Ontology-Style Relation Annotation: A Case Study

Savong Bou, Naoki Suzuki, Makoto Miwa and Yutaka Sasaki
Computational Intelligence (COIN) Lab, Toyota Technological Institute
{savong, sd16042, makoto-miwa, yutaka.sasaki}@toyota-ti.ac.jp

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 OS-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/
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 $\langle C2, \text{rdfs:subClassOf}, C1 \rangle$ 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 $\langle R1, \text{rdfs:domain}, C1 \rangle$ and $\langle R1, \text{rdfs:range}, C2 \rangle$. 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.

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

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

Table 2: Chapters of the Rules of the Road.

| 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 |

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 numeric values of height, length, distance, displacement, speed, 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.

- **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 subclasses are “Case”, “Cause”, “Require”, etc.
  - **Quantitative property**: Some example subclasses are “Capacity”, “Displacement”, “Speed”, “Height”, “Length”, “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, 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.
The conversion was done by using BRAT \cite{stenetorp2012}, which is a popular Web-based tool for NLP-assisted text annotation.

We summarized the statistics of our OSR-RoR corpus in Table \ref{tab:statistics}. The four attributes are the prohibition/permission attributes explained in Section \ref{sec:annotation}. 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 1 of those in the original RoR corpus (c.f. #Relation types in Table \ref{tab:RoR}).

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 \cite{stenetorp2012}, which is a popular Web-based tool for NLP-assisted text annotation.

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

| Class                  | Example of Japanese Terms                  |
|------------------------|-------------------------------------------|
| Noise                  | 異音(strange sound), 騒音(noisy sound)   |
| Vibration              | 振動(vibration), 搖揺(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(incident), 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), 車転の邪魔(disturb driving) |
| Information            | 名称(name), 情報(information), 知識(knowledge) |
| Driving                | 乗りる(ride), 使用(use), 利用(use), 動き(move), 始める(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     | 緊急救護処置(first aid), 救護(aid)         |
| Beware                 | 注意(caution), 配慮(concern), 協力(cooperation), 気を配り(attention) |
| Judgement              | 判断(judge), 確認(confirm)                 |
| Misjudgement           | 見落としあや間違い(oversight), 誤る(mistake) |
| Recognition            | 感知(detect), 確認(confirm), 認識(recognition) |
| Obeying                | 守る(protect), 従う(follow)                |
| Setting                | 配給(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.

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

### 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, “トーネル = Tunnel” is a part of the “トンネル通行帯 = VehicularLane”.

![Figure 4: Example of the partOf relation](image)

### 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 represented in Table 5.

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

| Class         | Example of Japanese Terms                                                                 |
|---------------|------------------------------------------------------------------------------------------|
| Person        | 人(person), 住民(resident), 利用者(passerby), 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), 利用者(passerby), 関係者(related people)                             |
| 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), 廃棄物(garbage), 指(指), 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), 道路路Surface, 道路(road)                                      |
| Place         | ところ(place), 位置(position), 地域(area), 学校(school)                                    |
| RoadSide      | 沿道(roadside), 道路面に面した場所(road facing place)                                    |
| TrafficLight  | 信号機(traffic lights)                                                                  |
| Sign          | 識別(sign)                                                                               |

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

- 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: 夕方(night), 朝(morning), 昼日(evening)
- AfterTime: 後(after), から(from)
- BeforeTime: 前に(before), 直前に(before)
- Tool: を(with), で(with)
- Frequency: (1, 2, ...)回(times)
- Case: 場合(case), 時(when), 以外(except), 必要(necessary)
- Require: 必要(necessary)
- 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 6: Example of some classes and their corresponding Japanese terms under the class VALUE.

| Class           | Example of Japanese terms |
|-----------------|---------------------------|
| SpeedValue      | 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 7: Example of some classes and their corresponding Japanese terms under the class MODIFIER.

| 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 8: Statistics of our OSR-RoR corpus. OSR links denote “domain”, “range”, “subClassOf”, “partOf”, and “equivalentClass” links.

| 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 |

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 “ 道路 を 通行する” 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, disas-

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 ex-
ample 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 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,

| 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.
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 frequent, 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 (e1) and (e2) 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 biomedical 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 (Abkib 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 (Christopoulos 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.

Acknowledgement

This study was partly supported by JSPS KAKENHI Grant Number 17K00318.
Bibliographical References

Akbik, A., Bergmann, T., Blythe, D., Rasul, K., Schweter, S., and Vollgraf, R. (2019). FLAIR: an easy-to-use framework for state-of-the-art NLP. 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, Demonstrations, pages 54–59.

Christopoulou, F., Miwa, M., and Ananiadou, S. (2018). A walk-based model on entity graphs for relation extraction. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 2: Short Papers, pages 81–88.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota, June. Association for Computational Linguistics.

Doddington, G., Mitchell, A., Przybocki, M., Ramshaw, L., Strassel, S., and Weischedel, R. (2004a). The automatic content extraction (ACE) program – tasks, data, and evaluation. In Proceedings of the Fourth International Conference on Language Resources and Evaluation (LREC’04), Lisbon, Portugal, May. European Language Resources Association (ELRA).

Doddington, G. R., Mitchell, A., Przybocki, M. A., Ramshaw, L. A., Strassel, S. M., and Weischedel, R. M. (2004b). The automatic content extraction (ACE) program - tasks, data, and evaluation. In Proceedings of the Fourth International Conference on Language Resources and Evaluation, LREC 2004, May 26-28, 2004, Lisbon, Portugal.

dos Santos, C. N., Xiang, B., and Zhou, B. (2015). Classifying relations by ranking with convolutional neural networks. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers, pages 626–634.

Fillmore, C. J., Johnson, C. R., and Petruccik, M. R. (2003). Background to framenet. International journal of lexicography, 16(3):235–250.

He, Z., Chen, W., Li, Z., Zhang, M., Zhang, W., and Zhang, M. (2018). SEE: syntax-aware entity embedding for neural relation extraction. In Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018, pages 5795–5802.

Jacob, C. (1960). A coefficient of agreement for nominal scales. In Educational and Psychological Measurement, pages 37–46.

Ji, G., Liu, K., He, S., and Zhao, J. (2017). Distant supervision for relation extraction with sentence-level attention and entity descriptions. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA., pages 3060–3066.

Kim, J.-D., Ohta, T., and Tsujii, J. (2008). Corpus annotation for mining biomedical events from literature. BMC bioinformatics, 9(1):10.

Kingsbury, P. and Palmer, M. (2002). From TreeBank to PropBank. In Proceedings of the Third International Conference on Language Resources and Evaluation (LREC’02), Las Palmas, Canary Islands - Spain, May. European Language Resources Association (ELRA).

Lin, Y., Shen, S., Liu, Z., Luan, H., and Sun, M. (2016). Neural relation extraction with selective attention over instances. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7–12, 2016, Berlin, Germany, Volume 1: Long Papers.

Liu, C., Sun, W., Chao, W., and Che, W. (2013). Convolutional neural network for relation extraction. In Advanced Data Mining and Applications - 9th International Conference, ADMA 2013, Hangzhou, China, December 14-16, 2013, Proceedings, Part II, pages 231–242.

Mai, K., Pham, T.-H., Nguyen, M. T., Nguyen, T. D., Bollegala, D., Sasano, R., and Sekine, S. (2018). An empirical study on fine-grained named entity recognition. In Proceedings of the 27th International Conference on Computational Linguistics, pages 711–722, Santa Fe, New Mexico, USA, August. Association for Computational Linguistics.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, pages 3111–3119.

Miwa, M. and Bansal, M. (2016). End-to-end relation extraction using lstms on sequences and tree structures. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers.

Miyao, Y. and Tsujii, J. (2004). Deep linguistic analysis for the accurate identification of predicate-argument relations. In Proceedings of the 20th international conference on Computational Linguistics, page 1392. Association for Computational Linguistics.

National Public Safety Commission, Notice No. 3 (1978). Instructions on transportation methods. Japan, October. [https://www.npa.go.jp/koutsuu/kikaku/kyousoku/index.htm](https://www.npa.go.jp/koutsuu/kikaku/kyousoku/index.htm).

She, H., Wu, B., Wang, B., and Chi, R. (2018). Distant supervision for relation extraction with hierarchical attention and entity descriptions. In 2018 International Joint Conference on Neural Networks, IJCNN 2018, Rio de Janeiro, Brazil, July 8-13, 2018, pages 1–8.

Stenetorp, P., Pyysalo, S., Topic, G., Ohtsa, T., Ananiadou,
S., and Tsujii, J. (2012). brat: a web-based tool for nlp-assisted text annotation. In EACL 2012, 13th Conference of the European Chapter of the Association for Computational Linguistics, Avignon, France, April 23-27, 2012, pages 102–107.

Su, Y., Liu, H., Yavuz, S., Gur, I., Sun, H., and Yan, X. (2018). Global relation embedding for relation extraction. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 820–830.

Verga, P., Strubell, E., and McCallum, A. (2018). Simultaneously self-attending to all mentions for full-abstract biological relation extraction. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 872–884.

Wu, Y. and Jin, P. (2010). SemEval-2010 task 18: Disambiguating sentiment ambiguous adjectives. In Proceedings of the 5th International Workshop on Semantic Evaluation, SemEval@ACL 2010, Uppsala University, Uppsala, Sweden, July 15-16, 2010, pages 81–85.

Zeng, D., Liu, K., Lai, S., Zhou, G., and Zhao, J. (2014). Relation classification via convolutional deep neural network. In COLING 2014, 25th International Conference on Computational Linguistics, Proceedings of the Conference: Technical Papers, August 23-29, 2014, Dublin, Ireland, pages 2335–2344.

Zeng, D., Liu, K., Chen, Y., and Zhao, J. (2015). Distant supervision for relation extraction via piecewise convolutional neural networks. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015, pages 1753–1762.

Zhang, Y., Zhong, V., Chen, D., Angelii, G., and Manning, C. D. (2017). Position-aware attention and supervised data improve slot filling. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing (EMNLP 2017), pages 35–45.

Zhou, P., Shi, W., Tian, J., Qi, Z., Li, B., Hao, H., and Xu, B. (2016). Attention-based bidirectional long short-term memory networks for relation classification. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 2: Short Papers.