DiS-ReX: A Multilingual Dataset for Distantly Supervised Relation Extraction

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Abstract

Our goal is to study the novel task of distant supervision for *multilingual* relation extraction (Multi DS-RE). Research in Multi DS-RE has remained limited due to the absence of a reliable benchmarking dataset. The only available dataset for this task, RELX-Distant (Köksal and Özgür, 2020), displays several unrealistic characteristics, leading to a systematic overestimation of model performance. To alleviate these concerns, we release a new benchmark dataset for the task, named DiS-ReX. We also modify the widely-used bag attention models using an mBERT encoder and provide the first baseline results on the proposed task. We show that DiS-ReX serves as a more challenging dataset than RELX-Distant, leaving ample room for future research in this domain.

1 Introduction

Relation Extraction (RE) identifies the relation r between a pair of entities (e_1, e_2) given some text mentioning both of them. To avoid large manual annotation, RE is often trained via distant supervision (DS-RE) (Mintz et al., 2009). DS-RE uses facts $r(e_1, e_2)$ in an existing KB to associate a label r with the bag containing all sentences that mention e_1 and e_2. Research in DS-RE has been mostly monolingual and limited to English. Our goal is to study multilingual RE via distant supervision (Multi DS-RE). We expect multilingual RE models to have several benefits over monolingual RE. First, training data from multiple languages may be pooled to create a large dataset, enabling cross-lingual knowledge transfer (Zoph et al., 2016; Feng et al., 2020). Second, it may encourage RE models to be consistent across languages (Lin et al., 2017), e.g., extraction of a fact already seen in one language should be easier in another.

To the best of our knowledge, RELX-Distant (Köksal and Özgür, 2020) is currently the only dataset available for Multi-DSRE, but even so, it has never been evaluated as a benchmark for the task. Our analysis reveals that it suffers from a poor selection of relation classes. Firstly, there are no examples of NA class (sentences with no relation between the two entities). Therefore, a model trained on RELX-Distant would find limited utility in any real world setting. Secondly, its choice of relation classes is highly disjoint, resulting in an absence of instances with multiple labels (unusual for a DS-RE dataset). Finally, it is highly imbalanced – even though it has 24 relation classes, over 50% bags belong to just one "country" relation.

Owing to these attributes, we observe that models trained on RELX-Distant end up classifying the instances of the minority class based on just the entity type information. Due to high skew, such mistakes have negligible impact on evaluation scores and the model achieves an AUC of 0.99 after only 5 training epochs. Such numbers are unheard of, especially when compared to benchmarking datasets in mono-lingual RE (mono-lingual variant of the same architecture obtains an AUC of 0.83 when trained and tested on the GDS dataset (Jat et al., 2018).

In response, we contribute a more realistic benchmark dataset for the task called DiS-ReX. Our dataset has over 1.8 million sentences in four languages: English, French, Spanish and German. It has 37 relation types including 1 No-Relation (NA) class and also has instances with multiple labels similar to the widely-used New York Times (NYT) dataset for English DS-RE (Riedel et al., 2010), thus comparing favorably to RELX-Distant.

We also adopt state-of-the-art DS-RE models in the multilingual setting by using the mBERT encoder (Devlin et al., 2019), to create a strong baseline for this task. We achieve an AUC of 0.82 and a Micro-F1 of 0.76, suggesting that the dataset is not trivial to optimize on, and could act as a good benchmark for the task. We publicly release DiS-ReX and the baseline (link to DiS-ReX).

2 Related Work

Supervised RE datasets such as ACE05 (Walker et al., 2006) and KLUE (Han, 2010) are generally small, owing to the supervision needs per relation. Distant supervision (Mintz et al., 2009) is a popular alternative to large-scale human annotation, but necessitate more complex models to handle dataset noise. The standard English DS-RE dataset is New York Times (NYT) corpus (Riedel et al., 2010), which has served as the benchmark for research over the years. DS-RE models have evolved to use multi-instance learning (Hoffmann et al., 2011), multi-label learning (Surdeanu et al., 2012), corrections for false negatives (Ritter et al., 2013), and neural models such as piecewise CNNs (Zeng et al., 2015), intra-bag attention (Lin et al., 2016), and reinforcement learning (Qin et al., 2018).

Lin et al. (2017) and Wang et al. (2018) propose extensions of bag-attention models for bilingual (English-Mandarin) datasets. However, their adoption to multiple languages has been lacking, due to absence of a reliable multilingual dataset. Although RELX-Distant is the only Multilingual DS-RE dataset so far, it was originally used not for Multi DS-RE task but to pre-train a model that gets fine-tuned for *supervised* RE task.

3 Dataset Curation

All distant supervision datasets are curated by aligning known KB facts with sentences in a large corpus. We follow the same for DiS-ReX, while paying attention to cross-lingual normalization, and overall data and language statistics.

First, we harvest a large number of sentences from English, French, Spanish and German Wikipedias.[1] We use DBPedia language editions (Lehmann et al., 2015) for our KB – this gives us good coverage of entities that are local to different language speakers. DBPedia entities are associated with Wikidata IDs, which are normalized across languages. This enables us to fuse these DBPedia KBs and establish equivalence between entities like *USA* and *Estados Unidos de América*.

Next, we use a language-specific NER tagger, spaCy (Honnibal and Montani, 2017), returning a rich set of sentences. To contrast, ReLX-Distant finds entity mentions using Wikipedia hyperlinks. This severely limits its pool of sentences, since often only the first mention of an entity in a Wiki document has a hyperlink and others do not.

Linking each mention with its entity can be challenging, due to unavailability of high-quality entity linking software for every language. We take the pragmatic approach of using simple string matching, but only on the subset of entities that have an unambiguous surface form (or alias) in our fused KB. This maintains scalability to many languages, while ensuring high enough precision of linking.

For each entity-pair, we create a language-specific bag of all sentences that mention both. We also search for all relations between them in our fused KB. We associate the bag with all those relation labels, or "NA", if no relation is found.

Our next steps select a balanced subset of this dataset, so that it can serve as a good benchmark for Multi DS-RE. We first select the subset of relations that have at least 50 bags in all languages. This yields the 36 positive relation types used in our data. For each relation type, we limit the number of bags in a language to a max of 10,000. This helps curb the skew due to highly frequent relations such as $country$ and $birthPlace$. During this filtering, we ensure that bags of entity pairs common across more than one language are not removed, so that we have an abundant number of cross-lingual bags. Models can take advantage of such bags for establishing representation consistency across languages (Wang et al., 2018). Finally, we add bags of entity pairs that have no relation between them. Similar to NYT dataset, "NA" is the majority class in DiS-ReX (kept at roughly 70%).

Hence, we obtain a dataset with over 1.8 million sentences, and over 250,000 language-specific (non-NA) bags (see appendix for more statistics). The 36 relations include frequent relations between persons, locations and organizations (e.g., *capital, headquarter, works-at*), and also some relations with fine-grained types such as *bandMember, starring* and *recordLabel*.

We estimate the percentage of bags satisfying "at-least one" assumption by manually labelling sentences across 50 randomly selected bags. We find that 82% of the bags satisfy "at-least one" assumption. For the test set of NYT Corpus, this percentage is close to 62% (Zhu et al., 2020)

Finally, we create train-dev-test splits by splitting the bags in the ratio $70 : 10 : 20$. While splitting we ensure that entity-pairs in three sets are mutually exclusive, so the model does not extract by memorizing a fact.

[1] Our pipeline applies to non-Wikipedia sentences too.

4 Experiments and Data Analysis

4.1 Comparison: DiS-ReX vs. RELX-Distant

We now compare the two datasets: DiS-ReX and RELX-Distant. We find that the our dataset showcases several desirable properties expected from a challenging DS-RE dataset, including the presence of NA relations, inverse relations, multi-label bags, and better class balance.

70% of bags in DiS-ReX are NA bags, whereas RELX-Distant has none. We also note that a few relation pairs (from our 36 relations) represent inverses of each other, e.g., {*influenced by, influenced*}, {*successor, predecessor*}, and {*associatedBand, bandMember*}. Inverse relations test an extractor's ability to output related relations from the same bag, but with different entity ordering. RELX-Distant has no inverse relations in its relation vocabulary.

A key characteristic of DS-RE problems is that they need multi-label modeling (Surdeanu et al., 2012), since multiple relations commonly exist between an entity pair. RELX-Distant has no such bags, primarily because its choice of relation types is such that almost no entity-pair can have multiple relations. E.g., its Person-Person relations are *mother, spouse, father, sibling, partner*, where multi-label bags are highly unlikely. In contrast, DiS-ReX has 21,642 bags that have more than one relation label. As an example, the entity pair (*Isaac Newton, England*) is associated with four relations – *birthPlace, country, deathPlace* and *nationality*.

To compare the imbalance among non-NA relation classes in DiS-ReX and RELX-Distant, we calculate normalized entropy (Shannon, 1948), also known an Efficiency (η). Value closer to 1 indicates that the class-wise distribution is closer to the uniform distribution. Results in Table 2 indicate that DiS-ReX is a more balanced dataset (more details regarding calculation of η in appendix)

4.2 Baseline Performance

We implement three DS-RE baselines for our DiS-ReX dataset. Our first baseline is PCNN+Att (Lin et al., 2016), which uses a piece-wise CNN as the sentence encoder and performs bag-level multi-label classification using Intra-Bag attention. In this model, each language is trained and tested upon separately. Inspired by Ni and Florian (2019), we extend this to design a second baseline, mBERT+Att. It replaces PCNN encoders with a shared mBERT encoder (Devlin et al., 2019) and retains the intra-bag attention architecture for constructing the bag representation. Our last baseline is mBERT+MNRE, which adapts the MNRE model (Lin et al., 2017) to our setting. MNRE introduced cross-lingual attention for bilingual RE. We extend this attention module to more than two languages and also replace its language-specific CNN encoders with a shared mBERT encoder. More details on baselines and training are in appendix.

Lang.	RELX-Distant			DiS-ReX		
	AUC	μF1	M-F1	AUC	μF1	M-F1
English	0.99	0.95	0.78	0.78	0.71	0.69
French	0.99	0.96	0.79	0.81	0.75	0.68
Spanish	0.98	0.94	0.77	0.80	0.73	0.66
German	0.99	0.95	0.80	0.76	0.72	0.59
All	0.99	0.95	0.79	0.81	0.74	0.68

Table 1: Language-wise performance of mBERT + Att. μF1 and M-F1 refer to micro and macro F1 scores.

	RELX-Distant	DiS-ReX
Efficiency (η)	0.522	0.856
M-F1 (top 3)	94.29	82.06
M-F1 (bottom 3)	49.47	63.28

Table 2: Key statistics representing class imbalance between RELX-Distant and DiS-ReX

Model	AUC	Micro-F1	Macro-F1
PCNN+ Att	0.678	0.634	0.437
mBERT+ Att	0.806	0.741	0.676
mBERT+ MNRE	0.817	0.759	0.706

Table 3: Performance of DS-RE models on DiS-ReX

We first compare mBERT+Att model on both DiS-ReX and RELX-Distant in Table 1. We find that RELX-Distant achieves an unreasonably high AUC and micro-F1. Since Micro-F1 may be overwhelmed by a few highly frequent relations, we also report Macro-F1 scores. Even the Macro-F1 scores of RELX-Distant are over 10 pt higher, suggesting that DiS-ReX is a more challenging dataset for our task. We also report the Macro-avg of F1 scores of 3 most frequent and 3 least frequent classes of both the datasets in Table 2. We observe that the performance drops by 45pts in RELX-Distant, more than double the decrease observed in our dataset. For the model trained on RELX-Distant, we notice that the person-person relation types, which are minority classes, obtain the lowest F1 scores. We notice that the model gets confused between *mother* and *spouse* or between *father* and *sibling*. In some cases, the confidence is as high as 95% on such errors. This suggests that the model is making predictions based solely on head-tail entity types in instances belonging to the

person-person relation classes. Such mistakes depress the evaluation scores negligibly due to severe class imbalance and inspite of such mistakes, the model manages to achieve a 0.99 AUC. Therefore, these numbers do not reflect high model quality

We report results of three models on DiS-ReX in Table 3 – mBERT+MNRE achieves 0.82 AUC and 0.76 micro-F1, establishing the best baseline performance on our task.

4.3 Error Analysis

We find that due to incorporation of NA class, multi-label bags and fine-grained relation classes, DiS-ReX offers several new challenges. We observe that on multi-label bags, micro-F1 falls drastically from roughly 0.8 (bags with 1 label) to 0.4 (4 labels), primarily due to reducing recall (statistics in Appendix).

We also perform manual error analysis of 100 random and 100 most confident mistakes made by the model trained on DiS-ReX. For errors where a non-NA relation is incorrectly predicted as another, we find one major error class – highly confident mistakes in predicting closely related relation types that have high overlaps, such as {*author*, *director*}, and {*homeTown*, *birthPlace*}. Some model errors correspond to confusion in predicting inverse relations such as {*successor*,*predecessor*} and {*influenced*,*influencedBy*}. Such cases are absent in the RELX-Distant test set. We found less than 10% errors within the confident errors are due to entity disambiguation mistakes in ground truth, however, we found no such data error in the 100 random errors, suggesting that this failure mode is not the most frequent, and the test data is relatively clean. Predicting non-NA as NA and NA as non-NA relation make up 60-85% of total errors (see appendix).

4.4 Is mBERT+Att Language Agnostic?

It is believed that sharing mBERT encoder across languages is advantageous for cross-lingual transfer (Wu and Dredze, 2019). This is reflected in our experiments too where mBERT+Att strongly outperforms PCNN+Att.

mBERT+Att produces a *single* embedding for a multilingual bag, summarizing mBERT embeddings of individual sentences. We posit that for this model to achieve its true potential on DiS-ReX, mBERT encoder must learn to map all sentences to a language-agnostic representation space, or else the downstream bag attention model may get confused between intra-language and inter-language variability. We investigate this further by raising the question: is the mBERT encoder learning language agnostic embeddings?

For this we encode all sentences in multilingual bags (that contain all languages) using the encoder of trained mBERT+Att model and plot the sentence embeddings using tSNE. We show an illustrative figure for the bag (Swiss, Switzerland) in Figure 1. We find that mBERT clusters sentences of one language together, irrespective of their content (more figures in Appendix). This suggests that mBERT embeddings strongly retain language information, and are not language-agnostic.

This may prove to be a significant obstactle towards progress on our task, since the noise-filtering intra-bag attention may end up capturing variance across languages more than variance in semantics. This may also explain why mBERT+MNRE performs better, since it generates embeddings of sub-bags of each language separately, instead of a single embedding for a multilingual bag.

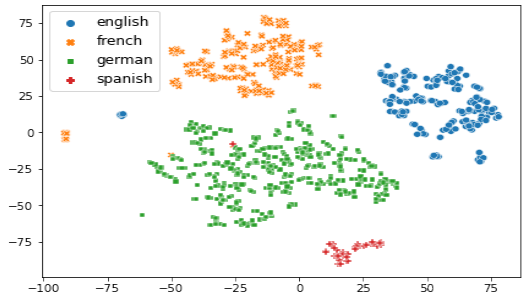

Figure 1: tSNE plot of bag (Swiss, Switzerland)

5 Conclusion

We propose DiS-ReX, a novel dataset for Multi DS-RE in 4 languages. We show that it is a more realistic and challenging benchmark compared to the existing dataset. DiS-ReX has a fairly well-represented distribution of relation types, includes instances with no-relation between entity-pairs and the relation-types selected show several real-world characteristics like inverse relations, different relations with high overlap, etc. We also publish first baseline numbers on the task of Multi-DSRE by extending existing state-of-the-art models. A detailed analysis of model performance suggests several research challenges for future: (1) learning language-agnostic sentence embeddings, (2) robustness to related relations (inverse; overlapping but semantically different), and (3) handling multi-label entity-pairs.

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A Appendix

B Calculation of Efficiency

For a dataset of size n over k classes, where i^{th} class has n_i instances:

$$Efficiency = -\sum_{i=1}^{k} \frac{\frac{n_i}{n} \log \frac{n_i}{n}}{\log k}$$

Efficiency lies between 0 and 1. A higher value suggests that the class-distribution is closer to uniform.

C Baseline architecture

C.1 BERT Encoder

To obtain a distributed representation of a sentence x, we use mBERT. In order to encode positional information into the model we use Entity Markers scheme introduced by (Soares et al., 2019). We add special tokens $[E1]$, $[\backslash E1]$ to mark start and end of the head entity and $[E2]$, $[\backslash E2]$ to mark start and end of the tail entity. This modified sentence is fed into a pretrained BERT model and the output head and tail tokens are concatenated to get the final sentence representation $\tilde{\mathbf{x}}_i^j$ for each sentence x_i^j in our bag.

C.2 Intra Bag Attention

To obtain representation of bag B, we apply selective sentence-level attention (Lin et al., 2016). We obtain real-valued vector $\tilde{\mathbf{B}}$ for the bag as a weighted sum of sentence representations $\tilde{\mathbf{x}}_i^j$:

$$\tilde{\mathbf{B}} = \sum_{i,j} \alpha_i^j * \tilde{\mathbf{x}}_i^j$$

where α_i^j measures attention score of $\tilde{\mathbf{x}}_i^j$ with a specific relation $\mathbf{r}$:-

$$\alpha_i^j = \frac{exp(\tilde{\mathbf{x}}_i^j \cdot \mathbf{r})}{\sum_{k,l} exp(\tilde{\mathbf{x}}_l^k \cdot \mathbf{r})}$$

This reduces the effect of noisy labels on the final bag representation.

Finally, we obtain conditional probability $p(r|B, \theta) = softmax(\mathbf{o})$. Here we obtain $\mathbf{o}$ which represents scores for all relation types.

$$\mathbf{o} = \mathbf{R}\tilde{\mathbf{B}} + \mathbf{d}$$

$\mathbf{R}$ is the matrix of relation representations. Our objective function is the cross-entropy loss and is defined as follows :-

$$L(\theta) = \sum_{i=1}^{b} p(r_i|B_i, \theta)$$

where b denotes the number of bags in our training data

C.3 MNRE and Cross-Lingual Attention

In order to extend the Intra Bag Attention to multilingual setting, (Lin et al., 2017) introduce separate relation embeddings for each language and propose creating several representations of a bag by taking attention of sentences in language j with relation embedding of language k. Formally, the cross-lingual representation $\mathbf{S}_{jk}$ is defined as a weighted sum of those sentence vectors $\tilde{\mathbf{x}}_i^j$ in the j_{th} language where α_{jk}^i is the attention score of each sentence with respect to the k^{th} language.

$$\mathbf{S}_{jk} = \sum_i \alpha_{ik}^j * \tilde{\mathbf{x}}_i^j$$

$$\alpha_{ik}^j = \frac{exp(\tilde{\mathbf{x}}_i^j \cdot \mathbf{r}_k)}{\sum_l exp(\tilde{\mathbf{x}}_l^j \cdot \mathbf{r}_k)}$$

$$\mathbf{o} = (\mathbf{R}_k + \mathbf{M})\mathbf{S}_{jk} + \mathbf{d}$$

$\mathbf{R}_k$ is the matrix of relation representations ($\mathbf{r}_k$) in language k and $\mathbf{M}$ is a global relation matrix initialized randomly. Similar to (Lin et al., 2016), probability $p(r|\mathbf{S}_{jk}, \theta) = softmax(\mathbf{o})$. To obtain score of relation r for bag B :

$$f(B, r) = \sum_{jk} \log p(r|\mathbf{S}_{j,k}, \theta)$$

Loss function is negative log likelihood over all bags in the dataset.

D Training details

For training we use AdamW optimizer (Kingma and Ba, 2017; Loshchilov and Hutter, 2019), with lr=0.001, betas=(0.9, 0.999), eps=1e-08. Weight decay is 0.01 for all parameters except bias and layer norm parameters. Hyperparameters were selected using manual tuning on the dataset. We train the mBERT models for 5 epochs and the PCNN+Att model for 60 epochs. We follow the framework of OpenNRE (Han et al., 2019) and select bag size = 2 for all models. For testing, we choose the weights with best validation AUC. Correct prediction of NA class is not counted in the calculation of Micro F1 and AUC. We use a single Tesla V100 32 GB GPU for all of our experiments.

mBERT+MNRE baseline takes 8 hours for 1 epoch. mBERT+Att takes 3 hours for 1 epoch. PCNN+Att takes 3 hours for 60 epochs.

Training, validation and testing splits for both DiS-ReX and RELX-Distant are in the ratio of 7:1:2. We made sure that the bags in testing set do not overlap with the bags in the training set.

E Detailed Statistics of mBERT Baselines

In table 4, we present results on all langauges for our three baselines on DiS-ReX. In tables 5, 6 , we investigate the errors made by our baseline models. We discover the following type of errors:

- Type-1 Error : Model predicts a positive(Non-NA) relation label and ground label is also a positive(Non-NA) relation label
- Type-2 Error : Model predicts NA relation label but ground label is a positive(Non-NA) relation label.
- Type-3 Error : Model predicts positive(Non-NA) relation label but ground label is NA relation label.

In table 7 and 8, we present the results on bags having 1,2,3 and 4 labels in ground truth.

In table 9, we present the results on all classes of the best baseline model (mBERT+MNRE) when run on our DiS-ReX dataset.

Language	DiS-ReX (PCNN+Att)		DiS-ReX (mBERT+Att)		DiS-ReX (mBERT+MNRE)	
	AUC	Micro F1	AUC	Micro F1	AUC	Micro F1
English	0.687	0.642	0.781	0.713	0.796	0.733
French	0.714	0.662	0.814	0.746	0.822	0.760
Spanish	0.697	0.644	0.799	0.729	0.816	0.751
German	0.614	0.588	0.757	0.716	0.755	0.717
All languages	0.678	0.634	0.806	0.741	0.817	0.759

Table 4: Language-wise AUC and Micro F1 for baseline models on DiS-ReX

Language	Type-1 Error (%)	Type-2 Error (%)	Type-3 Error (%)
English	43.44	26.66	29.90
French	29.73	30.45	39.82
Spanish	33.82	30.61	35.57
German	15.03	39.60	45.37

Table 5: Types of Errors made in different languages for mBERT+Att

F Some more examples of tSNE plots for mBERT+Att

In figure 2, we provide some more example of tSNE plots for multilingual bags.

We take the following bags:

Language	Type-1 Error (%)	Type-2 Error (%)	Type-3 Error (%)
English	44.49	31.17	24.33
French	29.69	36.14	34.15
Spanish	35.08	36.37	28.54
German	14.94	45.28	39.77

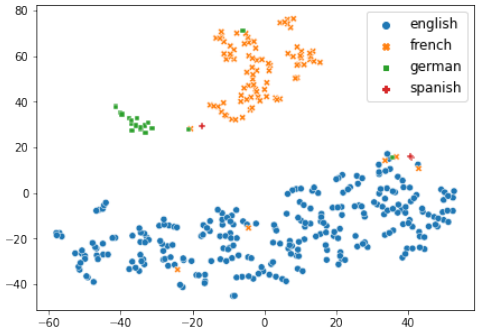
Table 6: Types of Errors made in different languages for mBERT+MNRE

Number of relation labels	Micro-F1	Precision	Recall
1	0.836	0.846	0.825
2	0.662	0.912	0.520
3	0.500	0.939	0.341
4	0.449	0.846	0.305

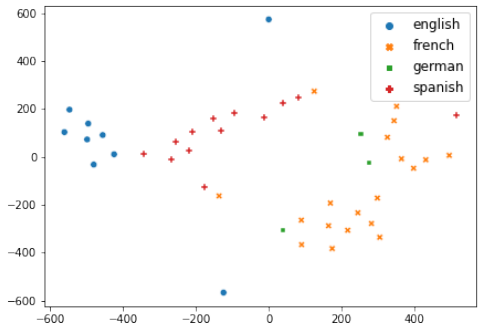
Table 7: Comparing performance of mBERT+Att on entity pairs with different number of labels in the ground truth

Number of relation labels	Micro-F1	Precision	Recall
1	0.842	0.865	0.820
2	0.673	0.934	0.525
3	0.518	0.959	0.354
4	0.348	0.937	0.214

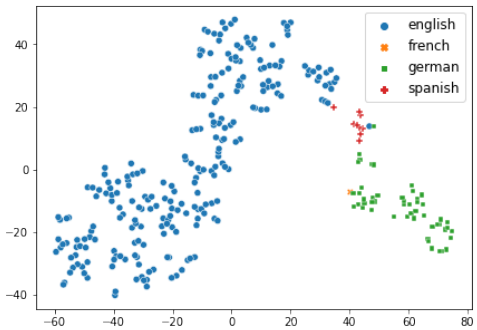
Table 8: Comparing performance of mBERT+MNRE on entity pairs with different number of labels in the ground truth



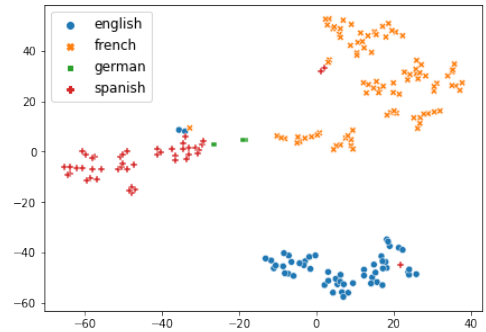
(a) (cincinnati,ohio)



(b) (black sabbath, tony iommi)



(c) (miami,florida)



(d) (sumatra, indonesia)

Figure 2: tSNE plot of a few multilingual bags. Languages are marked with different colours

(cincinnati, ohio) ; (black sabbath, tony iommi)
(miami, florida) ; (sumatra, indonesia)

We use sklearn implementation of tSNE and set the perplexity to be 5.

Relation Label	F1	Precision	Recall
predecessor	67.58	76.31	60.65
nationality	67.29	64.68	70.12
artist	76.78	74.79	78.87
region	81.43	81.14	81.73
department	95.08	95.28	94.88
successor	72.16	75.32	69.26
location	69.82	65.36	74.93
bandMember	73.45	73.45	73.45
isPartOf	66.50	59.52	75.33
hometown	73.03	70.14	76.17
previousWork	68.83	64.89	73.27
riverMouth	72.63	78.97	67.24
team	81.66	85.85	77.86
recordLabel	86.85	87.24	86.46
associatedBand	71.26	61.69	84.36
author	78.87	83.30	74.88
influenced	61.35	65.81	57.46
birthPlace	75.00	75.52	74.48
formerBandMember	57.94	59.62	56.36
leaderName	71.16	70.97	71.35
deathPlace	66.24	64.15	68.46
city	78.96	81.93	76.19
province	78.82	78.73	78.92
influencedBy	59.29	65.26	54.32
locationCountry	62.58	64.76	60.55
related	75.94	74.35	77.59
director	83.59	79.36	88.29
capital	53.68	48.69	59.82
largestCity	65.89	71.57	61.04
NA	95.08	95.56	94.61
country	86.57	85.77	87.39
starring	86.32	86.52	86.12
subsequentWork	71.65	70.23	73.12
producer	53.30	51.20	55.58
headquarter	68.54	66.08	71.18
state	82.54	78.32	87.26
locatedInArea	72.23	70.44	74.10
All relations	70.67	-	-

Table 9: Class-wise performance scores for MNRE (our best performing model)

G Qualitative Analysis

In this section, we give some examples of randomly selected non NA instances in our dataset:
English:

- ***Sentence:*** *another dialect spoken in tioman island is a distinct malay variant and most closely related to riau archipelago malay subdialect spoken in natuna and anambas islands in the south china sea together forming a dialect continuum between the bornean malay with the mainland malay*
  Entities: *(tioman island, the south china sea)*

Relations: *http://dbpedia.org/ontology/location*

- ***Sentence:*** *in 2017 jenny durkan was elected as the first openly lesbian mayor of seattle*
  Entities: *(jenny durkan, seattle)*
  Relations: *http://dbpedia.org/ontology/birthPlace*

German:

- ***Sentence:*** *danach kamen abgeleitete klassen hinzu ein strengeres typsystem und während stroustrup "c with classes" ("c mit klassen") entwickelte woraus später c++ wurde schrieb er auch cfront einen compiler der aus c with classes zunächst c-code als erzeugte*
  Entities: *(c,c++)*
  Relations: *http://dbpedia.org/ontology/influenced*

- ***Sentence:*** *früher auch ur ist ein 96.1 km langer nebenfluss der sauer entlang der grenze von deutschland zu den westlichen nachbarstaaten belgien und luxemburg*
  Entities: *(sauer, deutschland)*
  Relations: *http://dbpedia.org/ontology/locatedInArea*

French:

- ***Sentence:*** *à la mort de boleslas v le pudique duc princeps de pologne la guerre civile en mazovie empêche conrad de revendiquer le trône de cracovie*
  Entities: *(boleslas v le pudique, cracovie)*
  Relations: *http://dbpedia.org/ontology/deathPlace*

- ***Sentence:*** *les entreprises masson masson est le dirigeant effectif des trois entreprises du groupe cette situation se reflète désormais dans l actionnariat et les raisons sociales des sociétés qui deviennent joseph masson sons and company (montréal) masson langevin sons and company (québec) masson sons and company (glasgow) cette dernière société basée en écosse a surtout vocation de gérer les achats*
  Entities: *(joseph masson, québec)*
  Relations: *http://dbpedia.org/ontology/birthPlace*

Spanish:

- ***Sentence:*** *en 2003 apareció en anything else película de woody allen junto a christina ricci y jason biggs además actuó en la película para televisión l*
  Entities: *(anything else, jason biggs)*
  Relations: *http://dbpedia.org/ontology/starring*

- ***Sentence:*** *es una comuna y población de francia en la región de borgoña departamento de yonne en el distrito de sens y cantón de sens-ouest*
  Entities: *(sens, yonne)*
  Relations: *http://dbpedia.org/ontology/department*

H Dataset Statistics

In table 10, we present statistics of our dataset across languages. In table 11, we present the number of bags common across 2,3 and all 4 languages. In table 12 and 13, we present the number of bags and sentences in each class on all 4 languages in our dataset.

Language	#sentences	# bags	# non-NA bags	Average bag-size
English	532499	216806	66932	4.50
French	409087	226418	83951	2.88
Spanish	456418	229512	80706	2.88
German	438315	194942	45908	3.48

Table 10: Key statistics for DiS-ReX

Number of languages	Number of Bags
2	59709
3	9494
4	1488

Table 11: Number of bags common across 2,3 and all languages

Relation Label	English	French	German	Spanish	All languages
NA	149874	142467	149034	148806	590181
isPartOf	2548	645	465	490	4148
state	1882	1762	3537	429	7610
largestCity	265	342	199	393	1199
birthPlace	7861	9532	3341	9484	30218
deathPlace	4377	5629	277	4709	14992
nationality	2205	4413	143	2265	9026
country	10024	9618	3065	9808	32515
capital	544	651	397	891	2483
city	1415	4257	7930	1844	15446
author	1483	1224	94	460	3261
previousWork	348	696	305	1127	2476
location	5655	1300	1180	1685	9820
riverMouth	464	880	3303	154	4801
locatedInArea	1324	785	5715	608	8432
hometown	1689	435	163	4474	6761
successor	1574	2959	74	1618	6225
influenced	820	453	61	188	1522
headquarter	1122	922	460	1895	4399
province	225	1121	1272	2405	5023
associatedBand	3669	384	107	2555	6715
subsequentWork	390	760	344	1248	2742
locationCountry	925	799	2237	361	4322
bandMember	1327	1909	300	3092	6628
director	1258	3003	1592	2089	7942
team	1329	564	461	634	2988
artist	1188	3891	1241	2670	8990
related	1439	375	117	6262	8193
producer	1381	2848	1401	3044	8674
predecessor	475	2814	81	273	3643
leaderName	353	236	270	223	1082
formerBandMember	960	1153	174	1345	3632
recordLabel	791	881	199	2107	3978
region	1529	3673	1907	2249	9358
influencedBy	954	533	86	291	1864
starring	3040	7018	3087	4179	17324
department	99	5486	323	3157	9065
All relations	216806	226418	194942	229512	876743

Table 12: Comprehensive bag-wise statistics of the dataset

Relation Label	English	French	German	Spanish	All languages
NA	231271	167509	278360	224156	901296
isPartOf	16085	2794	2566	1880	23325
state	11979	13135	13705	1405	40224
largestCity	18811	4163	8949	3136	35059
birthPlace	15738	16624	4376	14359	51097
deathPlace	11498	12208	539	8888	33133
nationality	5848	9560	219	4330	19957
country	88787	43911	13148	64660	210506
capital	19887	4713	17227	5318	47145
city	4490	11156	23631	3740	43017
author	3387	4121	335	1417	9260
previousWork	6507	1276	450	2318	10551
location	15538	4757	4656	6014	30965
riverMouth	1172	2442	12467	420	16501
locatedInArea	4320	4152	18890	1904	29266
hometown	7648	796	1067	8971	18482
successor	4700	6963	128	3118	14909
influenced	2416	1147	635	394	4592
headquarter	5419	2399	2030	5736	15584
province	1082	2472	2710	11672	17936
associatedBand	7390	713	136	8437	16676
subsequentWork	6541	1318	517	2526	10902
locationCountry	3204	2836	8226	1229	15495
bandMember	3592	5910	475	8763	18740
director	2005	7811	2970	3961	16747
team	1830	814	694	1396	4734
artist	2893	9591	3156	6472	22112
related	4526	928	171	17432	23057
producer	2459	6398	2647	6384	17888
predecessor	2592	7003	162	600	10357
leaderName	1549	1074	452	448	3523
formerBandMember	2975	3452	279	4091	10797
recordLabel	1320	1214	219	4149	6902
region	5836	11860	5901	4485	28082
influencedBy	2524	1482	913	536	5455
starring	4484	14578	4616	6676	30354
department	196	15807	693	4997	21693
All relations	532499	409087	438315	456418	1858012

Table 13: Comprehensive sentence-wise statistics of the dataset