Konooz: Multi-domain Multi-dialect Corpus for Named Entity Recognition

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Abstract

We introduce *Konooz*, a novel multi-dimensional corpus covering 16 Arabic dialects across 10 domains, resulting in 160 distinct corpora. The corpus comprises about 777k tokens, carefully collected and manually annotated with 21 entity types using both nested and flat annotation schemes - using the Wojood guidelines. While *Konooz* is useful for various NLP tasks like domain adaptation and transfer learning, this paper primarily focuses on benchmarking existing Arabic Named Entity Recognition (NER) models, especially cross-domain and cross-dialect model performance. Our benchmarking of four Arabic NER models using *Konooz* reveals a significant drop in performance of up to 38% when compared to the in-distribution data. Furthermore, we present an in-depth analysis of domain and dialect divergence and the impact of resource scarcity. We also measured the overlap between domains and dialects using the Maximum Mean Discrepancy (MMD) metric, and illustrated why certain NER models perform better on specific dialects and domains. *Konooz* is open-source and publicly available at https://sina.birzeit.edu/wojood/#download

1 Introduction

NER is crucial in various NLP tasks, including machine translation (Hassan and Sorensen, 2005; Darwish et al., 2021), word sense disambiguation (Jarrar et al., 2023b; Al-Hajj and Jarrar, 2021), data extraction (Barbon Junior et al., 2024), language understanding (Khalilia et al., 2024), question answering (Badawy et al., 2011), and interoperability (Jarrar et al., 2011). State-of-the-art Arabic NER models demonstrate impressive performance, achieving F_1-scores above 90% (Jarrar et al., 2024). However, these models continue to face challenges across various domains and dialects (Singhal et al., 2023). Arabic dialects are low-resource in many NLP tasks, including Arabic NER.

	Dialects/Domains	Politics	Economics	Finance	History	Law	Science	Health	Agriculture	Art	Sport	Total
1	MSA	12712	8010	8149	8165	8083	8378	8777	8882	8015	9386	**88557**
2	Syria	4020	4025	4043	4004	4018	4139	4018	4151	7648	4055	**44121**
3	Palestine	4447	4511	4006	4455	4021	4253	4580	4002	4012	4036	**42323**
4	Lebanon	4396	4205	4341	4163	4173	4002	4229	4085	5939	4131	**43664**
5	Saudi Arabia	4270	4165	4162	4104	3996	4036	4079	4079	4650	4054	**41595**
6	Oman	5094	4049	4484	4209	5275	4123	5024	4227	4023	4486	**44994**
7	Yemen	5312	4375	4212	4045	5479	4100	4000	4011	4242	4042	**43818**
8	Iraq	4000	4777	4014	4003	4007	4000	4012	4008	4045	4002	**40868**
9	Kuwait	4148	4656	5322	3998	5894	4022	4518	4044	4013	4073	**44688**
10	Egypt	4096	4085	4306	4124	4141	4196	4041	4286	4095	4072	**41442**
11	Sudan	4145	4508	4078	4004	4138	4207	4371	4158	4135	4013	**41757**
12	Libya	11898	4172	4041	5775	5350	4307	6757	16044	4151	4802	**67297**
13	Tunisia	4113	4594	4019	14918	4778	4070	6073	4787	9159	5170	**61681**
14	Algeria	3073	3030	3025	3294	3050	3016	3557	3059	3063	3069	**31236**
15	Morocco	5378	4913	5193	5019	4107	4078	4887	4079	8989	4268	**50911**
16	Mauritania	6991	5424	4007	5492	4015	4050	4620	4039	4005	6147	**48790**
	Total	**88093**	**73499**	**71402**	**83772**	**74525**	**68977**	**77543**	**81941**	**84184**	**73806**	**777742**

Figure 1: *Konooz* statistics, by domain and dialect.

MSA benefits from a large pool of annotated NER resources, while dialects suffer from a lack of such datasets (Khbir et al., 2023). Additionally, existing datasets have mainly focused on a limited number of domains, such as *Wojood* (Jarrar et al., 2022, 2023a) which covers two dialects and five domains. Other resources such as *OntoNotes* (Weischedel et al., 2013b) and *ANERCorp* (Benajiba et al., 2007) focus exclusively on MSA and are limited to the political news domain. The lack of labeled datasets for multiple dialects and domains makes developing and evaluating NER models in cross-domain and cross-dialect more challenging (Mekki et al., 2022; Jia et al., 2019).

Konooz is a novel multi-dimensional NER corpus designed for benchmarking NER models across various domains and dialects. To the best of our knowledge, *Konooz* is the first rich corpus that contains 10 domains in 16 different dialects. As shown in Figure 1, each corpus contains about 4k tokens. The MSA corpus contains about 8k tokens. The corpus was manually collected from diverse sources, reflecting the diversity of Arabic dialects. Then, it was manually annotated by a team of 45 people. The annotation process involved labeling tokens with 21 distinct entity types, utilizing both flat and nested NER tags, adhering to the annotation guidelines presented in Jarrar et al. (2022).

We used *Konooz* for benchmarking four Arabic NER models, which revealed low performance across domains and dialects. The variations in the results underscore the urgent need for more diverse Arabic NER datasets. Furthermore, we leveraged *Konooz* to conduct an in-depth analysis of lexical similarity across domains and dialects. We hypothesized that (i) dialects from the same geographic region are expected to exhibit low divergence, and (ii) the named entities from the same country or region in the training data improve model performance. By measuring the divergence between domains and dialects, we uncovered several insightful patterns and correlations. These divergences reveal the linguistic variations that directly impact the performance degradation of the trained models. Efficiently measuring and reducing divergence is crucial for adapting models to the new domain—the topic of domain adaptation (Kashyap et al., 2021).

In short, the main contributions of this paper are:

1. *Konooz*, 160 corpora covering 10 domains and 16 dialects (777k tokens) manually labeled with 21 entity types in flat and nested annotations.
2. Benchmark of four Arabic NER models using *Konooz* in cross-domain and cross-dialect.
3. Insightful lexical similarity analysis that uncovers distinctions and similarities across different domains and dialects.

The paper is organized as: Section 2 reviews related work; Section 3 presents *Konooz*; Section 4 reveals the lexical similarity; Section 5 benchmarks NER models; and we conclude in Section 6.

2 Related Work

2.1 Arabic NER Datasets

Most available NER corpora cover MSA with limited coverage of domains and dialects. *ANERCorp* is an Arabic news corpus comprising $150k$ tokens annotated with four entity types (Benajiba et al., 2007). *OntoNotes* 5.0 includes $300k$ MSA tokens annotated with 17 entity types (Weischedel et al., 2013a). *Wojood* is a larger corpus containing $550k$ annotated for both flat and nested entities. *Wojood* uses the 17 entity types used in *OntoNotes* , and introduces four additional types: `Occupation (OCC)`, `WEBSITE`, `UNIT`, and `Currency (CURR)` (Jarrar et al., 2022). *Wojood* was later extended with $Wojood_{fine}$, $Wojood^{Hadath}$ and $Wojood^{Gaza}$. $Wojood_{fine}$ is the same as *Wojood*, but it introduces 30 fine-grained sub-entity types (Liqreina et al., 2023; Jarrar et al., 2023a). $Wojood^{Hadath}$ is the Wojood corpus annotated with event argument relations (Aljabari et al., 2024). $Wojood^{Gaza}$ consists of 60k tokens (Jarrar et al., 2024) focusing on news related to the Israeli War on Gaza across and Nakba NLP (Jarrar et al., 2025). It covers five domains (politics, law, economy, finance, and health) annotated with 51 entity types and subtypes following Wojood guidelines.

There are only a few dialectal NER corpora covering limited number of entity types. Zirikly and Diab (2014) presented an Egyptian NER corpus containing 40k tokens. DarNERCorp is a Moroccan NER corpus comprising 65k tokens annotated with four entity types (Moussa and Mourhir, 2023). NERDz is an Algerian corpus annotated with eight entity types (Touileb, 2022). DzNER is another Algerian corpus (220k) annotated with three entity types (Dahou and Cheragui, 2023).

Several publicly available dialectal corpora exist, such as the *Lisan* corpora (Jarrar et al., 2023c), which covers Iraqi, Libyan, Sudanese, and Yemeni dialects; the $Nabra^{Syrian}$ corpus (Nayouf et al., 2023); and the *Curra+Baladi* corpora for Palestinian and Lebanese dialects (Haff et al., 2022; Jarrar et al., 2017). All of these corpora are fully annotated with morphological tags and lemmas linked with Qabas (Jarrar and Hammouda, 2024) and the Arabic Ontology (Jarrar, 2021). However, among these, only *Curra+Baladi* is annotated with NER tags, as it is part of the Wojood dataset. Other spoken dialectal corpora with transcriptions exist, such as Casablanca (Talafha et al., 2024), but none include NER annotations.

In other languages, BarNER is the first manually annotated NER dataset,comprising 161k tokens sourced from Bavarian Wikipedia articles and tweets, annotated according to a schema adapted from the German CoNLL 2006 guidelines. The dataset includes both coarse-grained and fine-grained entity types (Peng et al., 2024).

2.2 Benchmarking NER Models

Previous research has focused on building benchmark datasets and evaluating NER models. Vajjala and Balasubramaniam (2022) challenge the reliance on micro-F_1 scores and propose a broader evaluation framework assessing models across entity categories, sources, and genres. Using *OntoNotes* 5.0 and six adversarial test sets, they evaluate Spacy, Stanza, and SparkNLP, revealing F_1-score drops of 12%-20% across sources and genres. This highlights that NER models struggle with unseen genres, even with multi-genre training.

3 *Konooz* Corpus

Konooz was manually collected and covers 16 dialects, including MSA, with each dialect represented across 10 domains.

3.1 Corpus Collection Guidelines

We manually collected dialectal threads from various sources—including Facebook, X, YouTube comments, and blogs—ensuring that only public posts and comments from public accounts were included. For MSA, we retrieved articles from specific domains on public media websites, like AlJazeera, AlArabiya, and SkyNewsArabia.

We collected dialectal threads consisting of one or more sentences, each containing more than five words to ensure sufficient context. Additionally, every sentence is manually categorized into a specific domain by analyzing its context and identifying domain-specific keywords. Each sentence should include multiple entity types, such as person names, organizations, events, and more. All sentences were written between 2010 and 2022. To ensure a balanced dataset, each domain within each dialect must include about 4k tokens.

3.2 Collection Procedure

Since recruiting native speakers for each dialect is challenging, we hired 40 students—at a rate of 5 USD per hour — to collect the corpus, taking into account the following measures to ensure high-quality collection:

- **Dialect Familiarization**: To help a student become familiar with the necessary vocabulary in a dialect, we asked the student to watch about two hours of content in that dialect.

- **Dialect and Domain Identification**: We identified local TV and radio stations and located their social media channels to target dialect-specific content. With this strategy, we assumed people not native to the target dialect are less likely to comment on local issues outside their country. We also identified local and domain-specific pages, such as the Homs Agriculture Chamber of Syria, NBK Bank in Assiut-Kuwait, Khamsint Ektesad in Egypt, and Ask Software Engineers in Palestine.

- **Dialect Similarity Verification**: After collecting the corpora, we conducted dialect identification tests. We randomly selected 10% of the sentences from a specific dialect and mixed them with similar dialects (e.g., Syrian and Lebanese). Native speakers were then tasked to identify the dialects of these sentences. The results showed an average of 87% accuracy.

- **MSA Divergence Verification**: To ensure our dialectal corpora are not MSA, we used the Arabic Level of Dialectness (ALDi) model (Keleg et al., 2023). It helps to quantify the divergence of sentences from MSA. Sentences scoring below 0.2 were manually reviewed to confirm they were truly MSA, resulting in the removal of 8% of sentences. The ALDi scores for all dialects are shown in Figure 2.

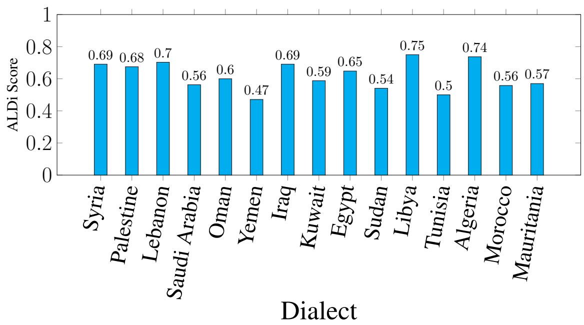


Figure 2: ALDi score for each dialect in *Konooz*.

The collected data was stored in separate Google Sheets for each dialect for manual annotation.

3.3 Annotation Methodology

Phase I To bootstrap the annotation process, we used the *Wojood* NER model in *SinaTools* (Hammouda et al., 2024) to tokenize and tag the corpus.

Phase II We recruited five annotators, each holding a master's degree in linguistics and experience in NER and multilingual annotation projects, at a rate of 8USD/hour. They were introduced to the NER guidelines (Jarrar et al., 2022) to familiarize themselves with 21 entity types (see §A.1). Each annotator was initially assigned $1k$ tokens to annotate, which was reviewed by a NER expert. Once verified, they were assigned to annotate 2-4 dialects over a span of 15 months. Regular group discussions were held to address challenging cases and ambiguities in named entities.

Phase III We trained a NER model using the *Wojood* dataset (Jarrar et al., 2022), *Wojood*^{Gaza} (Jarrar et al., 2024), and the first version *Konooz* (See the details in §A.2). The trained model is used to annotate the *Konooz* for a second round. Then, the annotators reviewed the results to identify errors. In this round, $1,500$ errors were corrected. This process was repeated again, in which we identified 10 changes only, indicating a significant improvement in annotation accuracy.

3.4 Annotation Challenges

We faced several annotation challenges. First, annotators often struggle to recognize local and dialect-specific landmarks and place names. They had to search for these mentions in each dialect or consult native speakers for clarification, such as the (جسر الزرقا *ǧsr ālzrqā* /Az-Zarqa Bridge) a GPE in Palestine, (نزل تاب *nzl tāb*) a FAC in Tunis and (الكولا *ālkwlā*) a FAC in Lebanon. In contrast, identifying people's names is much more straightforward. Second, certain named entities, such as dates, times, and numbers, vary across dialects, which makes annotation more challenging. For example, the number (اثنين *āṯnyn* /two) in Saudi, Omani, and Yemeni is (جوج *ǧwǧ*) in Moroccan. The word (الآن *ālʾān* /now) in MSA is (دابا *dābā*) in Moroccan, (تو *tw*) in Omani, (للحين *llḥyn*) in Kuwaiti, (هلا *hlā*) in Syrian, and (هسا *hsā*) in Palestinian. To handle such variations, annotators engaged in group discussions and consulted native speakers to ensure accurate labeling.

3.5 Inter-Annotator Agreement

To evaluate the consistency of our annotations, we used Cohen's Kappa (Cohen, 1960), a standard metric for inter-annotator agreement (IAA) (Hripcsak and Rothschild, 2005). We randomly selected about 7% (39k tokens) from each domain in each dialect to be annotated by another annotator. We calculated both Kappa and F_1 scores. Table 1 demonstrates high agreement in all entity types.

The high IAA can be attributed to several factors. Continuous feedback to annotators from native speakers and periodic discussions ensured consistency during the process. The annotation conducted during Phase III was instrumental in enhancing consistency among annotators. Comparing annotator outputs with model annotations provided valuable insights, especially in cases where the model correctly identified entities missed by annotators. This collaborative and human-in-the-loop approach significantly improved the overall data quality.

Entity Type	**TP**	**FN**	**FP**	$\mathcal{K}$	F_1**-Score**
ORG	1255	8	25	0.987	0.987
DATE	950	17	16	0.983	0.983
WEBSITE	59	1	1	0.983	0.983
OCC	594	6	11	0.986	0.986
CURR	94	0	2	0.989	0.989
PERS	975	4	12	0.992	0.992
LAW	71	0	0	1	1.000
PRODUCT	213	1	13	0.968	0.968
EVENT	394	0	12	0.985	0.985
GPE	985	5	12	0.991	0.991
NORP	1122	18	52	0.970	0.970
UNIT	77	2	0	0.987	0.987
LANGUAGE	25	0	0	1	1.000
TIME	234	4	6	0.979	0.979
MONEY	170	2	0	0.994	0.994
LOC	236	10	5	0.969	0.696
QUANTITY	150	5	0	0.984	0.984
PERCENT	195	0	0	1	1.000
CARDINAL	521	6	4	0.99	0.99
ORDINAL	283	4	20	0.961	0.961
FAC	123	0	8	0.969	0.969
Overall	**8726**	**93**	**199**	**0.984**	**0.971**

Table 1: IAA for each entity type.

3.6 *Konooz* Statistics

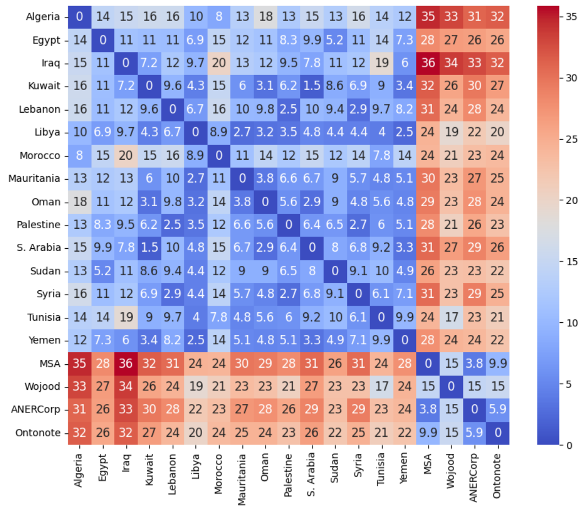
Konooz comprises 31,265 sentences, with an average sentence length of 28.18 words, annotated nested and flat entities, all tagged with 21 coarse-grained tags. Table 2 presents the overall statistics, while Table 11 in §A.5 provides detailed statistics.

Tag	Flat	Nested	Total
PERS	9,564	652	10,216
ORG	8,512	1213	9,725
LOC	1,680	235	1,915
GPE	9,947	1,969	11,916
NORP	11,583	494	12,077
CARDINAL	6,764	92	6,856
ORDINAL	4,350	344	4,694
OCC	6,270	91	6,361
FAC	757	28	785
PRODUCT	746	10	756
EVENT	1,612	66	1,678
DATE	7,526	195	7,721
TIME	2,432	4	2,436
LANGUAGE	315	2	317
WEBSITE	410	4	414
LAW	369	3	372
PERCENT	810	4	814
QUANTITY	827	13	840
UNIT	125	773	898
MONEY	1,495	67	1,562
CURR	974	1128	2,102
Total	77,068	7,387	84,455

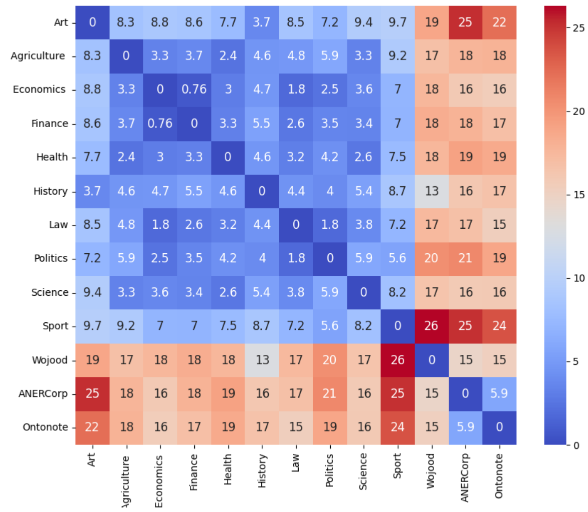
Table 2: Statistics about NER annotations in *Konooz*.

4 Lexical Similarity Analysis

The performance of trained models on out-of-distribution data is heavily influenced by data distribution divergence. Efficiently measuring and minimizing this divergence is crucial for effective



(a) Dialects heatmap



(b) Domains heatmap

Figure 3: Heatmaps of the MMD distances among *Konooz* dialects and domains using linear kernel and between *Konooz*, *Wojood*, *ANERCorp* and *OntoNotes* (last three rows).

domain adaptation (Ben-David et al., 2010). Lexical similarity measures vocabulary overlap between different data distributions (i.e., domains and dialects). It is used to identify source domains or dialects most aligned with the target distribution to enhance domain adaptation (Dai et al., 2019). Domains and dialects that have the same underlying distribution often exhibit high lexical similarity (Pogrebnyakov and Shaghaghian, 2021). We hypothesize that dialects from the same geographic region are expected to exhibit low divergence. To verify this, different metrics are utilized to measure the overlap between dialects and domains.

Jaccard similarity coefficient and cosine similarity metrics failed to differentiate between dialects and domains, as shown in §A.5, and according to Kashyap et al. (2021) Maximum Mean Discrepancy (MMD) (Gretton et al., 2008) outperforms traditional similarity metrics like cosine similarity and KL divergence, making it a more reliable indicator of performance shifts across domains. We used AraBERTv2 (Antoun et al., 2020) sentence representations as the bases for MMD and revealed lexical similarity variations from 1.1 to 13 across domains and 1.5 to 36 across dialects, where higher values indicate dissimilarity (see Figure 3).

Dialect Lexical Similarity Figure 4 is a t-SNE plot generated using the AraBERTv2 sentence representations to visualize the overlap among dialects, including MSA. One can clearly see MSA (red cluster) is notably distinct from the other dialects. Some dialects form compact clusters, such as Moroccan (fuchsia color), Algerian (light green) and Iraqi (yellow), while others show more overlap. Figure 3a quantifies the distances among the clusters in Figure 4. The results reveal significant variations between the dialects. The highest scores are observed between MSA and other dialects, with the highest MMD of 36 recorded between MSA and Iraqi. This indicates significant differences in vocabulary and contextual usage between the MSA and the other dialects. Conversely, the lowest MMD score of 1.5 is observed between the Kuwaiti and Saudi dialects. Such low divergence indicates that data comes from closely related dialects and reflects their close linguistic and contextual similarities, as well as their shared cultural and geographic ties within the Gulf region.

The Moroccan dialect demonstrates the highest level of dissimilarity, aligning with expectations due to its pronounced divergence from other Arabic dialects. Its distinct phonetic, lexical, and syntactic features differentiate it significantly, particularly from Gulf and Levantine dialects. In datasets with high divergence, models are more likely to generate lower confidence scores or misclassify entities, highlighting the need for dialect-specific adaptations to improve performance.

Figure 3a has two distinct clusters. The 15 dialects (excluding MSA) cluster in the top left of the figure and a smaller cluster containing MSA,

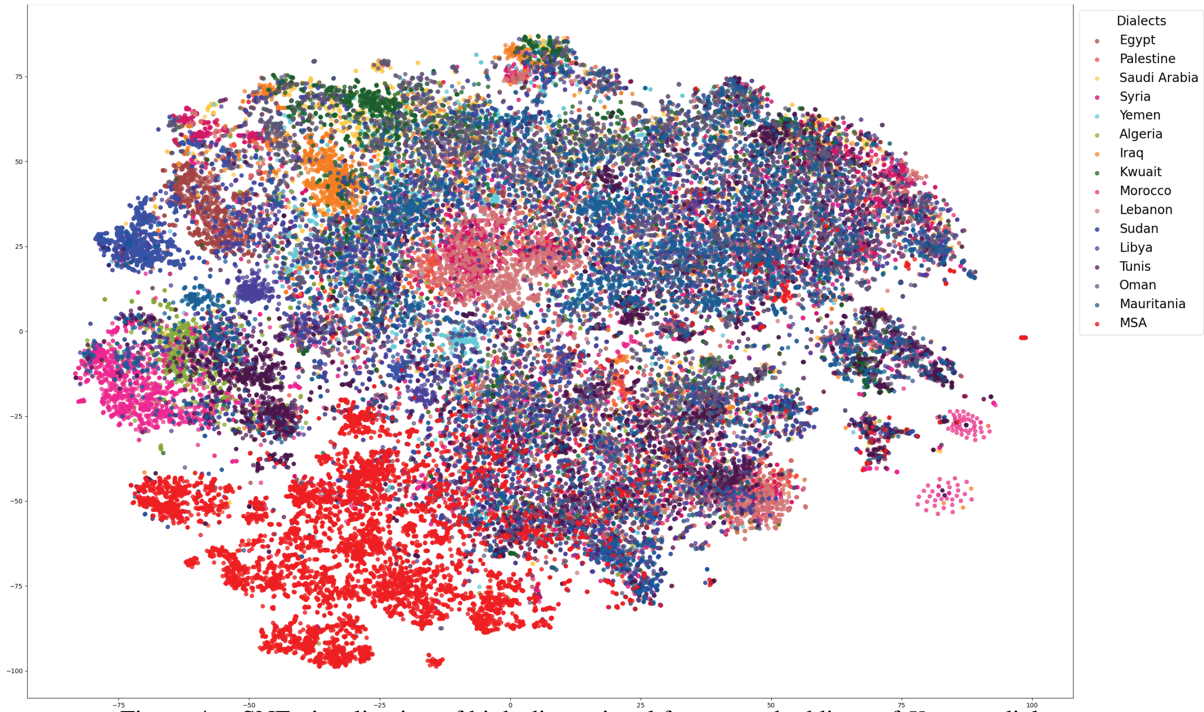


Figure 4: t-SNE visualization of high-dimensional feature embeddings of *Konooz* dialects.

Wojood, *ANERCorp* and *OntoNotes* datasets (the MMD values in the smaller cluster are computed between MSA and the entirety of the three training datasets). The most important observation is the inclusion of MSA and the three training datasets in one cluster, which demonstrates the heavy representation of MSA in the NER datasets. Wojood includes Palestinian and Lebanese data; however, this subset represents only 12% of the corpus. As a result, the lexical distances for these dialects are not the lowest in Figure 3a. One possible explanation is limited overlap between the training and test sets in terms of domain and named entities. Regarding to some dialects such as Tunisia, which shows the lowest lexical distance despite not being explicitly represented in *Wojood*, our hypothesis is that shared named entities—especially in formal contexts may contribute to this reduced surface-level lexical distance across dialects. In these cases, entity classification becomes more challenging as the model encounters unfamiliar linguistic structures and patterns. Effective domain adaptation techniques are needed to bridge the gap between dialects and MSA.

Finally, we measured the MMD between MSA and dialectal data across domains to assess genre influence. Figure 5 shows that intra-domain MMDs (diagonal) are high, indicating significant divergence even within the same domain. Some inter-domain MMDs (off-diagonal) show even greater divergence, highlighting the impact of domain differences. As noted earlier, MSA data is sourced from online news articles, which follow a rigid structure and have clear domain distinctions. In contrast, dialectal data is collected from social media platforms, where it is written informally and may lack domain-specific vocabulary.

Domain Lexical Similarity Figure 3b highlights the significant lexical differences among domains. The greatest dissimilarity is observed between the Art and Science and Art and Sport, with a value of 13. This can be attributed to specific and unique topics discussed in these domains. Art corpora often reference creative works, artists, and cultural institutions, whereas Science corpora emphasize research, scientific disciplines, and technical terminology. The difference in entity types and contexts leads to a small semantic overlap in vocabulary. In contrast, the highest similarity is found between Finance and Economics, with a value of 1.1. This indicates that Finance and Economics share the strongest overlap, likely due to common topics like markets, investments, and risk.

We also measured the MMD between the domains of *Konooz* and the entirety of *Wojood*, *ANERCorp*, and *OntoNotes*. As shown in the lower right part of Figure 3b, the MMD is higher compared to that between other domains, indicating greater divergence. This aligns with the significant performance degradation discussed in Section 5.2.

Measuring divergence highlights the level of effort needed to adapt a model trained on one domain to perform effectively in another. Our analysis aims to provide an indicator of lexical variation for cross-domain transfer learning rather than a definitive measurement of language differences, which would require comprehensive coverage of all dialects.

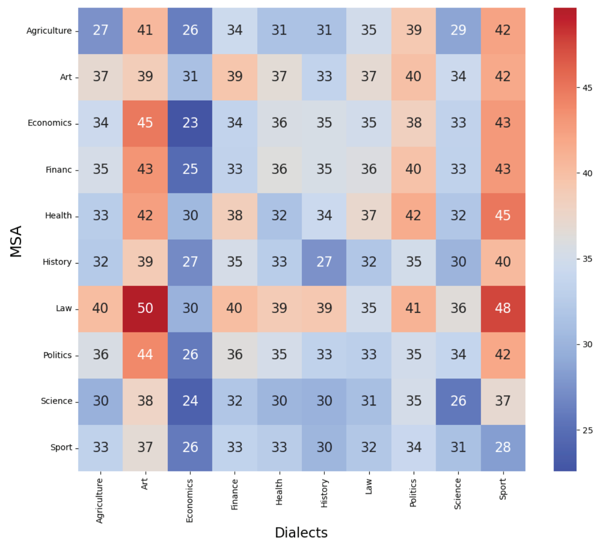


Figure 5: Heatmap showing the genre differences between the MSA and dialectal data.

5 NER Benchmarks using *Konooz*

This section benchmarks four state-of-the-art Arabic NER models in cross-domain and cross-dialect scenarios using *Konooz*. First, we conducted in-distribution evaluations by training and evaluating four models using their testing datasets ($Wojood_{Nested}$, $Wojood_{Flat}$, *OntoNotes* and *ANERCorp*). Second, we benchmarked these models against the 10 domains (out-of-domain evaluation) and the 16 dialects of *Konooz* (out-of-dialect evaluation). Since the four NER models follow different annotation guidelines, we mapped *Konooz* entity types to align with each training data accordingly. The mapping and the benchmarking preparations are provided in Appendix §A.6. We named the models based on their corresponding trained dataset.

5.1 Cross-Dialect Benchmarking

We benchmarked the four NER models across the 16 dialects of *Konooz*. As shown in Table 3, all models demonstrated a significant drop in performance when evaluated on *Konooz* (out-of-dialect). We observed performance degradation in cross-dialect evaluation ranging from 25% to 30%. There are multiple patterns can be observed. First, three dialects have demonstrated higher performance across all models, which are MSA, Lebanese, and Egyptian. $Wojood_{Nested}$ and $Wojood_{Flat}$ achieved the highest performance on *Konooz* MSA - about 20% performance degradation. This is expected since the majority of Wojood training data consists of MSA collected in the same period (2010-2024). The *OntoNotes* performed better on Lebanese, which could be because of the OntoNotes $2,099$ named entity mentions related to Lebanon. Similarly, the ANERCorp model performed better on Egyptian because ANERCorp covers more news related to Egypt. Based on insights from Figure 3a, it is expected that MSA is expected to be one of the top performing dialects as it is closely clustered with the training data of *Wojood*, *OntoNotes* , and *ANERCorp* .

Second, aside from the dialects we discussed above, we see significant drop in performance for all the other dialects across all NER models because most MMD scores between the training datasets and *Konooz* dialects are significantly high reaching 20s to mid 30s. The dialectal differences limit the models' ability to recognize and adapt to unfamiliar linguistic patterns, including variations in vocabulary, syntax, and morphological structures. As shown in Figures 3a and 4, the MSA embeddings (red clusters) are scattered away from those of other dialects, indicating poor alignment in the feature space. This misalignment illustrates the models' struggle to generalize across dialects without robust domain adaptation techniques to bridge the gap between different domains.

Third, differences in annotation guidelines influence performance. Since *Konooz* follows the *Wojood* guideline (Jarrar et al., 2022), this may partly explain why $Wojood_{Nested}$ and $Wojood_{Flat}$ performed better. Table 5 presents the micro F_1-score per entity for all four models. The entity type with the highest confidence across all models was GPE, likely because geopolitical entities (e.g., countries and cities) remain consistent across domains and dialects. Additionally, PERS and PERCENT achieved high scores, as person names and percentage values are easier to identify. Nested annotations add another layer of complexity by capturing hierarchical relationships, such as a "university" (organization) within a "city" (location), which can

NER Models	In-dialect Performance	MSA	Syria	Palestine	Lebanon	S. Arabia	Oman	Yemen	Iraq	Kuwait	Egypt	Sudan	Libya	Tunisia	Algeria	Morocco	Mauritania	Average	**Performance Degradation**
Wojood$_{Nested}$ (21 tags)	**92%**	**73%**	**55%**	**65%**	**68%**	**61%**	**61%**	**66%**	**67%**	**65%**	**68%**	**62%**	**64%**	**63%**	**65%**	**63%**	**55%**	**64%**	28%
Wojood$_{Flat}$ (21 tags)	90%	71%	49%	59%	62%	60%	56%	61%	62%	61%	61%	60%	60%	58%	55%	59%	52%	59%	30%
OntoNotes (18 tag)	68%	45%	37%	41%	51%	42%	42%	41%	40%	45%	45%	44%	39%	38%	41%	46%	29%	42%	26%
ANERCorp (3 tags)	84%	58%	46%	45%	64%	54%	43%	58%	54%	54%	66%	55%	48%	41%	36%	38%	37%	59%	25%

Table 3: Micro-F_1, NER models trained on datasets (in-dialect) and benchmarked on *Konooz* dialects (out-of-dialect). *Wojood$_{Nested}$* is the model trained on the nested version of Wojood dataset, *Wojood$_{Flat}$* is trained on the flat version of Wojood, *ANERCorp* is trained on the ANERCorp dataset, and *OntoNotes* is trained on the OntoNotes dataset.

NER Models	In-domain Performance	Politics	Economics	Finance	History	Law	Science	Health	Agriculture	Art	Sport	**Average**	**Performance Degradation**
Wojood$_{Nested}$ (21 tags)	**92%**	**68%**	**66%**	**66%**	**68%**	**65%**	63%	**67%**	**62%**	**63%**	**59%**	**63%**	29%
Wojood$_{Flat}$ (21 tags)	90%	64%	60%	58%	66%	59%	**64%**	65%	60%	60%	54%	60%	30%
OntoNotes (18 tags)	68%	42%	35%	34%	39%	36%	35%	39%	35%	43%	43%	37%	31%
ANERCorp (3 tags)	84%	48%	46%	40%	53%	41%	41%	40%	48%	54%	48%	46%	38%

Table 4: Micro-F_1, NER models trained on datasets (in-domain) and benchmarked on *Konooz* domains (out-domain).

Tag	*Wojood$_{Nested}$*	*Wojood$_{Flat}$*	*OntoNotes*	*ANERCorp*
CARDINAL	0.5552	0.5605	0.1754	-
CURR	0.7853	0.0089	-	-
DATE	0.6165	0.5646	0.3508	-
EVENT	0.3531	0.3160	0.1835	-
FAC	0.4378	0.4641	0.2775	-
GPE	0.8298	0.7775	0.5422	-
LANGUAGE	0.4811	0.4991	0.0000	-
LAW	0.3478	0.1809	0.1044	-
LOC	0.4798	0.5313	0.1296	0.6403
MONEY	0.6442	0.6274	0.4517	-
NORP	0.5923	0.5774	0.2450	-
OCC	0.6293	0.5790	-	-
ORDINAL	0.6176	0.5922	0.4760	-
ORG	0.5539	0.5362	0.4033	0.2769
PERCENT	0.6752	0.7633	0.0811	
PERS	0.7271	0.7317	0.5365	0.5503
PRODUCT	0.0143	0.0184	0.0000	-
QUANTITY	0.2577	0.5770	0.3776	-
TIME	0.4242	0.4446	0.0739	-
UNIT	0.3780	0.0000	-	-
WEBSITE	0.3056	0.2774	-	-
Micro F_1	0.6316	0.6065	0.3702	0.4600
Macro F_1	0.4458	0.4585	0.2449	0.3892

Table 5: Micro F_1-score per entity in *Konooz*, across all dialects and domains.

vary across dialects. On the other hand, the lowest confidence for `EVENT`, `LAW`, `PRODUCT`, and `WEBSITE`, is likely due to their higher domain specificity.

5.2 Cross-Domain Benchmarking

We benchmarked state-of-the-art Arabic NER models across the 10 domains of *Konooz*. The results are summarized in Table 4. While *Wojood$_{Nested}$* achieved the highest performance (63%), all models showed significant performance degradation in out-of-domain evaluations, with drops ranging from 29% to 38%. *Wojood$_{Nested}$* and *Wojood$_{Flat}$* excelled in the history domain, which is the domain with the lowest MMD score to *Wojood* as shown in Figure 3b. This is not surprising as the Wojood training data was sourced from Awraq, the Birzeit University digital Palestinian archive, which covers modern history and cultural heritage.

Similar to the dialects, the performance degradation across the four models can be attributed to domain shift. As shown in Figure 3b, the MMD between *Konooz* and the training datasets is significant. This degradation is driven by significant statistical differences between the training and out-of-domain data, explaining the performance drop across all four models. These models lack domain-invariant features, which severely limits their ability to generalize beyond the specific characteristics of the out-of-domain data and ultimately hinders their performance. Additionally, as shown in Figure 11 in Appendix 7, the *Konooz* domains are scattered inconsistently, emphasizing the significant domain shift between *Konooz* domains.

5.3 Discussion

Although lexical similarity provides some indication of model performance, it cannot be directly leveraged to enhance that performance. For example, *Wojood* and the Iraqi corpus are lexically dissimilar (in Figure 3a), however, *Wojood* still achieved relatively-good results in recognizing named entities in the Iraqi corpus (Table 3). After reviewing all cases manually, we found that many of the names of people and geographical places are often shared and recognizable across both MSA/Wojood and Iraqi. This suggests that high lexical dissimilarity does not necessarily lead to poor NER performance. For example, many phrases related to Iraq (Iraq العراق *ālʿrāq* , Iraqi العراقي *ālʿrāqy* , اطفال العراق *āṭfāl ālʿrāq* Iraqi children) appear over 700 times in *Wojood*, which contributes to enhancing the performance of the model. Moreover, *Wojood* includes Palestinian and Lebanese data; however, this subset represents only 12% of the corpus. As a result, the lexical distances for these dialects are not the lowest in Figure 3a.

Furthermore, the improved performance of *OntoNotes* on Lebanese and *ANERCorp* on Egyptian may be better explained by entity coverage rather than overall lexical similarity. *ANERCorp* achieved the best result on Egyptian dialect with an F_1 of 66% , while *OntoNotes* obtained the best result on Lebanese, with F_1 of 51%. The *ANERCorp* and *OntoNotes* models are both trained primarily on MSA news. *ANERCorp* performs better on Egyptian, likely because it is trained on data with Egyptian content, particularly from news sources. Similarly, *OntoNotes* performs better on Lebanese, as it includes 2,099 named entities related to Lebanon. As noted, Figure 3a does not indicate low lexical distances for these pairs, suggesting that general language overlap is not the main factor. This supports our hypothesis that having named entities from the same country or region in the training data improves model performance, regardless of dialectal or lexical proximity.

6 Conclusion

We presented *Konooz*, a novel multi-dimensional corpus covering 16 dialects across 10 domains, resulting in 160 distinct corpora (777k tokens) annotated with 21 entity types. Our in-depth lexical similarity analysis reveals both distinctions and similarities across different domains and dialects. Our benchmarking of four Arabic NER models in cross-domain and cross-dialect scenarios highlighted the challenges inherent to Arabic dialects, revealing that models trained on MSA struggle to generalize effectively to dialectal Arabic.

Limitations

Although various measures were implemented to ensure the consistency and quality of the annotations, the annotation process was carried out by non-native speakers. Furthermore, AraBERTv2 embeddings were utilized to calculate MMD, which may influence the results due to model-specific embedding characteristics. Comparing the results obtained using other models, such as CamelBERT, ArBERT, and LLMs, would provide a broader perspective on performance and help identify the most effective embeddings for capturing cross-domain and cross-dialect variations. Moreover, the WojoodNER tokenizer is based on the AraBERT tokenizer, which is primarily trained on MSA text. This affects its ability to tokenize dialectal Arabic effectively, as it may struggle with out-of-vocabulary words. Additionally, our evaluations are influenced by the mappings between the three NER tagsets (*Wojood*, *OntoNotes* and *ANERCorp*) and the *Konooz* annotation guidelines.

7 Ethical Considerations

Konooz was collected from publicly available sources, including Facebook, X, YouTube, and blogs. However, we manually reviewed the content to avoid including private or sensitive information.

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References

Moustafa Al-Hajj and Mustafa Jarrar. 2021. ArabGlossBERT: Fine-Tuning BERT on Context-Gloss Pairs for WSD. In Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2021), pages 40–48, Online. INCOMA Ltd.

Alaa Aljabari, Lina Duaibes, Mustafa Jarrar, and Mohammed Khalilia. 2024. Event-Arguments Extraction Corpus and Modeling using BERT for Arabic. In Proceedings of the Second Arabic Natural Language Processing Conference (ArabicNLP 2024), Bangkok, Thailand. Association for Computational Linguistics.

Wissam Antoun, Fady Baly, and Hazem M. Hajj. 2020. Arabert: Transformer-based model for arabic language understanding. CoRR, abs/2003.00104.

Osama Badawy, Mohamed Shaheen, and Abdelbaki Hamadene. 2011. Arqa: An intelligent arabic question answering system. In Proceedings of Arabic Language Technology International Conference (ALTIC 2011), pages 1–8.

Sylvio Barbon Junior, Paolo Ceravolo, Sven Groppe, Mustafa Jarrar, Samira Maghool, Florence Sèdes, Soror Sahri, and Maurice Van Keulen. 2024. Are Large Language Models the New Interface for Data Pipelines? In Proceedings of the International Workshop on Big Data in Emergent Distributed Environments, BiDEDE '24, New York, NY, USA. Association for Computing Machinery.

Shai Ben-David, John Blitzer, Koby Crammer, Alex Kulesza, Fernando Pereira, and Jennifer Wortman Vaughan. 2010. A theory of learning from different domains. Mach. Learn., 79(1-2):151–175.

Yassine Benajiba, Paolo Rosso, and José Miguel Benedíruiz. 2007. Anersys: An arabic named entity recognition system based on maximum entropy. In Computational Linguistics and Intelligent Text Processing: 8th International Conference, CICLing 2007, Mexico City, Mexico, February 18-24, 2007. Proceedings 8, pages 143–153. Springer.

Jacob Cohen. 1960. A coefficient of agreement for nominal scales. Educational and psychological measurement, 20(1):37–46.

Abdelhalim Hafedh Dahou and Mohamed Amine Cheragui. 2023. Dzner: A large algerian named entity recognition dataset. Natural Language Processing Journal, 3:100005.

Xiang Dai, Sarvnaz Karimi, Ben Hachey, and Cécile Paris. 2019. Using similarity measures to select pretraining data for NER. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 1460–1470. Association for Computational Linguistics.

Kareem Darwish, Nizar Habash, Mourad Abbas, Hend Al-Khalifa, Huseein T. Al-Natsheh, Houda Bouamor, Karim Bouzoubaa, Violetta Cavalli-Sforza, Samhaa R. El-Beltagy, Wassim El-Hajj, Mustafa Jarrar, and Hamdy Mubarak. 2021. A Panoramic survey of Natural Language Processing in the Arab Worlds. Commun. ACM, 64(4):72–81.

Arthur Gretton, Karsten M. Borgwardt, Malte J. Rasch, Bernhard Schölkopf, and Alexander J. Smola. 2008. A kernel method for the two-sample problem. CoRR, abs/0805.2368.

Karim El Haff, Mustafa Jarrar, Tymaa Hammouda, and Fadi Zaraket. 2022. Curras + Baladi: Towards a Levantine Corpus. In Proceedings of the International Conference on Language Resources and Evaluation(LREC 2022), Marseille, France.

Tymaa Hammouda, Mustafa Jarrar, and Mohammed Khalilia. 2024. SinaTools: Open Source Toolkit for Arabic Natural Language Understanding. In Proceedings of the 2024 AI in Computational Linguistics (ACLING 2024), Procedia Computer Science, Dubai. ELSEVIER.

Hany Hassan and Jeffrey Sorensen. 2005. An integrated approach for arabic-english named entity translation. In Proceedings of the Workshop on Computational Approaches to Semitic Languages, SEMITIC@ACL 2005, Ann Arbor, MI, USA, June 29, 2005, pages 87–93. Association for Computational Linguistics.

George Hripcsak and Adam S. Rothschild. 2005. Technical brief: Agreement, the f-measure, and reliability in information retrieval. J. Am. Medical Informatics Assoc., 12(3):296–298.

Mustafa Jarrar. 2021. The Arabic Ontology - An Arabic Wordnet with Ontologically Clean Content. Applied Ontology Journal, 16(1):1–26.

Mustafa Jarrar, Muhammad Abdul-Mageed, Mohammed Khalilia, Bashar Talafha, AbdelRahim Elmadany, Nagham Hamad, and Alaa' Omar. 2023a. WojoodNER 2023: The First Arabic Named Entity Recognition Shared Task. In Proceedings of the 1st Arabic Natural Language Processing Conference (ArabicNLP), Part of the EMNLP 2023, pages 748–758. ACL.

Mustafa Jarrar, Anton Deik, and Bilal Faraj. 2011. Ontology-based data and process governance framework -the case of e-government interoperability in palestine. In Proceedings of the IFIP International Symposium on Data-Driven Process Discovery and Analysis (SIMPDA'11), pages 83–98.

Mustafa Jarrar, Nizar Habash, Faeq Alrimawi, Diyam Akra, and Nasser Zalmout. 2017. Curras: An annotated corpus for the palestinian arabic dialect. Journal Language Resources and Evaluation, 51(3):2-s2.0-85001544989.

Mustafa Jarrar, Nizar Habash, Mo El-Haj, Amal Haddad Haddad, Zeina Jallad, Camille Mansour, Diana Allan, Paul Rayson, Tymaa Hammouda, and Sanad Malaysha, editors. 2025. Proceedings of the first International Workshop on Nakba Narratives as Language Resources. Association for Computational Linguistics, Abu Dhabi, UAE.

Mustafa Jarrar, Nagham Hamad, Mohammed Khalilia, Bashar Talafha, AbdelRahim Elmadany, and Muhammad Abdul-Mageed. 2024. WojoodNER 2024: The Second Arabic Named Entity Recognition Shared Task. In Proceedings of the Second Arabic Natural Language Processing Conference (ArabicNLP 2024), Bangkok, Thailand. Association for Computational Linguistics.

Mustafa Jarrar and Tymaa Hasanain Hammouda. 2024. Qabas: An Open-Source Arabic Lexicographic Database. In Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024), pages 13363–13370, Torino, Italy. ELRA and ICCL.

Mustafa Jarrar, Mohammed Khalilia, and Sana Ghanem. 2022. Wojood: Nested Arabic Named Entity Corpus and Recognition using BERT. In Proceedings of the International Conference on Language Resources and Evaluation (LREC 2022), Marseille, France.

Mustafa Jarrar, Sanad Malaysha, Tymaa Hammouda, and Mohammed Khalilia. 2023b. SALMA: Arabic Sense-annotated Corpus and WSD Benchmarks. In Proceedings of the 1st Arabic Natural Language Processing Conference (ArabicNLP), Part of the EMNLP 2023, pages 359–369. ACL.

Mustafa Jarrar, Fadi Zaraket, Tymaa Hammouda, Daanish Masood Alavi, and Martin Waahlisch. 2023c. Lisan: Yemeni, Irqi, Libyan, and Sudanese Arabic Dialect Copora with Morphological Annotations. In The 20th IEEE/ACS International Conference on Computer Systems and Applications (AICCSA), pages 1–7. IEEE.

Chen Jia, Liang Xiao, and Yue Zhang. 2019. Cross-domain NER using cross-domain language modeling. In Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers, pages 2464–2474. Association for Computational Linguistics.

Abhinav Ramesh Kashyap, Devamanyu Hazarika, Min-Yen Kan, and Roger Zimmermann. 2021. Domain divergences: A survey and empirical analysis. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pages 1830–1849. Association for Computational Linguistics.

Amr Keleg, Sharon Goldwater, and Walid Magdy. 2023. Aldi: Quantifying the arabic level of dialectness of text. arXiv preprint arXiv:2310.13747.

Mohammed Khalilia, Sanad Malaysha, Reem Suwaileh, Mustafa Jarrar, Alaa Aljabari, Tamer Elsayed, and Imed Zitouni. 2024. ArabicNLU 2024: The First Arabic Natural Language Understanding Shared Task. In Proceedings of the Second Arabic Natural Language Processing Conference (ArabicNLP 2024), Bangkok, Thailand. Association for Computational Linguistics.

Niama El Khbir, Urchade Zaratiana, Nadi Tomeh, and Thierry Charnois. 2023. Cross-dialectal named entity recognition in arabic. In Proceedings of ArabicNLP 2023, Singapore (Hybrid), December 7, 2023, pages 140–149. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Haneen Liqreina, Mustafa Jarrar, Mohammed Khalilia, Ahmed Oumar El-Shangiti, and Muhammad Abdul-Mageed. 2023. Arabic Fine-Grained Entity Recognition. In Proceedings of the 1st Arabic Natural Language Processing Conference (ArabicNLP), Part of the EMNLP 2023, pages 310–323. ACL.

Abdellah El Mekki, Abdelkader El Mahdaouy, Ismail Berrada, and Ahmed Khoumsi. 2022. Adasl: An unsupervised domain adaptation framework for arabic multi-dialectal sequence labeling. Inf. Process. Manag., 59(4):102964.

Hanane Nour Moussa and Asmaa Mourhir. 2023. Darnercorp: An annotated named entity recognition dataset in the moroccan dialect. Data in Brief, 48:109234.

Amal Nayouf, Mustafa Jarrar, Fadi zaraket, Tymaa Hammouda, and Mohamad-Bassam Kurdy. 2023. Nâbra: Syrian Arabic Dialects with Morphological Annotations. In Proceedings of the 1st Arabic Natural Language Processing Conference (ArabicNLP), Part of the EMNLP 2023, pages 12–23. ACL.

Ossama Obeid, Nasser Zalmout, Salam Khalifa, Dima Taji, Mai Oudah, Bashar Alhafni, Go Inoue, Fadhl Eryani, Alexander Erdmann, and Nizar Habash. 2020. Camel tools: An open source python toolkit for arabic natural language processing. In Proceedings of The 12th Language Resources and Evaluation Conference, LREC 2020, Marseille, France, May 11-16, 2020, pages 7022–7032. European Language Resources Association.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. Pytorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc.

Siyao Peng, Zihang Sun, Huangyan Shan, Marie Kolm, Verena Blaschke, Ekaterina Artemova, and Barbara Plank. 2024. Sebastian, basti, wastl?! recognizing named entities in bavarian dialectal data. In Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation, LREC/COLING 2024, 20-25 May, 2024, Torino, Italy, pages 14478–14493. ELRA and ICCL.

Nick Pogrebnyakov and Shohreh Shaghaghian. 2021. Predicting the success of domain adaptation in text similarity. In Proceedings of the 6th Workshop on Representation Learning for NLP

(RepL4NLP-2021), pages 206–212, Online. Association for Computational Linguistics.

Peeyush Singhal, Rahee Walambe, Sheela Ramanna, and Ketan Kotecha. 2023. Domain adaptation: Challenges, methods, datasets, and applications. IEEE Access.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(56):1929–1958.

Bashar Talafha, Karima Kadaoui, Samar Mohamed Magdy, Mariem Habiboullah, Chafei Mohamed Chafei, Ahmed Oumar El-Shangiti, Hiba Zayed, Mohamedou Cheikh Tourad, Rahaf Alhamouri, Rwaa Assi, Aisha Alraeesi, Hour Mohamed, Fakhraddin Alwajih, Abdelrahman Mohamed, Abdellah El Mekki, El Moatez Billah Nagoudi, Benelhadj Djelloul Mama Saadia, Hamzah A. Alsayadi, Walid Al-Dhabyani, Sara Shatnawi, Yasir Ech-chammakhy, Amal Makouar, Yousra Berrachedi, Mustafa Jarrar, Shady Shehata, Ismail Berrada, and Muhammad Abdul-Mageed. 2024. Casablanca: Data and Models for Multidialectal Arabic Speech Recognition. In Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, Miami, Florida, USA. Association for Computational Linguistics.

Samia Touileb. 2022. Nerdz: A preliminary dataset of named entities for algerian. In Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing, AACL/IJCNLP 2022 - Volume 2: Short Papers, Online only, November 20-23, 2022, pages 95–101. Association for Computational Linguistics.

Sowmya Vajjala and Ramya Balasubramaniam. 2022. What do we really know about state of the art NER? In Proceedings of the Thirteenth Language Resources and Evaluation Conference, pages 5983–5993, Marseille, France. European Language Resources Association.

Ralph Weischedel, Martha Palmer, Mitchell Marcus, Eduard Hovy, Sameer Pradhan, Lance Ramshaw, Nianwen Xue, Ann Taylor, Jeff Kaufman, Michelle Franchini, Mohammed El-Bachouti, Robert Belvin, and Ann Houston. 2013a. Ontonotes release 5.0 ldc2013t19. In Technical report, Linguistic Data Consortium.

Ralph Weischedel, Sameer Pradhan, Lance Ramshaw, Martha Palmer, Nianwen Xue, Mitchell Marcus, Ann Taylor, Craig Greenberg, Eduard Hovy, Robert Belvin, et al. 2013b. Ontonotes release 5.0. LDC2011T03, Philadelphia, Penn.: Linguistic Data Consortium.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Ayah Zirikly and Mona T. Diab. 2014. Named entity recognition system for dialectal arabic. In Proceedings of the EMNLP 2014 Workshop on Arabic Natural Language Processing, ANLP@EMNLP 20104, Doha, Qatar, October 25, 2014, pages 78–86. Association for Computational Linguistics.

A Appendix

A.1 Named Entity classes

The *Konooz* dataset was annotated with 21 entity types, as summarized in Table 6, which provides brief descriptions and examples for each type.

A.2 Human-In-The-Loop NER Model

The purpose of the Human-In-The-Loop NER Mode is to assess *Konooz* annotation consistency and quality. For this model, we utilized the *Wojood* dataset (Jarrar et al., 2022), *Wojood*^{Gaza} provided in Subtask 3 of the WojoodNER 2024 shared task (Jarrar et al., 2024), and the initial version of the annotated *Konooz* dataset.

The Wojood dataset is divided into training (385k tokens, 70%), validation (55k tokens, 10%), and test (110k tokens, 20%) sets. The *Wojood*^{Gaza} dataset includes 60k tokens, collected and annotated specifically for the shared task. Additionally, the *Konooz* dataset contains $553,844$ tokens. All datasets adhere to the CoNLL format. For training, we used the training splits from *Wojood*, *Wojood*^{Gaza}, and *Konooz*, while the validation and test splits from *Wojood* were used for model evaluation. The total size of training data is $1,265,144$ tokens.

We fine-tuned AraBERTv2 (Antoun et al., 2020) on nested NER tasks with a learning rate of $\eta = 1e^{-5}$, a batch size of 8, and a maximum of 50 epochs, employing early stopping if validation performance did not improve for five consecutive epochs. The model generally converged around epoch 39. The source code is publicly available on GitHub[1].

[1] https://github.com/SinaLab/ArabicNER

Tag	Short Description
PERS	People names, - first, middle, last, and nicknames. Titles are not included except Prophets, kings.
NORP	Group of people.
OCC	Occupation or professional title.
ORG	Legal or social bodies - institutions, companies, academies, teams, parties, armies, governments.
GPF	Geopolitical entities like countries, cities, and states.
LOC	Geographical locations (Non-GPE), rivers, seas, mountains, and other geographical regions.
FAC	Name of a specific place, like roads, cafes, buildings, airports, and gates.
PRODUCT	Vehicles, weapons, foods, etc.
EVENT	Name of an event of general interest, - battles, wars, sports events, demonstrations, disasters, conferences, national/religious days. Place and date are included in the event name.
DATE	Reference to specific or relative dates including day, era, duration, month, and year. Characters to separate date components are part of the tag.
TIME	Specific or relative times which is less than a day, including day times like evening and night.
LANGUAGE	Named human language or named dialect.
WEBSITE	Any named website or specific URL.
LAW	Reference to legal text like a constitution, acts, contracts, or agreements.
CARDINAL	Numerals written in digits or words.
ORDINAL	Any ordinal number, digits or words, that does not refer to a quantity.
PERCENT	A word or a symbol referring to a percent.
QUANTITY	Any value measured by standard units, except dates, times, and money.
UNIT	A word or symbol referring to a unit.
MONEY	Absolute monetary value, including currency names.
CURR	Any name or symbol referring to currency.

Table 6: *Konooz*entity types and their description.

A.3 Maximum Mean Discripancy

MMD compares the distributions of two datasets by first projecting the data into Reproducing Kernel Hilbert Space (RKHS) and then computes the mean distance between two distributions in Hilbert Space. Formally, the MMD is defined as follows:

$$MMD(X,Y) = ||\frac{1}{m}\sum \phi(x_i) - \frac{1}{n}\sum \phi(y_i)||_H \quad (1)$$

where X and Y are two probability distributions between two different domains or dialects, x_i and y_i are the CLS token representation returned by the transformer, and $\phi : X \to H$ is the nonlionear projection to feature representation in RKHS. We experimented with two different kernels, linear and polynomial.

A.4 Inter-Annotator Agreement

Table 7 presents the IAA at the dialect level in *Konooz*.

Dialect	TP	FN	FP	K	F_1-Score
MSA	6948	64	61	0.9835	0.9825
Syria	3478	6	8	0.9952	0.9948
Palestine	2772	14	15	0.9687	0.9677
Lebanon	3445	2	2	0.9953	0.9953
S.Arabia	3814	35	41	0.9611	0.9594
Oman	3408	9	9	0.9628	0.9626
Yemen	55080	249	264	0.9848	0.9857
Iraq	3458	30	37	0.9192	0.9652
Kuwait	587	0	1	0.9979	0.9978
Egypt	3282	4	4	0.9511	0.9960
Sudan	3421	20	21	0.9814	0.9802
Libya	3426	7	8	0.9928	0.9927
Tunisia	3415	23	22	0.9821	0.9817
Algeria	2874	3	3	0.9979	0.9970
Morocco	3921	0	0	1	1
Mauritania	3413	20	18	0.9071	0.9066

Table 7: Overall IAA for each dialect in *Konooz*

A.5 *Konooz* Lexical Similarity and Statistics

This section covers the MMD analysis between dialects and domains using a polynomial kernel, along with word-level lexical similarity calculated using the Jaccard coefficient and cosine similarity. It also includes a t-SNE plot visualizing domain distributions and concludes with a detailed summary of the number of entities within each domain and dialect. The most basic metrics to measure similarity are the Jaccard similarity coefficient and cosine similarity. The Jaccard coefficient similarity is computed using unique words for each dialect and domain, while cosine similarity is measured based on sentence embeddings. However, we found that these methods did not differentiate between dialects or domains. For example, Figures 9 and 10 show that all dialects are homogeneous, exhibiting similar level of overlap (we observed same behavior for domains).

Tag	Politics	Economics	Finance	History	Law	Science	Health	Agriculture	Art	Sport	Total
PERS	1094 / 101	510 / 43	335 / 29	1822 / 237	588 / 62	427 / 24	274 / 30	186 / 22	2863 / 58	1465 / 46	9564 / 652
ORG	1354 / 165	1001 / 120	1141 / 110	467 / 63	902 / 176	857 / 138	509 / 148	164 / 16	261 / 46	1856 / 231	8512 / 1213
LOC	254 / 18	160 / 9	68 / 11	542 / 48	71 / 8	61 / 7	39 / 11	256 / 13	114 / 12	115 / 98	1680 / 235
GPE	1524 / 288	1214 / 140	776 / 240	2435 / 304	554 / 104	529 / 216	623 / 124	996 / 68	652 / 116	644 / 369	9947 / 1969
NORP	1739 / 63	1002 / 29	678 / 14	2930 / 101	1155 / 87	717 / 26	892 / 35	383 / 9	991 / 18	1096 / 112	11583 / 494
CARDINAL	519 / 7	856 / 23	932 / 5	561 / 14	702 / 12	568 / 2	590 / 4	757 / 12	472 / 3	807 / 10	6764 / 92
ORDINAL	337 / 20	312 / 22	296 / 20	455 / 58	393 / 74	536 / 37	425 / 20	488 / 30	518 / 23	590 / 40	4350 / 344
OCC	696 / 12	501 / 4	370 / 2	520 / 18	775 / 30	554 / 4	821 / 7	320 / 1	777 / 5	936 / 8	6270 / 91
FAC	65 / 5	51 / 1	27 / 0	270 / 10	37 / 0	22 / 3	70 / 1	59 / 0	80 / 4	76 / 4	757 / 28
PRODUCT	25 / 2	35 / 1	148 / 1	26 / 0	14 / 0	267 / 1	53 / 0	35 / 0	117 / 4	26 / 1	746 / 10
EVENT	251 / 11	121 / 3	64 / 3	285 / 12	143 / 2	62 / 1	40 / 3	27 / 1	163 / 9	456 / 21	1612 / 66
DATE	471 / 41	871 / 20	841 / 16	1128 / 29	605 / 18	581 / 10	666 / 14	999 / 2	820 / 13	544 / 32	7526 / 195
TIME	177 / 0	214 / 1	195 / 0	443 / 2	166 / 1	206 / 0	305 / 0	254 / 0	240 / 0	232 / 0	2432 / 4
LANGUAGE	8 / 0	7 / 0	10 / 0	104 / 2	18 / 0	102 / 0	5 / 0	4 / 0	48 / 0	9 / 0	315 / 2
WEBSITE	31 / 0	34 / 0	60 / 1	17 / 0	22 / 1	169 / 2	15 / 0	14 / 0	40 / 0	8 / 0	410 / 4
LAW	10 / 0	29 / 0	21 / 1	7 / 0	277 / 2	3 / 0	9 / 0	8 / 0	2 / 0	3 / 0	369 / 3
PERCENT	33 / 0	241 / 3	203 / 0	14 / 0	51 / 0	42 / 0	62 / 0	129 / 1	23 / 0	12 / 0	810 / 4
QUANTITY	20 / 0	112 / 3	19 / 1	30 / 0	5 / 0	49 / 4	43 / 0	526 / 3	8 / 0	15 / 2	827 / 13
UNIT	2 / 20	62 / 107	4 / 18	6 / 29	3 / 5	4 / 48	5 / 44	35 / 478	4 / 8	0 / 16	125 / 773
MONEY	27 / 5	496 / 19	460 / 30	19 / 2	88 / 4	54 / 0	39 / 1	234 / 3	45 / 0	33 / 3	1495 / 67
CURR	27 / 26	396 / 352	360 / 407	16 / 10	21 / 79	16 / 40	9 / 38	87 / 129	37 / 21	5 / 26	974 / 1128
Total	8664 / 784	8225 / 900	7008 / 909	12097 / 939	6590 / 665	5826 / 563	5494 / 480	5961 / 788	8275 / 340	8928 / 1019	77068 / 7387

Table 8: Total number of entities in each dialect in flat/nested.

Tag	Politics	Economics	Finance	History	Law	Science	Health	Agriculture	Art	Sport	Total
PERS	1094 / 101	510 / 43	335 / 29	1822 / 237	588 / 62	427 / 24	274 / 30	186 / 22	2863 / 58	1465 / 46	9564 / 652
ORG	1354 / 165	1001 / 120	1141 / 110	467 / 63	902 / 176	857 / 138	509 / 148	164 / 16	261 / 46	1856 / 231	8512 / 1213
LOC	254 / 18	160 / 9	68 / 11	542 / 48	71 / 8	61 / 7	39 / 11	256 / 13	114 / 12	115 / 98	1680 / 235
GPE	1524 / 288	1214 / 140	776 / 240	2435 / 304	554 / 104	529 / 216	623 / 124	996 / 68	652 / 116	644 / 369	9947 / 1969
NORP	1739 / 63	1002 / 29	678 / 14	2930 / 101	1155 / 87	717 / 26	892 / 35	383 / 9	991 / 18	1096 / 112	11583 / 494
CARDINAL	519 / 7	856 / 23	932 / 5	561 / 14	702 / 12	568 / 2	590 / 4	757 / 12	472 / 3	807 / 10	6764 / 92
ORDINAL	337 / 20	312 / 22	296 / 20	455 / 58	393 / 74	536 / 37	425 / 20	488 / 30	518 / 23	590 / 40	4350 / 344
OCC	696 / 12	501 / 4	370 / 2	520 / 18	775 / 30	554 / 4	821 / 7	320 / 1	777 / 5	936 / 8	6270 / 91
FAC	65 / 5	51 / 1	27 / 0	270 / 10	37 / 0	22 / 3	70 / 1	59 / 0	80 / 4	76 / 4	757 / 28
PRODUCT	25 / 2	35 / 1	148 / 1	26 / 0	14 / 0	267 / 1	53 / 0	35 / 0	117 / 4	26 / 1	746 / 10
EVENT	251 / 11	121 / 3	64 / 3	285 / 12	143 / 2	62 / 1	40 / 3	27 / 1	163 / 9	456 / 21	1612 / 66
DATE	471 / 41	871 / 20	841 / 16	1128 / 29	605 / 18	581 / 10	666 / 14	999 / 2	820 / 13	544 / 32	7526 / 195
TIME	177 / 0	214 / 1	195 / 0	443 / 2	166 / 1	206 / 0	305 / 0	254 / 0	240 / 0	232 / 0	2432 / 4
LANGUAGE	8 / 0	7 / 0	10 / 0	104 / 2	18 / 0	102 / 0	5 / 0	4 / 0	48 / 0	9 / 0	315 / 2
WEBSITE	31 / 0	34 / 0	60 / 1	17 / 0	22 / 1	169 / 2	15 / 0	14 / 0	40 / 0	8 / 0	410 / 4
LAW	10 / 0	29 / 0	21 / 1	7 / 0	277 / 2	3 / 0	9 / 0	8 / 0	2 / 0	3 / 0	369 / 3
PERCENT	33 / 0	241 / 3	203 / 0	14 / 0	51 / 0	42 / 0	62 / 0	129 / 1	23 / 0	12 / 0	810 / 4
QUANTITY	20 / 0	112 / 3	19 / 1	30 / 0	5 / 0	49 / 4	43 / 0	526 / 3	8 / 0	15 / 2	827 / 13
UNIT	2 / 20	62 / 107	4 / 18	6 / 29	3 / 5	4 / 48	5 / 44	35 / 478	4 / 8	0 / 16	125 / 773
MONEY	27 / 5	496 / 19	460 / 30	19 / 2	88 / 4	54 / 0	39 / 1	234 / 3	45 / 0	33 / 3	1495 / 67
CURR	27 / 26	396 / 352	360 / 407	16 / 10	21 / 79	16 / 40	9 / 38	87 / 129	37 / 21	5 / 26	974 / 1128
Total	8664 / 784	8225 / 900	7008 / 909	12097 / 939	6590 / 665	5826 / 563	5494 / 480	5961 / 788	8275 / 340	8928 / 1019	77068 / 7387

Table 9: Total number of entities in each domain in flat/nested.

A.6 Training Models for Benchmarking

We trained four models, one for each dataset. Following (Obeid et al., 2020), we addressed the absence of a development set in *ANERCorp* by creating three different data splits, each including train, test, and development sets. We followed a similar approach for the *OntoNotes* model by generating three distinct data splits. For the *Wojood* dataset, we used the official splits and source code (Jarrar et al., 2022). We then fine-tuned the pre-trained models on all splits, ensuring consistency by using the same hyperparameters specified in (Obeid et al., 2020).

We also trained all datasets ($Wojood_{Nested}$, $Wojood_{Flat}$, *ANERCorp* , and *OntoNotes*) using AraBERTv1, AraBERTv2, and ArBERT. Table 10 presents the results of all datasets trained on three different pre-trained models.

All models were implemented using HuggingFace Transformers (Wolf et al., 2020) and PyTorch (Paszke et al., 2019). We used Adam optimizer (Kingma and Ba, 2014) and a dropout rate of 0.1 (Srivastava et al., 2014). We fine-tuned the aforementioned pre-trained models using the hyperparameters presented in Table 11. Fine-tuning each model required approximately 6 hours, utilizing a system with a 1.2TB disk, 62Gi of memory, and 2 NVIDIA T4 GPUs.

After training, for each training data, we selected the best-performing split and pre-trained model based on results from the test sets.

Model	$Wojood_{Nested}$	$Wojood_{Flat}$	*ANERCorp*	*OntoNotes*
ArBERT	**91.73**	**89.71**	83.46	66.88
AraBERTv2	91.06	87.3	79.02	67.33
AraBERTv1	87.6	87.37	**83.5**	**67.73**

Table 10: The micro F1-score baseline for each model.

A.6.1 Preparing Benchmark Datasets

Since each dataset uses a different set of entity types, we aligned *Konooz* entity tags with those of other datasets to ensure consistency. *Konooz*, adhering to the *Wojood* guidelines (Jarrar et al., 2022), includes 21 entity types, requiring no mapping. The *OntoNotes* dataset overlaps significantly but lacks certain tags, such as `OCC`, `WEBSITE`, `UNIT`, and `CURR`. In contrast, *ANERCorp* uses only four

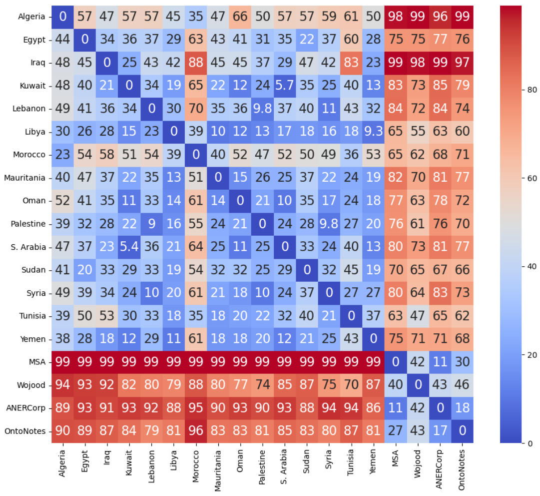

Figure 6: Heatmap showing the distances between different dialects in *Konooz* using MMD Polynomial kernel.

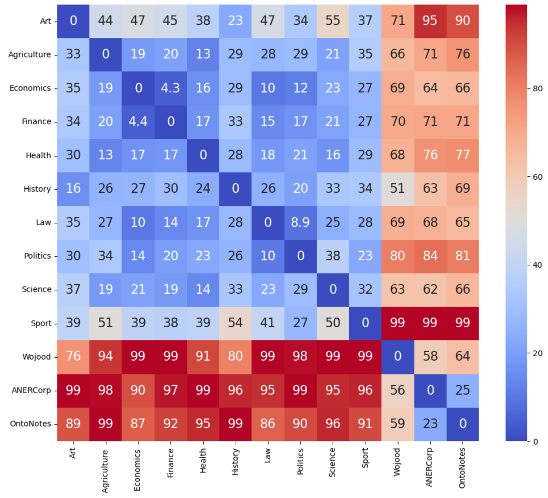

Figure 7: Heatmap showing the distances between different domains in *Konooz* using MMD Polynomial kernel.

tags (PERS, ORG, LOC, and MISC). To address this, we mapped *Konooz* entity types to the corresponding tags in *OntoNotes* and *ANERCorp* , ensuring compatibility and facilitating cross-dataset analysis.

For the *ANERCorp* model, *Konooz* tags were mapped to O, except GPE and FAC, which were mapped to LOC. The MISC tag in *ANERCorp* was also mapped to O, as *Konooz* does not support it. The *OntoNotes* dataset does not support the tags OCC, WEBSITE, UNIT, and CURR, which were mapped to O in *Konooz*.

	Model	Batch size	LR	Epochs
ANERCorp	AraBERTv1	32	$5e^{-5}$	3
OntoNotes	AraBERTv1	8	$5e^{-5}$	50

Table 11: Hyperparamters of best models of the *ANERCorp* and *OntoNotes* datasets.

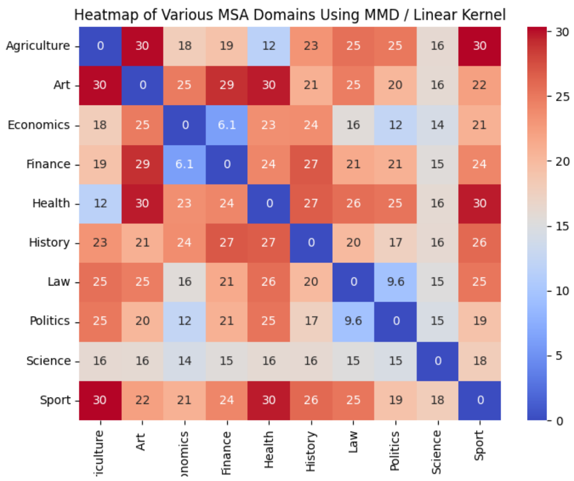

Figure 8: Heatmap showing the similarities between different MSA domains in *Konooz* using MMD Linear kernel.

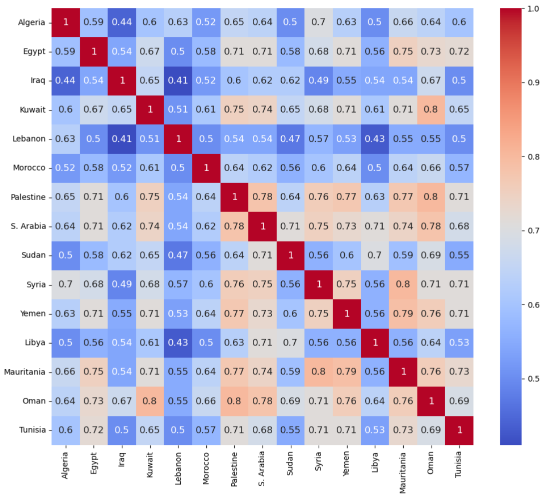

Figure 9: Heatmap showing the similarities between different dialects in *Konooz* using cosine similarity.

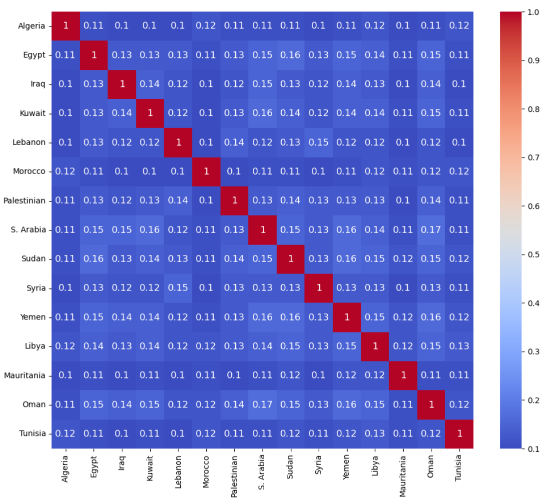

Figure 10: Heatmap showing the similarities between different dialects in *Konooz* using Jaccard coefficient.

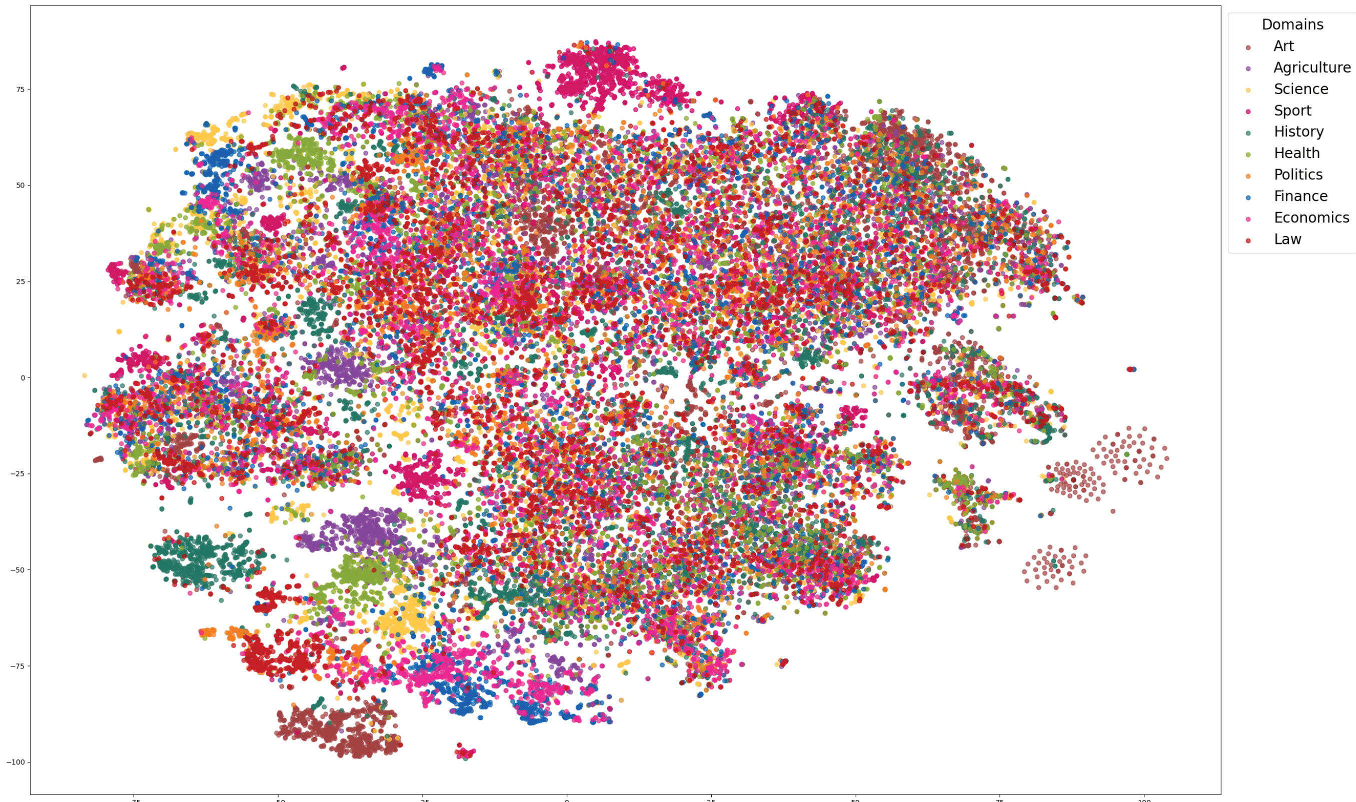

Figure 11: Lexical similarity and distribution of *Konooz* domains.