2010; Hoffart et al., 2011; Riedel et al., 2010), DWIE is entirely entity-centric. As explained before, we group entity mentions $s_i$ referring to the same entity into clusters $C_k$. While we can, and will, adopt the traditional coreference measures as defined by Pradhan et al. (2014) to judge this cluster formation, the NER and relation extraction (RE) evaluation (using precision, recall and $F_1$) can be done either on (i) mention level, or (ii) entity (cluster) level. The first option however would have the metrics being dominated by the more frequently occurring entities, while the second would penalize mistakes in the clustering (since partially correctly identified clusters would be seen as completely incorrect). This is illustrated in Fig. 4 and the corresponding performance metrics in Table 4, where scenarios 1 and 2 highlight the effect of making labeling mistakes on the cluster level for different sizes, and scenario 3 highlights the pessimistic view of hard entity-level metrics in case of clustering mistakes. Note that we indicate the mention-level metrics with subscript $m$, while the (hard) entity-level metrics will have subscript with $e$.

Because the (hard) entity-level metrics in our opinion overly penalize clustering mistakes (cf. scenario 3), we propose a variant of entity-level evaluation which we term soft entity-level metrics (denoted by subscript $s$). Basically, instead of adopting a binary count of 1 (all mentions correct) or 0 (as soon as a single mention is missed) on an entity cluster level, we rather count the fraction of its mentions that are correctly labeled. This is illustrated in the formula part of Fig. 4(a) for NER, and below we present the adopted
formulas in detail. Note that in case clusters are completely predicted correctly, the soft entity-level metrics are the same as hard entity-level metrics (and thus avoid the metric being dominated by frequent mentions, as in the mention-level case).

The formal definition of the metrics depends on counting true positives $tp_p(l)$ and $tp_g(l)$, false positives $fp(l)$, and false negatives $fn(l)$ for a particular NER tag/relation type $l$, which are specified in Eq. (24)–(25). These and other notation definitions are summarized in Table 6. Further, note that we define two true positives, false positives and false negatives as described for expressions $tp_p(l) + fp(l)$ and $tp_g(l) + fn(l)$ in Table 5. Thus our soft entity-level metrics are still cluster-based, while accounting for the mention-level predictions.

\[
\begin{align*}
    tp_p(l) &= \sum_{C_p \in P_C(l)} \frac{|C_p \cap G_M(l)|}{|C_p|}, \\
    tp_g(l) &= \sum_{C_g \in G_C(l)} \frac{|C_g \cap P_M(l)|}{|C_g|} \\
    fp(l) &= |P_C(l)| - tp_p(l), \\
    fn(l) &= |G_C(l)| - tp_g(l)
\end{align*}
\]

(24)–(25)

Our soft entity-level precision, recall and F₁ metrics are formally defined as follows, where $L$ refers to
Table 4: Comparison of different metrics for the example scenarios depicted in Fig. 4, for (a) NER and (b) relation extraction.

|                | Mention-Level | Hard Entity-Level | Soft Entity-Level |
|----------------|---------------|-------------------|-------------------|
|                | Prm Re cm     | Prs Re s          | Pr e Re e F1 e     |
| (a) NER        |               |                   |                   |
| Ground Truth   | 1.000         | 1.000             | 1.000             |
| Scenario 1     | 0.143         | 0.100             | 0.118             |
| Scenario 2     | 0.931         | 0.900             | 0.915             |
| Scenario 3     | 1.000         | 0.900             | 0.947             |
| (b) RE         |               |                   |                   |
| Ground Truth   | 1.000         | 1.000             | 1.000             |
| Scenario 1     | 1.000         | 0.027             | 0.053             |
| Scenario 2     | 1.000         | 0.973             | 0.986             |
| Scenario 3     | 0.983         | 0.783             | 0.872             |

Table 5: The relations between the weighted true positives by the size of predicted ($tp_p(l)$) and ground truth ($tp_g(l)$) entity clusters allows us to achieve the constraints needed for the denominators of precision ($tp_p(l) + fp(l)$) and recall ($tp_p(l) + fn(l)$) functions (Eq. (26)) in terms of the number of entity clusters.

| Expression | (a) Meaning for NER | (b) Meaning for RE |
|------------|---------------------|--------------------|
| $tp_p(l) + fp(l)$ | Number of predicted entity clusters with tag $l$. | Number of predicted relations of type $l$ between entity clusters. |
| $tp_g(l) + fn(l)$ | Number of ground truth entity clusters with tag $l$. | Number of ground truth relations of type $l$ between entity clusters. |

either the number of all possible tags for NER or the number of all possible relation types for RE:

$$
Pr_s = \frac{\sum_{l=1}^{L} tp_p(l)}{\sum_{l=1}^{L} tp_p(l) + fp(l)}, \quad Re_s = \frac{\sum_{l=1}^{L} tp_g(l)}{\sum_{l=1}^{L} tp_g(l) + fn(l)}, \quad F_{1,s} = \frac{2 \cdot Pr_s \cdot Re_s}{Pr_s + Re_s} \tag{26}
$$

6. Experimental results

6.1. Experimental Setup

We train and evaluate our model as described in Section 4 on three tasks: NER, coreference, and relation extraction (RE) independently and jointly. We experiment with three main model variations:

1. **Single**: Experiments on individual tasks by training with the respective loss functions as described in Section 4.5.

2. **Joint**: Experiments jointly on all three tasks using pre-trained GloVe representations\footnote{http://nlp.stanford.edu/data/glove.840B.300d.zip} concatenated to character embeddings in the shared input layer (see Fig. 3). For training we use the joint loss defined in Section 4.2.

3. **Joint+BERT**: as in the Joint setting, experiments jointly on all three tasks, but using pre-trained BERT\textsubscript{BASE} embeddings\footnote{https://storage.googleapis.com/bert_models/2018_10_18/cased_L-12_H-768_A-12.zip} concatenated to the GloVe and character embeddings. We use an input window size of 250 tokens and concatenate the last 2 hidden layers of BERT to get token representations.
Table 6: Short definition of the symbols and expressions involved in our soft-entity level metric formulation in Eq. (24)–(26) for both NER and RE tasks.

| Symbol   | (a) Meaning for NER                                                                 | (b) Meaning for RE                                                                 |
|----------|------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|
| $P_C(l)$ | Set of predicted entity clusters with tag $l$.                                    | Set of predicted relations of type $l$ between the predicted entity clusters.     |
| $C_r \in P_C(l)$ | Set of predicted entity mentions for a particular entity cluster in $P_C(l)$. | Set of relations between the predicted entity mentions for a particular pair of related entity clusters in $P_C(l)$. |
| $G_C(l)$ | Set of ground truth entity clusters annotated with tag $l$.                        | Set of ground truth relations of type $l$ between the ground truth entity clusters. |
| $C_g \in G_C(l)$ | Set of ground truth entity mentions for a particular entity cluster in $G_C(l)$. | Set of relations between the ground truth entity mentions for a particular pair of related entity clusters in $G_C(l)$. |
| $P_M(l)$ | Set of predicted entity mentions with tag $l$.                                    | Set of predicted relations of type $l$ between the predicted entity mentions.     |
| $G_M(l)$ | Set of ground truth entity mentions annotated with tag $l$.                        | Set of ground truth relations of type $l$ between the ground truth entity mentions. |
| $tp_p(l)$ | Number of true positive predictions of tag $l$ on mentions re-weighted by predicted cluster sizes. | Number of true positive predictions of relation type $l$ between mentions re-weighted by the number of mention level relations between the connected pairs of predicted clusters. |
| $tp_g(l)$ | Number of true positive mention level predictions of tag $l$ re-weighted by ground truth cluster sizes. | Number of true positive predictions of relation type $l$ between mentions re-weighted by the number of mention level relations between the connected pairs of ground truth clusters. |
| $fp(l)$ | Number of false positive mention level predictions of tag $l$ re-weighted by predicted cluster sizes. | Number of false positive predictions of relation type $l$ between mentions re-weighted by the number of mention level relations between the connected pairs of predicted clusters. |
| $fn(l)$ | Number of false negative mentions with ground truth tag $l$ re-weighted by ground truth cluster sizes. | Number of false negative relations of type $l$ between mentions re-weighted by the number of mention level relations between the connected pairs of ground truth clusters. |
Table 7: Main results of the experiments grouped in three model setups: (i) Single models trained individually, (ii) Joint model trained using as input GloVe and character embeddings, and (iii) Joint+BERT model trained on BERT BASE embeddings. To report the results, we use MUC, CEAF_e, B3 as well as the average (Avg.) of these three metrics for coreference resolution. For NER and RE we use mention-level (F1,m), hard entity-level (F1,e), and soft entity-level (F1,s) metrics described in Section 5.

In bold we mark the best results for each model setup, the best overall results are underlined. Note that the metrics are expressed in percentage points.

| Model Setup | Coreference F1 | NER F1 | RE F1 |
|-------------|----------------|--------|-------|
|              | MUC | CEAF_e | B3   | Avg. | F1,m | F1,e | F1,s | F1,m | F1,e | F1,s |
| Single       |     |        |      |      |      |      |      |      |      |      |
| +AttProp     | 93.2 | 91.5   | 88.7 | 91.1 | 87.1 | -    | -    | -    | -    | -    |
| +CorefProp   | 92.8 | 90.9   | 88.3 | 90.7 | -    | -    | -    | -    | -    | -    |
| +RelProp     | -    | -      | -    | -    | 68.2 | -    | -    | -    | -    | -    |
| Joint        |     |        |      |      |      |      |      |      |      |      |
| +AttProp     | 92.3 | 90.4   | 87.3 | 90.0 | 87.1 | 72.9 | 86.1 | 72.1 | 50.4 | 72.1 |
| +CorefProp   | 92.3 | 90.3   | 87.2 | 89.9 | 87.2 | 73.2 | 86.0 | 71.6 | 50.2 | 71.0 |
| +RelProp     | 92.6 | 90.2   | 86.8 | 89.9 | 86.7 | 72.4 | 85.2 | 69.5 | 48.2 | 68.8 |
| Joint+BERT   | 93.8 | 92.1   | 89.0 | 91.6 | 87.6 | 74.2 | 86.4 | 70.6 | 48.7 | 68.9 |
| +AttProp     | 93.2 | 91.4   | 88.6 | 91.1 | 88.8 | 74.2 | 87.7 | 72.3 | 50.4 | 73.0 |
| +CorefProp   | 93.5 | 91.8   | 88.7 | 91.3 | 88.7 | 74.4 | 87.4 | 72.7 | 50.0 | 71.9 |
| +RelProp     | 93.7 | 91.8   | 88.7 | 91.4 | 88.4 | 74.8 | 87.0 | 72.0 | 49.9 | 71.4 |

Additionally, for each of the three model setups we experiment with the graph propagation techniques defined in Section 4.4. To maximize result consistency, we train each model 5 times and report the average of these 5 results for each of the experiments.

We use a single-layer BiLSTM with forward and backward hidden states of 200 dimensions each. All our FFNNs used to obtain confidence scores (Fpruner, Fcoref, Fmention, Frelation, and Fatt) have two 150-dimensional hidden layers trained with a dropout of 0.4. We set the maximum span width wmax to 5 and the pruner ratio to 0.2 of the total number of tokens in a document. For training, we use Adam with a learning rate of 1e−3 for 100 epochs with a linear decay of 0.1 starting at epoch 15.

6.2. Results and Analyses

Table 7 gives an overview of the results achieved in Single as well as Joint and Joint + BERT setups. Additionally, Fig. 5 illustrates the impact of the number of graph propagation iterations for each of the span graph propagation methods on the final results.

First, we observe a general improvement in all our Single tasks when using graph propagation techniques. More specifically, our proposed latent AttProp achieves superior results compared to the relation (RelProp) and coreference (CorefProp) propagations when added to the Single setup. The biggest improvement across iterations (see Fig. 5) is for the single RE task mention-level F1,m score with a boost of ∼3 percentage points when incorporating AttProp. We also observe an improvement of ∼1.5 percentage points in F1,m for the NER task and a consistent but smaller improvement of 0.5 F1 percentage points for the coreference task. These results illustrate the effectiveness of AttProp when applied to single task models.

A further improvement in results is achieved by training our model jointly (see the Joint setup in Table 7 and graphs in Fig. 5) for NER and RE tasks. This illustrates that, besides the positive effect of neural graph propagation on single task models, training our model jointly has an additional benefit by exploiting the interaction between tasks. In particular, this effect can be seen for RE, where our Joint model achieves a boost in performance of 0.8 percentage points for the mention-level F1,m metric compared to the best result for the Single setup. Furthermore, our AttProp graph propagation method achieves the best performance on all the metrics for the RE task in the Joint setting with up to ∼5.5 percentage points improvement in our newly proposed F1,s metric. Additionally, we observe a beneficial effect of graph propagation for the
Table 8: Deltas of improvement in performance for each of the graph propagation methods (AttProp, CorefProp, RelProp) in F1 scores for (a) NER and (b) relation extraction tasks.

|                | Joint | Joint+BERT |
|----------------|-------|------------|
|                | F1,m | F1,e | F1,s | F1,m | F1,e | F1,s |
| **(a) NER**    |       |       |       |       |       |       |
| Δ AttProp      | 1.69  | 1.18  | **1.67** | 1.16  | −0.02 | **1.31** |
| Δ CorefProp    | **1.78** | **1.50** | 1.54  | 1.05  | 0.20  | 1.02  |
| Δ RelProp      | 1.33  | 0.70  | 0.75  | 0.78  | 0.56  | 0.60  |
| **(b) RE**     |       |       |       |       |       |       |
| Δ AttProp      | **3.97** | **3.62** | **5.56** | 1.66  | 1.69  | **4.05** |
| Δ CorefProp    | 3.48  | 3.45  | 4.47  | 2.02  | 1.29  | 2.95  |
| Δ RelProp      | 1.35  | 1.47  | 2.32  | 1.37  | 1.20  | 2.48  |

NER task in the Joint setup with slightly better results for the F1,m metric compared to the Single setting. Our AttProp technique performs on par with CorefProp, outperforming the latter by a small margin in terms of F1,s metric.

Similarly to the Joint model variation, we observe benefits when using graph propagation techniques in the Joint+BERT models. Table 8 illustrates the deltas in performance for the NER and relation extraction tasks. This way, we can see more clearly the difference in impact of our neural message passing methods grouped by the model setup and metric type. First, we observe that the general performance boost from using graph propagation techniques is lower in Joint+BERT than in the Joint setup. We hypothesize that this effect is due to the fact that BERT itself has a better long-range context extraction due to the attention-based mechanism, which spans the input window as opposed to purely local (non-contextualized) GloVe embeddings used in the Joint setting. This is in line with the findings in Han & Wang (2020), Wadden et al. (2019), and Wu & He (2019) that show the advantage of using large BERT input window sizes to produce better IE results. Second, we observe that our AttProp method achieves consistently superior performance on our proposed soft entity-level metric F1,s, capturing thus better the mention-based predictions as weighted by their cluster sizes. Finally, from Table 8(b) we notice that adding BERT to our joint model does not affect the boost in performance caused by the RelProp method for relation extraction. We hypothesize that this is due to the fact that RelProp propagation can capture relational semantics that goes beyond BERT’s contextual span representation similarity (which mainly drives the positive impact of Joint+BERT).

Unlike for the NER and RE tasks, where we observe a consistent positive impact of span graph propagation and joint modeling across all our experiments, the impact on the coreference task is not clear. Our experiments on Single setup show small, but constant improvement of the Avg.-F1 score with the number of AttProp propagation iterations (see Fig. 5). However, in our Joint and Joint+BERT setups the graph propagation appears to not have any positive impact on Avg.-F1 coreference scores. We hypothesize that the main reason for this phenomenon lies in the coreference annotations in DWIE: since we only annotate clusters of proper nouns, leaving out the nominal (e.g., “the prime minister”) and anaphoric expressions (e.g., “he”, “she”, “they”, etc), there might be little to no additional benefit in propagating information between co-referenced entity mentions, since the representation of proper nouns likely is not much influenced by textual context (e.g., the span “Merkel” can have very similar span representation to “Angela Merkel”, gaining nothing in adding contextual graph propagation).

Additionally, we explore in more detail the effect of the number of AttProp, CorefProp, RelProp graph propagation iterations on the final F1 score of all the tasks in Fig. 5. We observe that the number of iterations have a decreasing effect on the improvement of performance for the NER and RE tasks. Furthermore, the positive effect of CorefProp and RelProp tends to saturate or even become negative after 1 or 2 iterations. This is in line with findings of Luan et al. (2019) on other datasets, where the performance peak is usually achieved at 2 graph propagation iterations. For our AttProp however, we observe that the positive effect of additional iterations tends to persist longer, particularly on the Joint setup where the positive effect of AttProp seems to be still growing after the last iteration (3) in our experiments.
7. Conclusions and Future Work

In this work we introduced DWIE, a manually annotated multi-task dataset that comprises Named Entity Recognition, Coreference, Relation Extraction and Entity Linking as main tasks. We highlight how DWIE is different from the mainstream datasets by focusing on document-level and entity-centric annotations. This also makes the predictions on this dataset more challenging by having not only to consider explicit, but also implicit document-level interactions between entities. Furthermore, we showed how Graph Neural Networks can help to tackle this issue by propagating local contextual mention span information on a document level for a single task as well as across the tasks on the DWIE dataset. We experiment with known graph propagation techniques driven by the scores of the coreference resolution (CorefProp) and relation extraction (RelProp) components, as well as introduced a new latent task-independent attention-based graph propagation method (AttProp). We demonstrated that, without relying on the task-specific scorers, AttProp can boost the performance of single-task as well as joint models, performing on par and even outperforming significantly in some scenarios the RelProp and CorefProp graph propagations.

In future work we will aim to integrate an entity linking component into our joint architecture. As a consequence, we expect to obtain a further boost in performance of different tasks included in DWIE by taking advantage of the information coming from Wikipedia 2018, the reference knowledge base for the entity linking annotations. Conversely, we conjecture that the results of the entity linking component can be improved when training it jointly with other tasks, such as NER and coreference resolution. Finally, we plan extending the coreference annotations to include nominal and anaphoric expressions. We expect that including these diverse mention types, whose initial span embedding representation can be different from coreferenced named entities, will make our coreference resolution task more challenging, allowing to investigate further the potential benefits of using graph-based neural networks.

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\[\text{https://www.projectcpn.eu/}\]
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Appendix A. Dataset Insights

Table A.1: Statistics depicting the hierarchical structure of entity types described in Section 3.2. Only the most frequent entity types/sub-types are shown (% Mentions > 0.5%)

| Entity Type             | # Entities | % Entities | # Mentions | % Mentions |
|-------------------------|------------|------------|------------|------------|
| ENTITY                  | 13,151     | 56.9%      | 30,719     | 70.8%      |
| location                | 4,957      | 21.4%      | 11,548     | 26.6%      |
| gpe                     | 3,965      | 17.1%      | 9,830      | 22.7%      |
| gpe0                    | 2,225      | 9.6%       | 6,559      | 15.1%      |
| gpe2                    | 1,497      | 6.5%       | 2,873      | 6.6%       |
| gpe1                    | 244        | 1.1%       | 406        | 0.9%       |
| regio                   | 479        | 2.1%       | 916        | 2.1%       |
| facility                | 259        | 1.1%       | 385        | 0.9%       |
| organization            | 3,434      | 14.8%      | 8,165      | 18.8%      |
| media                   | 659        | 2.8%       | 984        | 2.3%       |
| igo                     | 547        | 2.4%       | 1,992      | 4.6%       |
| so                      | 171        | 0.7%       | 912        | 2.1%       |
| party                   | 381        | 1.6%       | 949        | 2.2%       |
| company                 | 368        | 1.6%       | 932        | 2.1%       |
| sport_team              | 367        | 1.6%       | 1,106      | 2.5%       |
| governmental_organisation | 342     | 1.5%       | 636        | 1.5%       |
| agency                  | 228        | 1.0%       | 444        | 1.0%       |
| armed_movement          | 108        | 0.5%       | 374        | 0.9%       |
| person                  | 3,390      | 14.7%      | 8,259      | 19.0%      |
| politician              | 1,184      | 5.1%       | 3,326      | 7.7%       |
| head_of_state           | 380        | 1.6%       | 1,271      | 2.9%       |
| head_of_gov             | 247        | 1.1%       | 673        | 1.6%       |
| minister                | 217        | 0.9%       | 458        | 1.1%       |
| sport_player            | 405        | 1.8%       | 844        | 1.9%       |
| artist                  | 260        | 1.1%       | 586        | 1.4%       |
| politics_per            | 209        | 0.9%       | 457        | 1.1%       |
| manager                 | 104        | 0.4%       | 297        | 0.7%       |
| offender                | 75         | 0.3%       | 347        | 0.8%       |
| misc                    | 823        | 3.6%       | 1,646      | 3.8%       |
| work_of_art             | 174        | 0.8%       | 247        | 0.6%       |
| event                   | 354        | 1.5%       | 701        | 1.6%       |
| sport_competition       | 183        | 0.8%       | 410        | 0.9%       |
| ethnicity               | 84         | 0.4%       | 242        | 0.6%       |
| VALUE                   | 5,903      | 25.5%      | 7,104      | 16.4%      |
| time                    | 2,907      | 12.6%      | 3,608      | 8.3%       |
| role                    | 2,390      | 10.3%      | 2,865      | 6.6%       |
| money                   | 606        | 2.6%       | 631        | 1.5%       |
| OTHER                   | 2,724      | 11.8%      | 5,482      | 12.6%      |
| gpe0-x                  | 1,596      | 6.9%       | 3,827      | 8.8%       |
| footer                  | 413        | 1.8%       | 413        | 1.0%       |
| loc-x                   | 353        | 1.5%       | 585        | 1.3%       |
| religion-x              | 255        | 1.0%       | 486        | 1.1%       |
| TOTAL                   | 23,130     | 100.0%     | 43,373     | 100.0%     |
Table A.2: Illustration of NER entity types in DWIE. Each cell contains possible entity sub-types (of different hierarchy levels) corresponding to the respective parent entity type (column) and topic (row).

| person       | organization                          | event         | location                     | misc                                      |
|--------------|---------------------------------------|---------------|------------------------------|-------------------------------------------|
| politics     | politics_institution, politics_org, party, ngo, igo, so, policy_institute, movement, agency, ministry, military_alliance | summit_meeting, scandal, politics_event | politics_facility | politics_misc, project, treaty, report |
| culture      | music_band, culture_org, theatre_org, dance_org | festival, filmfestival | culture_facility | art_title, culture_title, exhibition_title, culture_misc, work_of_art, book_title, film_title, tv_title, music_title, theatre_title, musical_title, film_award, book_award, music_award, tv_award, column_title, game, comic, radio_title, dance_title, opera |
| education    | teacher, education_per, education_student | education_org | education_facility | education_study |
| religion     | deity, clergy | religion_org | religious_event | religion_facility | religion, religion_misc |
| human        | royalty | religion_org | religious_event | religion_facility | religion, religion_misc |
| conflict     | military_personnel, military_rebel | army, military_alliance, armed_movement | war, protest | military_facility | military_equipment, military_mission |
| media        | journalist | media | | |
| science      | researcher, science_per | research_center | | species, research_journals, technology |
| sport        | sport_player, sport_coach, sport_head, sport_referee, sport_person | sport_team, sport_org | sport_competition | sport_facility | sport_award |
| labor        | union_head, union_member, union_rep, union_per | union | | |
| business     | manager, employee, business_per | company, business_org, brand, trade_fair, market_exchange, advocacy | business_facility | product, market_index, business_misc |
| health       | health_per | health_org | | health_facility | health_disease, health_drug |
| justice      | offender, advisor, victim, judge, police_per, justice_per | court, criminal_org, police_org, justice_org | prison | justice_misc, case |
| weather      | | | | storm |
Table A.3 describes the statistics of linked entities with respect to the total number of entities in each of the Entity sub-types. The columns % Linked Entities and % Linked Mentions indicate the percentage of annotated linked entities and mentions with respect to the total number of annotated entities/mentions in a particular Entity type category. Furthermore, we calculate two accuracies on test split when linking the entity mention with the most frequent entity link used either in DWIE: (i) training set of DWIE dataset (“Acc. Prior Train”), or (ii) Wikipedia corpus (“Acc. Prior Wiki”). Overall, using prior linking annotations from Wikipedia gives 9 percentage points better performance (79.0%) than when using train set (70.0%). This difference is explained by the fact that Wikipedia has much larger corpus to calculate the prior linking information from. Nevertheless, we still observe that for some entity types such as sport_team and media the accuracy based on DWIE training set prior is higher. This suggests the use of domain-specific language to refer to some entities in DWIE not used in a more general Wikipedia domain.

Table A.3: Entity linking statistics, only the top 5 types and sub-types with largest number of linked entities are showed. The total is calculated on all the entity types. The accuracy (both for most likely prior links on train and Wiki corpora) is computed on test set.

| Entity Type   | # Linked Entities | % Linked Entities | # Linked Mentions | % Linked Mentions | Acc. Prior Train | Acc. Prior Wiki |
|---------------|-------------------|-------------------|-------------------|-------------------|-----------------|-----------------|
| LOCATION      | 4,863             | 99.1%             | 11,496            | 99.5%             | 85.7%           | 92.9%           |
| gpe           | 3,938             | 99.3%             | 9,810             | 99.8%             | 89.8%           | 95.6%           |
| regio         | 456               | 95.2%             | 889               | 97.1%             | 83.3%           | 76.3%           |
| facility      | 229               | 88.4%             | 381               | 99.0%             | 19.7%           | 73.8%           |
| waterbody     | 90                | 98.9%             | 145               | 100.0%            | 83.3%           | 91.7%           |
| district      | 37                | 94.9%             | 45                | 100.0%            | 33.3%           | 33.3%           |
| ORGANIZATION  | 3,145             | 91.6%             | 8,029             | 98.3%             | 69.8%           | 70.8%           |
| media         | 622               | 94.4%             | 979               | 99.5%             | 81.8%           | 59.5%           |
| igo           | 525               | 96.0%             | 1,952             | 98.0%             | 76.4%           | 78.8%           |
| party         | 355               | 91.0%             | 897               | 94.5%             | 77.5%           | 66.7%           |
| company       | 320               | 87.0%             | 923               | 99.0%             | 67.6%           | 89.7%           |
| sport_team    | 366               | 99.7%             | 1,105             | 99.9%             | 71.0%           | 47.5%           |
| PERSON        | 2,627             | 77.5%             | 8,217             | 99.5%             | 45.7%           | 69.4%           |
| politician    | 1,162             | 98.1%             | 3,324             | 99.9%             | 66.0%           | 78.1%           |
| sport_player  | 404               | 99.8%             | 843               | 99.9%             | 34.4%           | 71.3%           |
| artist        | 246               | 94.6%             | 567               | 96.8%             | 0.0%            | 29.4%           |
| politics_per  | 126               | 60.3%             | 456               | 99.8%             | 23.7%           | 42.1%           |
| manager       | 58                | 55.8%             | 296               | 99.7%             | 22.2%           | 33.3%           |
| MISC          | 607               | 73.8%             | 1,532             | 93.1%             | 58.4%           | 73.4%           |
| work_of_art   | 142               | 81.6%             | 246               | 99.6%             | 0.0%            | 100.0%          |
| award         | 72                | 80.0%             | 186               | 94.9%             | 63.6%           | 81.8%           |
| treaty        | 60                | 74.1%             | 149               | 99.3%             | 66.7%           | 50.0%           |
| product       | 50                | 76.9%             | 146               | 98.6%             | 52.0%           | 92.0%           |
| species       | 10                | 25.0%             | 14                | 18.4%             | 0.0%            | 100.0%          |
| EVENT         | 320               | 90.4%             | 683               | 97.4%             | 49.4%           | 67.1%           |
| sport_competition | 163            | 89.1%             | 397               | 96.8%             | 64.6%           | 87.5%           |
| summit_meeting | 15               | 68.2%             | 37                | 92.5%             | 100.0%          | 100.0%          |
| holiday       | 21                | 95.5%             | 39                | 97.5%             | 100.0%          | 100.0%          |
| history       | 17                | 89.5%             | 30                | 100.0%            | 100.0%          | 100.0%          |
| protest       | 14                | 100.0%            | 22                | 100.0%            | 80.0%           | 100.0%          |
| TOTAL         | 13,086            | 56.6%             | 28,482            | 65.7%             | 70.0%           | 79.0%           |
Table A.4: Main named entity tag categories with statistics of the number and % of covered entities and mentions as well as the number of classes in each and average number of labels per entity cluster.

| Entity Tag Category | # Entities | %_entities | # Mentions | % Mentions | # Classes | Labels per Entity |
|---------------------|------------|------------|------------|------------|-----------|-------------------|
| type                | 21,745     | 94.0%      | 43,122     | 99.4%      | 174       | 2.9               |
| topic               | 7,843      | 33.9%      | 18,359     | 42.3%      | 14        | 1.0               |
| iptc                | 7,059      | 30.5%      | 17,195     | 39.6%      | 114       | 1.3               |
| gender              | 3,352      | 14.5%      | 8,200      | 18.9%      | 2         | 1.0               |
| slot                | 3,232      | 14.0%      | 14,983     | 34.5%      | 7         | 1.2               |
| **TOTAL**           | **23,130** | **100.0%** | **43,373** | **100.0%** | **311**   | **4.0**           |

Table A.4 illustrates the number of annotated entities and mentions per each tag category (type, topic, iptc, gender and slot). It also showcases the multi-label nature of entity classification task in DWIE, with the average number of labels per entity of 4.0.

Table A.5: This table groups the number of related pairs in DWIE by the number of assigned relation labels to each of these pairs. We compare with other two entity-centric datasets: BC5CDR [Li et al., 2016a] and DocRED [Yao et al., 2019] datasets.

| # Relation labels | DWIE | BC5CDR | DocRED |
|-------------------|------|--------|--------|
|                    | # Related ent. pairs | % Related ent. pairs | # Related mention pairs | % Related mention pairs | % Related ent. pairs | % Related ent. pairs |
| 1                  | 12,856 | 76.32% | 112,708 | 69.40% | 100% | 92.89% |
| 2                  | 3,101  | 18.41% | 34,948  | 21.52% | 0%   | 6.82%  |
| 3                  | 884    | 5.25%  | 14,650  | 9.02%  | 0%   | 0.26%  |
| 4                  | 3      | 0.02%  | 100     | 0.06%  | 0%   | 0.03%  |
| **TOTAL**          | **16,844** | **100.0%** | **162,406** | **100.0%** | **100.0%** | **100.0%** |
Table A.6: Relation type statistics. We compare the number of related entity and mention pairs per relation type. Only the most frequent relation types are shown (% Related Mention Pairs > 0.1%)

| Relation Type     | # Related Ent. Pairs | % Related Ent. Pairs | # Related Men. Pairs | % Related Men. Pairs |
|-------------------|----------------------|----------------------|----------------------|----------------------|
| based_in0         | 2,361                | 14.0%                | 18,771               | 11.6%                |
| in0               | 2,120                | 12.6%                | 15,810               | 9.7%                 |
| citizen_of        | 1,969                | 11.7%                | 25,752               | 15.9%                |
| based_in0-x       | 1,882                | 11.2%                | 12,211               | 7.5%                 |
| citizen_of-x      | 1,844                | 10.9%                | 17,049               | 10.5%                |
| member_of         | 1,616                | 9.6%                 | 19,953               | 12.3%                |
| gpe0              | 1,569                | 9.3%                 | 18,110               | 11.2%                |
| in0-x             | 1,474                | 8.8%                 | 8,784                | 5.4%                 |
| agent_of          | 954                  | 5.7%                 | 15,776               | 9.7%                 |
| head_of           | 564                  | 3.3%                 | 7,710                | 4.7%                 |
| agency_of         | 435                  | 2.6%                 | 4,775                | 2.9%                 |
| player_of         | 401                  | 2.4%                 | 5,692                | 3.5%                 |
| agency_of-x       | 382                  | 2.3%                 | 2,108                | 1.3%                 |
| head_of_state     | 380                  | 2.3%                 | 7,986                | 4.9%                 |
| head_of_state-x   | 343                  | 2.0%                 | 3,853                | 2.4%                 |
| appears_in        | 294                  | 1.7%                 | 4,555                | 2.8%                 |
| vs                | 281                  | 1.7%                 | 7,187                | 4.4%                 |
| head_of_gov       | 273                  | 1.6%                 | 4,015                | 2.5%                 |
| head_of_gov-x     | 247                  | 1.5%                 | 2,383                | 1.5%                 |
| minister_of       | 234                  | 1.4%                 | 2,280                | 1.4%                 |
| minister_of-x     | 213                  | 1.3%                 | 1,629                | 1.0%                 |
| based_in2         | 185                  | 1.1%                 | 971                  | 0.6%                 |
| event_in0         | 181                  | 1.1%                 | 843                  | 0.5%                 |
| part_of           | 164                  | 1.0%                 | 2,858                | 1.8%                 |
| in2               | 157                  | 0.9%                 | 1,055                | 0.6%                 |
| created_by        | 134                  | 0.8%                 | 945                  | 0.6%                 |
| agent_of-x        | 125                  | 0.7%                 | 897                  | 0.6%                 |
| award_received    | 111                  | 0.7%                 | 969                  | 0.6%                 |
| institution_of    | 105                  | 0.6%                 | 2,113                | 1.3%                 |
| ministry_of       | 81                   | 0.5%                 | 666                  | 0.4%                 |
| coach_of          | 65                   | 0.4%                 | 1,211                | 0.7%                 |
| won_vs            | 61                   | 0.4%                 | 1,531                | 0.9%                 |
| spouse_of         | 55                   | 0.3%                 | 599                  | 0.4%                 |
| directed_by       | 44                   | 0.3%                 | 318                  | 0.2%                 |
| is_meeting        | 41                   | 0.2%                 | 968                  | 0.6%                 |
| event_in2         | 40                   | 0.2%                 | 259                  | 0.2%                 |
| spokesperson_of   | 39                   | 0.2%                 | 177                  | 0.1%                 |
| plays_in          | 38                   | 0.2%                 | 330                  | 0.2%                 |
| gpe1              | 35                   | 0.2%                 | 135                  | 0.1%                 |
| product_of        | 31                   | 0.2%                 | 334                  | 0.2%                 |
| parent_of         | 22                   | 0.1%                 | 281                  | 0.2%                 |
| child_of          | 22                   | 0.1%                 | 281                  | 0.2%                 |
| based_in1         | 22                   | 0.1%                 | 376                  | 0.2%                 |
| signed_by         | 20                   | 0.1%                 | 521                  | 0.3%                 |
| law_of            | 16                   | 0.1%                 | 286                  | 0.2%                 |
| TOTAL             | 16,844               | 100.0%               | 162,406              | 100.0%               |
Appendix B. Inter-annotator agreement calculations

In order to measure the agreement we use Cohen’s kappa coefficient \cite{Cohen1960}, defined as

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$  \hspace{1cm} (B.1)

where \(p_o\) represents the observed agreement between the two annotators and \(p_e\) is the expected agreement between the annotators (i.e., agreement by chance). More specifically, in our case we calculate the observed probability \(p_o\) as in Eq. (B.2) where \(N\) is the number of annotated items, \(A_{i,j}\) is the annotation made by annotator \(i\) for item \(j\), and \(\mathbb{1}\{A_{1,j} = A_{2,j}\}\) returns 1 if \(A_{1,j}\) is equal to \(A_{2,j}\) and 0 otherwise. Thus, \(p_o\) can be interpreted as the fraction of the labels two annotators agree, also called percent agreement \cite{McHugh2012,Scott1955}.

$$p_o = \frac{\sum_{j=1}^{N} \mathbb{1}\{A_{1,j} = A_{2,j}\}}{N}$$  \hspace{1cm} (B.2)

To calculate the expected agreement probability we use the formulation in Eq. (B.3). It can be interpreted as the probability that both annotators, when randomly distributing all of their label annotations among the items to be annotated, assign the same label to a given item.

$$p_e = \frac{\sum_{l=1}^{L} n_{1,l} n_{2,l}}{N^2}$$  \hspace{1cm} (B.3)

In this context, \(n_{i,l}\) is the number of items the annotator \(i\) annotated with label \(l\) and \(L\) is the total number of labels. For multi-label annotations where it is possible to assign multiple classes for a particular annotation item (i.e., named entity and relation types), we report a weighted kappa score.
Appendix C. Relation consistency rules

This appendix enumerates the logical predicates used as a consistency check in our dataset.

\[
\begin{align*}
\text{spouse_of}(Y, X) & \implies \text{spouse_of}(X, Y) \quad \text{(C.1)} \\
\text{vs}(Y, X) & \implies \text{vs}(X, Y) \quad \text{(C.2)} \\
\text{won_vs}(X, Y) & \implies \text{vs}(X, Y) \quad \text{(C.3)} \\
\text{won_vs}(X, Y) & \implies \text{vs}(Y, X) \quad \text{(C.4)} \\
\text{child_of}(Y, X) & \implies \text{parent_of}(X, Y) \quad \text{(C.5)} \\
\text{parent_of}(Y, X) & \implies \text{child_of}(X, Y) \quad \text{(C.6)} \\
\text{minister_of}(X, Y) & \implies \text{agency_of}(X, Y) \quad \text{(C.7)} \\
\text{agency_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{agency_of}(X, Y) \quad \text{(C.8)} \\
\text{agency_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{gpe}(X, Z) \quad \text{(C.9)} \\
\text{agent_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{agent_of}(X, Y) \quad \text{(C.10)} \\
\text{agent_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{gpe}(X, Z) \quad \text{(C.11)} \\
\text{minister_of}(X, Y) & \implies \text{agent_of}(X, Y) \quad \text{(C.12)} \\
\text{head_of_gov}(X, Y) & \implies \text{agent_of}(X, Y) \quad \text{(C.13)} \\
\text{head_of_state}(X, Y) & \implies \text{agent_of}(X, Y) \quad \text{(C.14)} \\
\text{citizen_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{citizen_of}(X, Y) \quad \text{(C.15)} \\
\text{citizen_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{gpe}(X, Z) \quad \text{(C.16)} \\
\text{minister_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{minister_of}(X, Y) \quad \text{(C.17)} \\
\text{minister_of}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{gpe}(X, Z) \quad \text{(C.18)} \\
\text{head_of_state}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{head_of_state}(X, Y) \quad \text{(C.19)} \\
\text{head_of_state}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{gpe}(X, Z) \quad \text{(C.20)} \\
\text{head_of_gov}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{head_of_gov}(X, Y) \quad \text{(C.21)} \\
\text{head_of_gov}(X, Y) & \land \text{gpe}(Z, Y) \implies \text{gpe}(X, Z) \quad \text{(C.22)} \\
\text{in}_0(X, Y) & \land \text{gpe}(Z, Y) \implies \text{in}_0(X, Y) \quad \text{(C.23)} \\
\text{in}_0(X, Y) & \land \text{gpe}(Z, Y) \implies \text{in}_0(X, Z) \quad \text{(C.24)} \\
\text{in}_2(X, Z) & \land \text{in}_0(Z, Y) \implies \text{in}_0(X, Y) \quad \text{(C.25)} \\
\text{in}_1(X, Z) & \land \text{in}_0(Z, Y) \implies \text{in}_0(X, Y) \quad \text{(C.26)} \\
\text{based_in}_2(X, Z) & \land \text{in}_0(Z, Y) \implies \text{based_in}_0(X, Y) \quad \text{(C.27)} \\
\text{based_in}_1(X, Z) & \land \text{in}_0(Z, Y) \implies \text{based_in}_0(X, Y) \quad \text{(C.28)} \\
\text{agent_of}(X, Y) & \land \text{type}::\text{gpe}(Y) \implies \text{based_in}_0(X, Y) \quad \text{(C.29)} \\
\text{event_in}_2(X, Z) & \land \text{in}_0(Z, Y) \implies \text{event_in}_0(X, Y) \quad \text{(C.30)} \\
\text{event_in}_1(X, Z) & \land \text{in}_0(Z, Y) \implies \text{event_in}_0(X, Y) \quad \text{(C.31)} \\
\text{head_of}(X, Y) & \implies \text{member_of}(X, Y) \quad \text{(C.32)} \\
\text{coach_of}(X, Y) & \implies \text{member_of}(X, Y) \quad \text{(C.33)} \\
\text{spokesperson_of}(X, Y) & \implies \text{member_of}(X, Y) \quad \text{(C.34)} \\
\text{member_of}(X, Y) & \land \text{::sport_player}(X) \implies \text{player_of}(X, Y) \quad \text{(C.35)} \\
\text{mayor_of}(X, Y) & \implies \text{head_of_gov}(X, Y) \quad \text{(C.36)} \\
\text{directed_by}(X, Y) & \implies \text{created_by}(X, Y) \quad \text{(C.37)} \\
\text{character_in}(X, Y) & \land \text{played_by}(X, Z) \implies \text{plays_in}(Z, Y) \quad \text{(C.38)} \\
\text{institution_of}(X, Y) & \implies \text{part_of}(X, Y) \quad \text{(C.39)} \\
\text{based_in}_0(X, Z) & \land \text{gpe}(Z, Y) \implies \text{based_in}_0(X, Y) \quad \text{(C.40)} \\
\text{based_in}_0(X, Y) & \land \text{gpe}(Z, Y) \implies \text{based_in}_0(X, Z) \quad \text{(C.41)}
\end{align*}
\]
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