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Ontology-Style Relation Annotation: A Case Study

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Abstract

This paper proposes an *Ontology-Style Relation (OSR)* annotation approach. In conventional *Relation Extraction (RE)* datasets, relations are annotated as links between entity mentions. In contrast, in our OSR annotation, a relation is annotated as a *relation mention* (*i.e.*, not a link but a node) and *domain* and *range* links are annotated from the relation mention to its argument entity mentions. We expect the following benefits: (1) the relation annotations can be easily converted to *Resource Description Framework (RDF)* triples to populate an Ontology, (2) some part of conventional RE tasks can be tackled as *Named Entity Recognition (NER)* tasks. The relation classes are limited to several RDF properties such as *domain*, *range*, and *subClassOf*, and (3) OSR annotations can be clear documentations of Ontology contents. As a case study, we converted an in-house corpus of Japanese traffic rules in conventional annotations into the OSR annotations and built a novel *OSR-RoR (Rules of the Road) corpus*. The inter-annotator agreements of the conversion were 85-87%. We evaluated the performance of neural NER and RE tools on the conventional and OSR annotations. The experimental results showed that the OSR annotations make the RE task easier while introducing slight complexity into the NER task.

Keywords: Ontology-style relation annotation, relation extraction, named entity recognition, corpus construction

1. Introduction

Relation Extraction (RE) is the task to find predefined relations between target entity terms in a text. Traditionally, RE studies rely on corpora that have term annotations and relation link annotations between two terms.

In *conventional relation annotations*, relations are annotated as links between target entity mentions. In contrast, in our *Ontology-Style Relation (OSR) annotations*, a relation is annotated as a *relation mention* (i.e., not a link but a node) and then *domain* and *range* links are annotated from the relation mention to its entity mentions. Similar to the Ontology structures, the domain link connects the relation mention to the source target entity while the range link connects the relation mention to the destination entity. By taking this approach, we expect the following benefits:

- Since the relation annotations can be easily converted to Ontology *RDF (Resource Description Framework)*[1] triples, the annotated relations can be used to populate Ontology entries.
- Because relations are annotated as relation mentions, some part of the relation-type classification task on a conventional RE corpus become a *Named Entity Recognition (NER)* task, in which deep learning is quite effective to achieve over 80% F-scores for many NE types (Mai et al., 2018), compared to less investigated RE task with many relation types, e.g., (Zhang et al., 2017). It is also worth addressing that the number of Ontology relation classes to be annotated is limited to several relation classes (*i.e.*, RDF properties) such as *domain*, *range*, and *subClassOf*, which makes the RE task much easier.
- Ontology-style relation annotations can be used as clear documentations of Ontology contents. If we have all the Ontology contents in text, we can well understand the Ontology content. Moreover, embedding vectors of not only entity terms (*i.e.*, Ontology classes) but also relation mentions (*i.e.*, Ontology properties) can be obtained using word2vec (Mikolov et al., 2013) or *Bidirectional Encoder Representations from Transformers (BERT)* (Devlin et al., 2019) based on Ontologically annotated corpora. This will lead to a new way to integrate textual information and knowledge structures in the future.

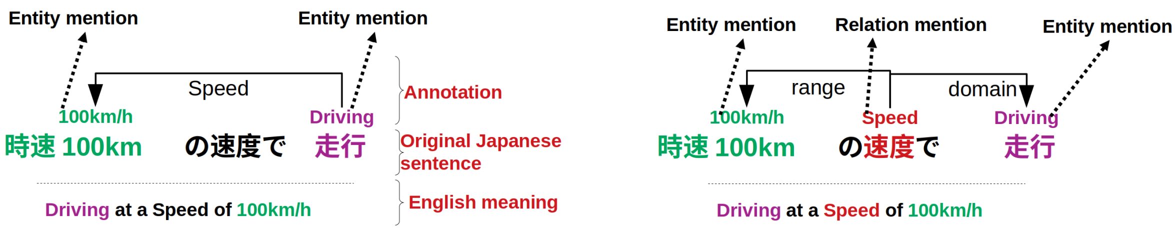
This paper presents our experience in the OSR annotations on the documents titled *Rules of the Road (RoR)* that deal with Japanese traffic rules. We converted the in-house corpus in the conventional annotations into the OSR annotations, and we built a new corpus named the *OSR-RoR corpus*. The inter-annotator agreements (IAA) are high among the annotators, and this shows that the conversion into the OSR annotations is easy. We also applied neural NER and RE tools on the OSR-RoR corpus and compared the performance of the tools on the corpus with one on the conventional annotations. The results shows that the OSR annotations make the RE task easier while they introduce slight complexity in the NER task.

The reminder of this paper is organized as follows. Section 2. gives a basic idea of Ontology-style relation annotation. Section 3. summarizes the target document RoR. Section 4. describes our methodology for annotating the RoR document, and Section 5. introduces some main annotation examples in our OSR-RoR corpus. Evaluations of our OSR-RoR corpus are explained in Section 6.. Related Work is included in Section 7. Finally, Section 8. concludes this paper.

2. Ontology-Style Annotation

The representation foundation of an Ontology is RDF. In RDF, all the information is described using RDF triples (*subject*, *predicate*, *object*). We use three main RDF schema (rdfs) predicates: `rdfs:subClassOf`, `rdfs:domain`, and `rdfs:range`. Ontology classes

[1] `https://www.w3.org/RDF/`



(a) Conventional annotation

(b) Ontology-style annotation

Figure 1: Example of the conventional and proposed annotating methods

or concepts are hierarchically structured by the generalization relation named `rdfs:subClassOf`. For example, when a class C1 is a generalization of C2, it is represented as `(C2, rdfs:subClassOf, C1)` in the RDF triple format. In RDF, the predicate of a triple, or a binary relation, is called a property. Relations/properties are also represented as nodes in the Ontology. For example, when a class C1 has a relation/property R1 to C2, it is represented as `(R1, rdfs:domain, C1)` and `(R1, rdfs:range, C2)`. Same as `rdfs:subClassOf`, the generalization relation between two properties can be described by `rdfs:subPropertyOf`; however, we do not annotate `rdfs:subPropertyOf` in our OSR annotation. We adopt `owl:equivalentClass`, which is one of *Web Ontology Language (OWL)* class axioms for specifying an equivalence between two terms. Optionally, we add `osr:partOf` as an elemental property to describe the part-whole relation.

In our perception, the Ontology-style relation annotation and the conventional relation annotation correspond to the Ontology and the Semantic Network, respectively. Properties are represented as nodes in an Ontology while properties are represented as labeled links in the Semantic Networks, which are freely constructed using any link labels to describe properties/relations between two concepts.

In this respect, we propose to annotate the documents with relations in the same way as the Ontology. Figure 1 illustrates the main idea of the conventional annotations and the proposed OSR annotations. Figure 1(a) is a conventional annotation in which a relation *Speed* is annotated as a typed link. Figure 1(b) is the proposed Ontology-style annotation. Here a relation *Speed* is annotated as an intermediary relation mention (*i.e., PROPERTY*) and domain and range links connect *Driving* to *100km/h*. Note that, for annotation efficiency, we do not distinguish the Ontology class and datatype as they can be distinguished when converting relation annotations to proper RDF triples with referring to their NE categories.

3. Document Source and Conventional Relation Annotations

We already had an annotated in-house corpus in the conventional relation representation format on the document on safe driving in part of our autonomous vehicle project. The source of the corpus is from the provisions of Article 108 of the Rules of the Road (RoR) (National Public Safety Commission, Notice No. 3, 1978), which has been in use up to now. The RoR contains traffic regulations and driving knowledge that all the new car drivers ought to know. Specifically, the RoR contains rules and regulations, which regulate road users, traffic, and traffic-related priorities. They also include legal driving knowledge, requirements, punishment, and other information that are necessary to use the roads legally and safely. There are 11 chapters and 49 sections in the document. The details are summarized in Tables 1 and 2.

Type	Counts
#Chapters	11
#Sections	49
#Sentences	1,476
#Characters	68,655
#Term types	270
#Relation types	99

Table 1: Statistics of our in-house RoR corpus in the conventional relation annotation style

Ch.	Description
1	Common rules for pedestrians and drivers
2	Pedestrian knowledge
3	Riding a bicycle
4	Before getting behind the wheel
5	Driving tips
6	Dangerous spots and hazardous conditions
7	Driving on expressways
8	Riding a two-wheeled motor vehicle
9	The basics for drivers of passenger transport services and substitute drivers
10	Traffic accidents, breakdowns, and natural disaster
11	The basics for vehicle owners, users, safe driving supervisors and substitute driving service company

Table 2: Chapters of the Rules of the Road.

The annotation of the in-house conventional RoR corpus was done by the annotation professionals. In annotating the corpus, all traffic-related words/phrases from the sentences are annotated to keep the original meanings. The words/phrases from the sentences are annotated by the corresponding equivalent English words/phrases, which are chosen from the standard vocabulary list for driver's license and permit test.

4. Ontology-Style Relation Annotation of the Rule of the Road

In this section, we explain the criteria of the OSR annotations and the process of converting the conventional RoR corpus into the OSR-RoR corpus. We first explain the representations of ontology-style relations with exceptions in Section 4.1. We then summarize the entity and relation classes and their attributes on the OSR-RoR corpus in Sections 4.2. and 4.3., respectively. We finally explain the conversion process in Section 4.4.

4.1. Ontology-Style Relations

In the RoR corpus, words/phrases that are related to the traffic are called "term(s)". Terms are annotated by the corresponding classes.

The relations between terms are crucial to represent and maintain original meanings of the text. This paper proposes to convert the original relation annotations to the OSR Annotations. Rather than using links to maintain relations, an intermediary term, called "relation mention", is used to maintain the relations between two other terms, called "entity mentions". Then, the Ontology structures are adopted by using "domain" and "range" links to connect the relation mention to the source target entity mention and the destination entity mention, respectively.

In designing the annotation scheme, we aim at minimizing the number of link labels and using the standard RDF properties as much as possible to express the relations in the dataset. Exceptionally, if no appropriate intermediary relation mention to express a relation is found, entity mentions are directly linked by relation-specific link labels (corresponding to some of classes under the "PROPERTY" class explained in the next section) as in the conventional annotations. The examples of such labels include "Source", "Destination", "Location", "Tool", "Value", "Time", "Speed", "Property", etc.

4.2. Ontology Class

The RoR Ontology classes (Figure 2) are hierarchically structured concepts related to traffic rules. There are five main classes of all terms: (1) ABSTRACT concepts, (2) CONCRETE concepts, (3) PROPERTY concepts (relations), (4) VALUEs (datatypes), and (5) MODIFIERs. In the Ontology, values are treated as datatypes; however, in the annotation tool, classes and datatypes are arranged in the same hierarchy of concepts of terms because numerical values are classified into groups, such as the value of the speeds, distance, etc. Other datatypes are similar to those in ontology, which can refer to data values such as strings or integers. The details are explained as follows:

- **ABSTRACT**: All intangible things that are related with traffic are included in an "Abstract" class. Some example subclasses are "Noise", "Vibration", "Traffic", "Accident", etc.

- **CONCRETE**: All tangible things that are related with traffic are included in a "Concrete" class. Some example subclasses are "Person", "Inanimate", "Vehicle", "Sign", etc.

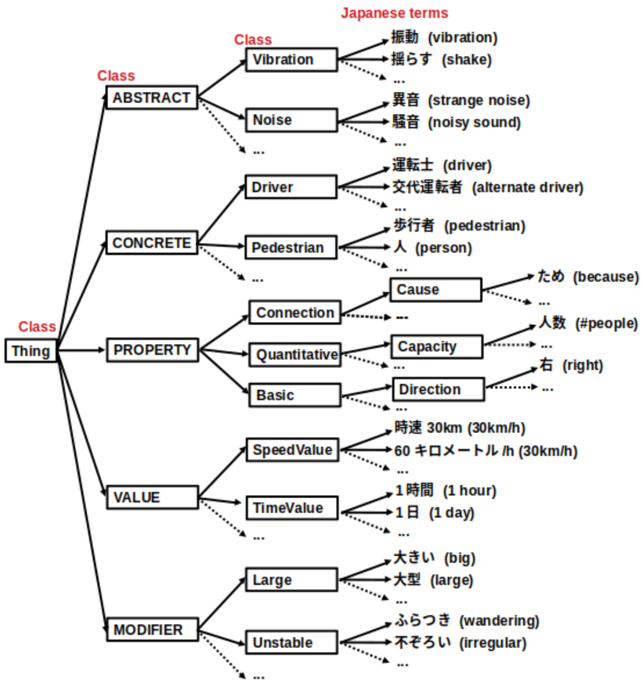


Figure 2: Class hierarchy of the Japanese road traffic law

- **PROPERTY (only for OSR-RoR)**: All relation classes are under the "PROPERTY" class. They are added so that original meanings can be maintained in the dataset. They are further classified as:
  - **Connection property**: Includes all terms that relate two or more terms. Some example subclasss are "Case", "Cause", "Require", etc.
  - **Quantitative property**: Some example subclasses are "Capacity", "Displacement", "Speed", "Height", "Lenght", "Volume", etc.
  - **Basic property**: Includes other terms that are not in all above properties. Some examples are "Source", "Destination", "Location", "Time", "Tool", "Frequency", "Property", etc.

- **VALUE**: The term that represents specific values such as the numeric values of height, length, distance, displacement, speed, etc. Its subclasses are "HeightValue", "LengthValue", "DistanceValue", etc.

- **MODIFIER**: The term that represents quality. Some example subclasses are "Many", "Large", "Smooth", etc.

Relations are annotated as the link in the original RoR corpus. Some examples of classes ABSTRACT, CONCRETE, PROPERTY, VALUE, and MODIFIER are shown in Tables 3, 4, 5, 6, and 7, respectively.

4.3. Prohibition/Permission Attributes

When textual content contains prohibition/permission information of an action, such information is annotated as an attribute of the mention. There are four attributes:

- **Prohibition**: When an action is expressed with words/phrases such as "refusal", a "Prohibition" attribute is attached.

Class	Example of Japanese Terms
Noise	異音(strange sound), 騒音(noisy sound)
Vibration	振動(vibration), 揺らす(shake)
Traffic	交通(traffic), 交通方法(transportation method), 交通環境(transportation environment), くるま社会(car society)
TrafficRule	交通規則(traffic rule), 仕方(rule), 方法(method), 規制(regulation), 通り方(way to go)
Accident	事故(accident), 交通事故(traffic accident), 接触事故(contact accident)
TrafficBlocking	交通の妨げ(traffic obstruction), 走行の妨害(driving obstruction), 通行の妨げ(traffic obstruction), 運転の邪魔(disturb driving)
Information	名称(name), 情報(information), 知識(knowledge)
Driving	乗る(ride), 使用(use), 利用(use), 動き(move), 始め(start), 行き(go)
Walk	歩く(walk), 歩行(walk), 独り歩き(walk alone)
Run	走る(run)
Pass	途切れた(interrupted), 通行(pass), 通過(passing), 進行(progress)
Contact	依頼(request), 呼ぶ(call), 問い合わせる(inquire), 報告(report)
EmergencyCall	連絡(contact)
EmergencyOperation	応急救護処置(first aid), 救護(aid)
Beware	注意(caution), 配慮(concern), 協力(cooperation), 気を配り(attentive)
Judgement	判断(judge), 確認(confirm)
Misjudgement	見落としや見間違い(oversight), 誤る(mistake)
Recognition	感知(detect), 確認(confirmation), 認識(recognition)
Obeying	守る(protect), 従う(follow)
Setting	配置(arrangement), 陳列(display), 備え付ける(prepare), 確保(secure)
Admission	加入(join)
CarProperty	構造(structure), 機能(function), 車の特徴(car features), 車の性能(car characteristics)
BlindSpot	死角(blind spot)
WheelDifference	内輪差(inner ring difference)
Safety	保護(protection), 安全(safety), 防護(protection), 安全性(safety)
Insurance	保険等(insurance, etc.), 自動車保険(car insurance)
Trouble	不安(anxiety), 不良(bad), 迷惑(disturbing), 異常(abnormal), 混乱(confusion)
Omitting	取り除く(remove), 脱落(drop out), 除去(removal), 抜き取る(pull out)
Understanding	理解(understanding), 知っておく(to know), 身に付けておく(keep on)
Need	必要(necessary)

Table 3: Example of some classes and their corresponding Japanese terms under the class ABSTRACT.

- **Negation**: When the actions are expressed with "not", "should not", etc, a "Negation" attribute is attached.
- **Permission**: When it is permissible to do an action with words/phrases such as "should", "can", and "may", a "Permission" attribute is attached.
- **Recommendation**: When it is recommended/suggested to do an action by words/phrases such as "it is better to do", a "Recommendation" attribute is attached.

4.4. Conversion Process for OSR Annotations

Five members of our research team converted the in-house corpus in conventional relation annotations into Ontology-style relation annotations, where a relation is annotated as a relation mention and then the domain and range links are annotated from the relation mention to its entity mentions.
Following the conventional annotations, all the words/phrases and their semantic relations from the sentences are annotated to keep the original meanings. The conversion was done by using BRAT (Stenetorp et al., 2012), which is a popular Web-based tool for NLP-assisted text annotation.
We summarized the statistics of our OSR-RoR corpus in Table 8. The four attributes are the prohibition/permission attributes explained in Section 4.3.. The used linked types are the direct link labels, which include both OSR links and other OSR-RoR specific links. OSR links are the link labels that are never converted into intermediary relation mentions, while other OSR-RoR links are the link labels that are supposed to convert into appropriate intermediary relation mentions but they still remain as direct links due to no appropriate relation mentions found in the sentences. This shows about 88% (=4,227 / (4,227 + 580)) of the relations were successfully converted into OSR relations. The number of link types in our new RoR corpus is largely reduced to only $\frac{1}{9}$ of those in the original RoR corpus (c.f. #Relation types in Table 1).

5. Annotation Examples

In this section, the examples of some main annotations are introduced to give a clearer picture of our dataset.

Class	Example of Japanese Terms
Person	人(person), 住民(resident), 利用客(passenger), 関係者(related people)
Driver	使用者(user), 運転士(driver), 交代運転者(alternate driver)
Pedestrian	歩行者(pedestrian), 人(person), 者(person)
Child	子供(children), 小児(child), 幼児(toddler), 胎児(fetus)
InjuredPerson	けが人(injured person), 病人(sick person), 傷病者(victim), 負傷者(wounded person)
Inanimate	貴重品(valuables), ごみ(garbage)、くぎ(nail)、汚水(sewage)
Car	車(car), 車種(car type)
Vehicle	四輪車(four-wheeler), 自動車(automobile),
Bicycle	普通自転車(normal bicycle), 自転車(bicycle)
FirstAidTool	救急用具(first aid)
Road	区間(section), 地面(ground), 路面(road surface), 道(road)
Place	ところ(place), 位置(position), 地域(area), 学校(school)
RoadSide	沿道(roadside), 道路に面した場所(road facing place)
TrafficLight	信号機(traffic lights)
Sign	標識(sign)

Table 4: Example of some classes and their corresponding Japanese terms under the class CONCRETE.

5.1. subClassOf Relation

The subClassOf relation is standard property used in RDF. Therefore, it is annotated directly without using intermediary relation mention. The example is shown in Fig. 3. In this example, "指示表示 = InstructionShow" and "規制表示 = RegulatoryShow" are the sub class of "道路標識 = RoadMark", so the subClassOf relations are maintained as shown in the figure.

Figure 3: Example of the subClassOf relation

5.2. partOf/equivalentClass Relations

The "partOf" relation is not included in the standard RDF properties, but since it is a component of the basic common structures in Ontologies (i.e., `osr:partOf`), it is directly linked with the relation "partOf". The link is connected from the whole to the part. In Fig. 4, the "車両通行帯 = VehicularLane" is a part of the "トンネル = tunnel",

Class	Example of Japanese terms
Location	で(at)
Source	から(from)
Destination	に(to)、
Direction	右(right)、左(left)、上(up)、後ろ(back)
Property	の(of)、は(is, are, was, were)、に(in)、について(about)
Time	夜(night)、朝(morning)、昼(afternoon)、夕日(evening)
AfterTime	後(after)、から(from)、
BeforeTime	前に(before)、直前(just before)
Tool	を(with)、で(with)
Frequency	(1, 2, ...)回(times)
Case	場合(case)、時(when)、以外(except)、
Cause	ため(because)、から(because)、ので(because)
Require	必要(necessary)、しなければなりません(must)、
Capacity	定員(capacity)、人数(number of people)、
Speed	速度(speed)、で(at)、最高速度(max. speed)
Height	高さ(height)
Length	長さ(length)
Displacement	排気量(displacement)、総排気量(total displacement)
Distance	距離(distance)
MoveTo	移動(move)、曲がる(turn)
Over	以上(more than)、超える(exceed)
Under	以下(less than)、未満(less than)
Restrict	除く(exclude)、制限(restriction)

Table 5: Example of some classes and their corresponding Japanese terms under the class PROPERTY.

so the "partOf" relation is maintained between the two entity mentions. We also annotated the equivalentClass relation, which corresponds to `owl:equivalentClass`, between two terms that represent identical entities.

Figure 4: Example of the partOf relation

5.3. Property Relation

When a term is used to describe another term or a modifier of another term, both terms are connected by the property relation. An example is shown in Fig. 5. In this example, the entity mention "自分勝手 = Selfish" is used to describe the characteristic of the entity mention "通行 = Move", so they are related by the "Property" relation, which is repre-

Class	Example of Japanese terms
SpeedValue	時速30キロメートル(30km/h)、時速6キロメートル(6km/h)
TimeValue	1時間(1 hour)、1日(1 day)
DistanceValue	0.5メートル(0.5m)、2キロメートル(2km)
CapacityValue	一台(1 car)、二人(2 people)
FrequencyValue	二回(2 times)
HeightValue	109センチメートル(109cm)、地上から4.1メートル(4.1m from ground)
LengthValue	0.3メートル(0.3m)、190センチメートル(190cm)
WidthValue	0.15メートル(0.15m)
AgeValue	50歳(50 years old)、2ヶ月(2 months)
DisplacementValue	６６０cc

Table 6: Example of some classes and their corresponding Japanese terms under the class VALUE.

Class	Example of Japanese terms
Many	多い(a lot of)、たくさん(many)
Large	大きい(big)、大型(large)
Smooth	スムーズに(smoothly)、円滑に(smoothly)
Unstable	ふらつき(wandering)、不ぞろい(irregular)
Bad	悪い(bad)

Table 7: Example of some classes and their corresponding Japanese terms under the class MODIFIER.

sented by an intermediary relation mention, "に = (a particle used to connect a description to its main)". Then, the standard RDF properties "domain" and "range" are used to maintain their relation as shown in the figure.

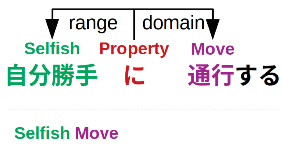


Figure 5: Example of the Property relation

5.4. Location/Source/Destination Relations

Existence of things or actions within a place is represented by the Location relation. Figure 6 shows an example for the Location relation. The entity mention " 通行 = Move" is a movement within the " 道路 = Road". Therefore, the relation between them is represented by the "Location" relations, which is represented by an intermediary relation mention, "を = along or within". Then, the standard RDF properties "domain" and "range" are used to maintain their relation.
Similarly, the actions/movements from the place, disaster, or other existing traffic entities are represented by the "Source" relations. The example is shown in Figure 7.

Type	Counts
#ABSTRACT classes	34
#CONCRETE classes	15
#PROPERTY classes	25
#VALUE classes	11
#MODIFIER classes	5
#Attributes	4
#Used link types	11
#Entity mentions	8,631
#Relation mentions	4,277
#OSR links	10,439
#Other OSR-RoR specific links	580

Table 8: Statistics of our OSR-RoR corpus. OSR links denote "domain", "range", "subClassOf", "partOf", and "equivalentClass" links.

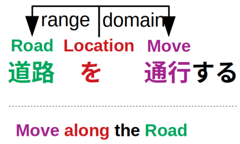


Figure 6: Example of the Location relation

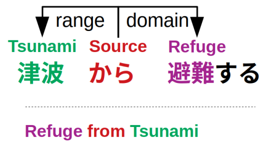


Figure 7: Example of the Source relation

5.5. Over/Under Relations

In traffic rule, it is very typical to have some associated numerical values. These numerical values are typically associated with other traffic entity mentions by "more/less than" (e.g., younger than 12 years old, less than 10 meter, etc). To reduce the number of possible relations associated with numeric values, we use "Over" and "Under" relations to relate with numerical values. The example is shown in Figure 8. The detail explanations are similar to those in Sections 5.4. and 5.3..

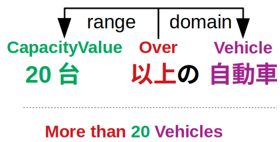


Figure 8: Example of the Over relation

5.6. Conditional Relation

When a certain action is done under a specific condition, such conditional relation must be properly denoted in the dataset. In our dataset, the "Case" property is used to represent all conditional expressions found in the text. An example is shown in Fig. 9. In this example, only the related terms and relations that are directly connected to the conditional expression are shown for simplicity. The relation mention "とき = Case" acts as an intermediary relation mention to create conditional relation between entity mentions "通行 = Move" with " 守る = Obey". Therefore the annotation is done as shown in the figure.

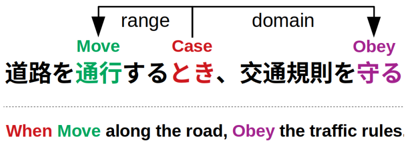


Figure 9: Example of the Case relation

5.7. Causal Relation

The annotation to express causes and results is also covered in our dataset. The "Cause" property is used to represent all causing expressions used in the text. Then, the relation between cause and reason are related by the intermediary relation mention "Cause". An example is shown in Fig. 10. The detail explanation is similar to that in Section 5.6..

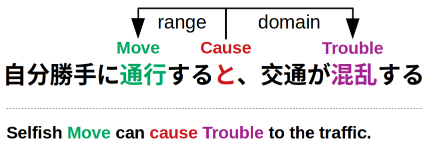


Figure 10: Example of the Cause relation

5.8. Obligatory Relation

Obligatory relations typically exist in traffic rules. Our dataset uses the "Require" property to represent all obligatory relations. The example is shown in Fig. 11. The detailed explanations are similar to those in Sections 5.6. and 5.7..

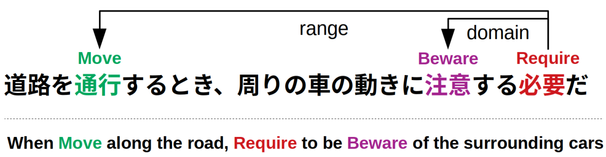


Figure 11: Example of the Require relation

6. Evaluations of OSR Annotations

6.1. Human Evaluation

The validity of the annotation from the Japanese road traffic law is evaluated by using Cohen's kappa (Jacob, 1960). For the purposes of the evaluation, two human annotators (one native Japanese and one foreigner who can speak both English and Japanese) converted the same set of the conventional relation annotations into the OSR annotations. First, the OSR annotation guideline was explained to them. Then, 105 sentences that are annotated in a conventional way were selected. The annotators independently converted the relation annotations of the sentences. The Inter-Annotator

Term annotation	Relation annotation
0.8484	0.8719

Table 9: IAA of human annotators (Cohen's Kappa)

NER		RE	
Class	F-score	Relation	F-score
Original RoR corpus			
Car	0.933	range	0.388
Road	0.921	location	0.369
Pass	0.913	case	0.281
Driving	0.849	property	0.264
Other classes	0.753	Other relations	0.275
Overall	**0.774**	Overall	0.305
New RoR corpus (OSR)			
Case	0.786	range	0.482
Location	0.704	property	0.472
Cause	0.611	domain	0.452
Property	0.591	subClassOf	0.21
Other classes	0.724	Other relations	0.227
Overall	0.731	Overall	**0.456**

Table 10: Results (F-scores) of the NER and RE tools over the top-4, the remaining, and overall term classes and relations.

Agreement is shown in Table 9. The scores of Cohen's kappa (κ-scores) for both terms and relations are 85-87%, which proves that both converted results are at the "almost perfectly agreed" level. The disagreements are mostly due to the ambiguity whether the selected terms should include the Japanese post-positions (e.g., "は、で、に、て、し、etc."). Including such particles to the selected terms is confusing even to the native Japanese, but keeping such particles is sometimes important to keep the original meaning. Two reasons affect the score of relation extraction: (1) some wrongly annotated terms caused the wrong relation annotation, and (2) the annotators disagreed when the relations should be normal or exceptional as explained in Section 4.1. In such cases, one user kept the terms as they are, while the other split the particle from the terms and used the particle as the intermediary relation mention for creating a converted relation. Anyhow, this result shows that the annotation guideline of our dataset are clear to human. We will leave the discovered problems as references for future improvement of the dataset.

6.2. NER and RE performance

In this experiment, our converted OSR-RoR corpus is compared against the conventional RoR Corpus annotated in the traditional relation format in terms of their usefulness in training deep learning systems. For this purpose, we employed Flair (Akbik et al., 2019) as a baseline NER tool and a variant of Bi-affine Relation Attention Networks (BRANs) (Verga et al., 2018), which omit entity extraction from BRAN and replace transformers with CNNs, as a baseline RE tool. Two separate corpora were compared: (1) RoR corpus and (2) OSR-RoR corpus. For each corpus, 20% was used as testing data and the rest was used as training data. Then, 5-fold cross validations were performed. The F-scores of NER and RE on the four most frequent top-4, the remaining, and overall term classes and relations are shown in Table 10. Note, the top-4 is computed by first selecting the four most frequents, then ranking them by their F-scores.

Although these scores are not directly comparable since they evaluate different entities and relations in different annotation schema, the result shows that the absolute F-scores of the top-4 relations using our dataset are much higher than the scores using the conventional dataset, which proves the easiness of the relation extraction in our dataset. However, the F-score for term extraction on the OSR-RoR corpus is a bit lower than that of the conventional RoR corpus since the OSR-RoR corpus contains more terms including relation mentions than the conventional corpus. We obtained a higher overall F-score by changing the relation annotation. This shows that even though NE performance slightly degrades, the OSR annotations make the RE task become a lot easier.

7. Related Work

Relation extraction (RE) from text is a very hard task, yet is of tremendous importance in many applications. A lot of RE corpora have been constructed for the RE tasks. In the *Automatic Content Extraction (ACE)* Program 2004 (Doddington et al., 2004b), Named Entities, such as Person names, and relations, such as Part-Whole and User-Owner, are annotated to general English, Arabic and Chinese articles. SemEval 2010 Task 8 (Wu and Jin, 2010) targets only relation extraction. The task is to determine a relation between two given two entities $\langle e1 \rangle$ and $\langle e2 \rangle$ in a sentence. The relation types includes Content-Container and Entity-Destination. In the biomedical area, the GENIA corpus (Kim et al., 2008) is an annotated corpus that includes term annotations related to GENIA Ontology and biological event annotations. In the existing corpora, relations are annotated as links.

The relations in the OSR annotations have structures close to those in predicate argument structures (PAS) (Miyao and Tsujii, 2004), semantic roles(Kingsbury and Palmer, 2002; Fillmore et al., 2003) and events (Doddington et al., 2004a; Kim et al., 2008), but they are different in three ways. First, the annotation targets are different. PAS and semantic roles do not consider named entities, so they do not connect long-range arguments and they deal with shallower semantic relations than ours. Events usually deal with dynamic relations. Second, relations are binary relations, while PAS, semantic roles and events can be n-ary relations. Finally, no other annotations consider RDF.

In our experiments, we used deep learning based NER and RE tools: Flair (Akbik et al., 2019) NER tool and our implementation of a variant of the BRAN RE model (Verga et al., 2018). Deep learning was first used to extract relation from text by (Liu et al., 2013). More works have adopted CNN; sentence encoding by using CNN was introduced by (Zeng et al., 2014). In this work, lexical position was adopted to improve the feature extraction. In (Zeng et al., 2015), the filter of CNN was partitioned into three pieces, on which the max-pooling operation was applied. A new loss function was introduced in (dos Santos et al., 2015) to achieve a similar purpose. Wrong labeling problems seriously impact the performance of relation extraction. To solve this issue, a sentence-level annotation-based model (Lin et al., 2016) for relation extraction was introduced.

RNNs have also been very popular for Relation Extraction. LSTM was adopted in (Miwa and Bansal, 2016). This work can capture both word sequence and dependency tree substructure information, which allows the model to jointly share parameters in representing both entities and relations. Attention-based bidirectional LSTM was introduced in (Zhou et al., 2016) for relation classification. This attention-based work can capture the most important semantic information in the sentence. (She et al., 2018) proposed hierarchical attention model to select valid instances and capture vital semantic information by incorporating entity descriptions from Wikipedia into hierarchical attention model as a supplementary background knowledge.

The main bottleneck of many works on relation extraction is the lack of background knowledge about the entities. To address the mention problem, a sentence-level attention model (Ji et al., 2017) was proposed to select the valid instances by making use of background knowledge from the Freebase and Wikipedia pages as supplementary knowledge. A syntax-aware entity embedding was proposed in (He et al., 2018). This work used both intra-sentence and inter-sentence attentions to obtain sentence set-level entity embedding for relation classification.

A walk-based model (Christopoulou et al., 2018) on entity graphs for relation extraction was proposed. This model considered multiple pairs in a sentence simultaneously to capture their interaction patterns. (Su et al., 2018) proposed a model to embed textual relations with global statistics of relations to combat the wrong labeling problem of distance supervision. This work discovered that this model could deal with noise incurred by the distance supervision.

8. Conclusion

This paper proposed a new annotation style called Ontology-Style Annotation. As a case study, we converted an in-house Relation Extraction corpus for the Japanese Rules of the Road into the OSR annotation. Evaluations of the corpus by human annotators and with baseline neural NER system (*i.e.*, Flair) and RE system (*i.e.*, a variant of BRAN) showed that (1) the conversion into the OSR annotation achieves high annotator agreement, (2) the OSR annotations make the RE task easier while introducing slight complexity into the NER task. Our future work includes converting English RE corpora into the OSR annotation and evaluating the advantages. Furthermore, we are going to bridge texts and Ontology entries by linking the two different information sources through the OSR annotation.

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