Event Extraction and Semantic Representation from Spanish Workers' Statute using Large Language Models

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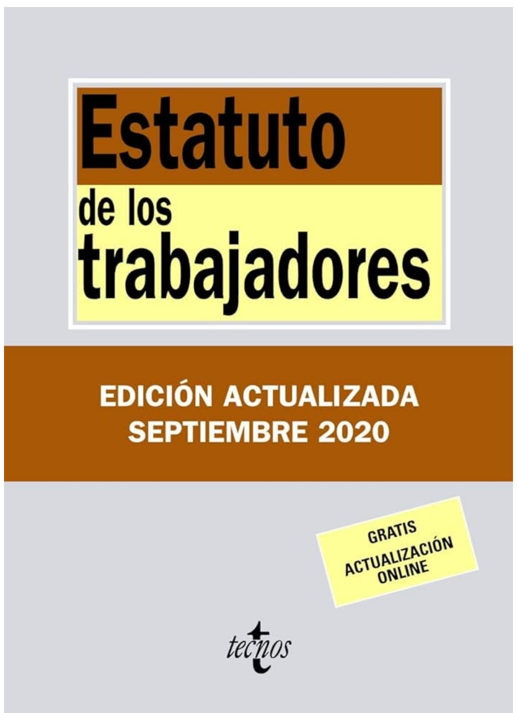
Maastricht, 20 Dec. 2023

Problem statement

Context: Workers' Statute

- Worker's Statute:
  - labor law that regulates the **rights and obligations of workers and employers**, outlining the framework for employment relationships in Spain

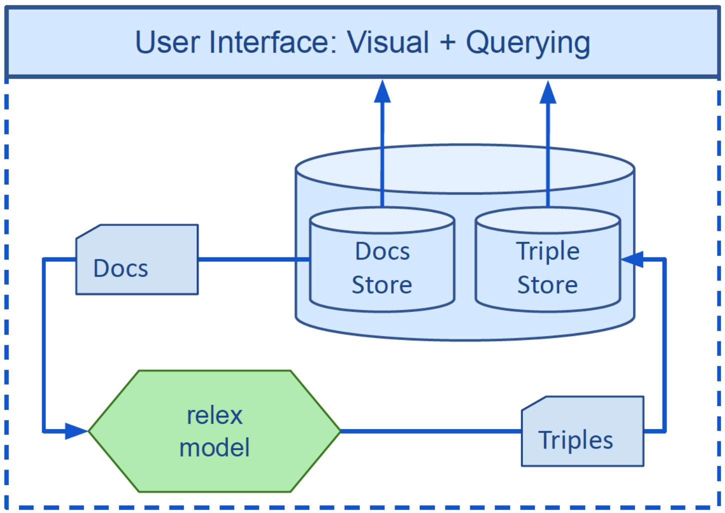


Size
~350,000 letters
~50,000 words
~1,300 paragraphs
3 titles, 92 articles
~3.65 relations per article
~600 entitites (terms, args.)

https://www.boe.es/eli/es/rdlg/2015/10/23/2/con

Objective

Objective: **Relation extraction** from a legal document:
— overcome **knowledge acquisition bottleneck** with a low **semantic annotation burden**
—respresent of the events in Semantic Web format



Event Extraction

Event Structure	**Example**
Mention	El jefe del grupo ostentará la representación de los que lo integren (*The group leader shall represent the members of the group*.)
Trigger	El jefe del grupo **ostentará** la representación de los que lo integren (*The group leader* **shall represent** *the members of the group*.)
Argument	El **jefe del grupo** ostentará la representación de **los que lo integren** (*The* **group leader** *shall represent the* **members of the group**.)
Argument Role	El **<subject>**jefe del grupo**</subject>** ostentará la representación de **<object>**los que lo integren**</object>** (*The* **<subject>***group leader***</subject>** *shall represent the* **<object>***members of the group***</object>**.)

G. R Doddington et al. (2004) “The automatic content extraction (ACE) program-tasks, data, and evaluation.” LREC

Legal Event Extraction

Event Structure	**Example**
Mention	El jefe del grupo ostentará la representación de los que lo integren (*The group leader shall represent the members of the group.*)
Trigger	El jefe del grupo **ostentará** la representación de los que lo integren (*The group leader* **shall represent** *the members of the group.*)
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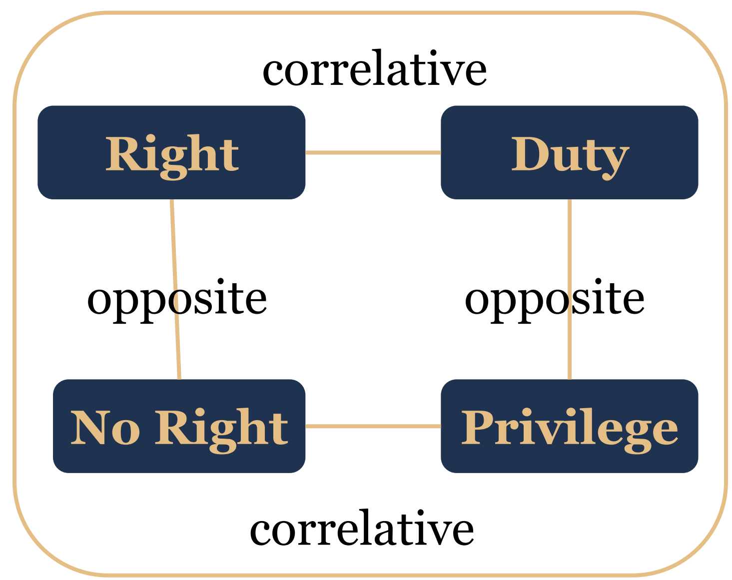
Argument Role	El **<subject>**jefe del grupo**</subject>** ostentará la representación de **<object>**los que lo integren**</object>** (*The* **<subject>***group leader***</subject>** *shall represent the* **<object>***members of the group***</object>**.)

Entities Classification[1]

- Legal Agent
- Legal Entity
- Legal Concept

Relation Classification[2]



[1]A. Revenko and **P. Martin-Chozas**. “Extraction and Semantic Representation of Domain-Specific Relations in Spanish Labour Law”. In: Proc. del Lenguaje Natural 69 (2022)

W. N. Hohfeld (1917) “Fundamental legal conceptions as applied in judicial reasoning”. In: The Yale Law Journal 26.8

Proposed method

Gold standards

- Dataset with questions and answers [1]
  - 150 questions and answers on Spanish Workers' Statute
  - Simple method to Q&A using ElasticSearch + Thesauri
- Datasets with annotated sentences [2,3]
  - 133 annotated sentences from Spanish Workers' Statute
  - Method to extract relations w. annotation expansion (R-BERT)[3]
  - Method to extract relations w. annotation exp (GRIT, Text2Event) [2]

trigger, subject, object, and complement roles

```
El <e1>empresario</e1> <rel>está obligado a comunicar</rel> a la <e2>oficina pública de
empleo</e2>, en el plazo de los diez días siguientes a su concertación y en los términos
que reglamentariamente se determinen, el contenido de los <comp>contratos de trabajo</comp>
que celebre o las prórrogas de los mismos, deban o no formalizarse por escrito.
RelationSignature: LegalAgent-LegalEntity (e1, e2)
RelationType: Duty (rel)
```

[1] Calleja, P., **Martín-Chozas, P**., Montiel-Ponsoda, E., **Rodríguez-Doncel, V.** (2021) Bilingual Dataset for Information Retrieval and Question Answering over the Spanish Workers Statute Proc. of the XIX Conf. of the Spanish Association for AI (CAEPIA)
[2] A. Revenko and **P. Martin-Chozas**. "Extraction and Semantic Representation of Domain-Specific Relations in Spanish Labour Law". In: Proc. del Lenguaje Natural 69 (2022)
[3] **Martin-Chozas, P.**, & Revenko, A. (2021). Thesaurus enhanced extraction of Hohfeld's relations from Spanish labour law. In DeepOntoNLP 2021, co-located with 18th ESWC

Event Extraction Methodologies

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Initial Methodologies

Pattern-matching technique

Rule-based approach

— *Expert knowledge required*

Supervised Learning

Models: SVM, ME

Methodology:

- joint (PoS etc.)
- pipeline

— *Requires large amount of tagged data*
— *Domain specific data required*

Deep Learning

Generative Adversarial Networks (GAN)

Attention Mechanisms

BERT

— *Requires large amount of tagged data*
— *Mostly used on English texts*

— w. Xiang and B. Wang (2019) "A Survey of Event Extraction From Text". In: IEEE Access (2019)
— M. Mejri and J. Akaichi. "A Survey of Textual Event Extraction from Social Networks." In: LPKM. 2017
— Navas-Loro, M., **Rodríguez-Doncel, V.** (2022) WhenTheFact: Extracting Events from European Legal Decisions. JURIX

Wang Shuo et al. "Joint Event Extraction Model based on Multi-feature Fusion". In: Procedia Computer Science 174 (2020)
David Ahn. "The stages of event extraction". In: Proc. of the W. on Annotating and Reasoning about Time and Events. 2006

A. Jettakul et al. (2019) "Relation extraction between bacteria and biotopes from biomedical texts with attention mechanisms and domain-specific contextual representations".

Small Corpora

Training Methodologies

Use multi- or single-lingual models

Transfer learning

LSTM architecture

Large amount of tagged data required

Dataset Expansion

Active learning

Distant supervision using structured knowledge bases

Thesauri enhance datasets

Manually verification of annotated data

Difficulties evaluating sample importance

Small Corpora

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Language Models

Masked language RoBERTalex model

Data augmentation using GPT-2

Zero- and few- shot learning strategies

Chatting approach for event extraction

Experimental Methodology

Prompt Refinement → **Zero-shot Learning** → **3-shot Learning** → **Example Selection**

Experimental Results

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Prompt Refinement → Zero-shot Learning → 3-shot Learning → Example Selection

Instructions for argument extraction and role assignment

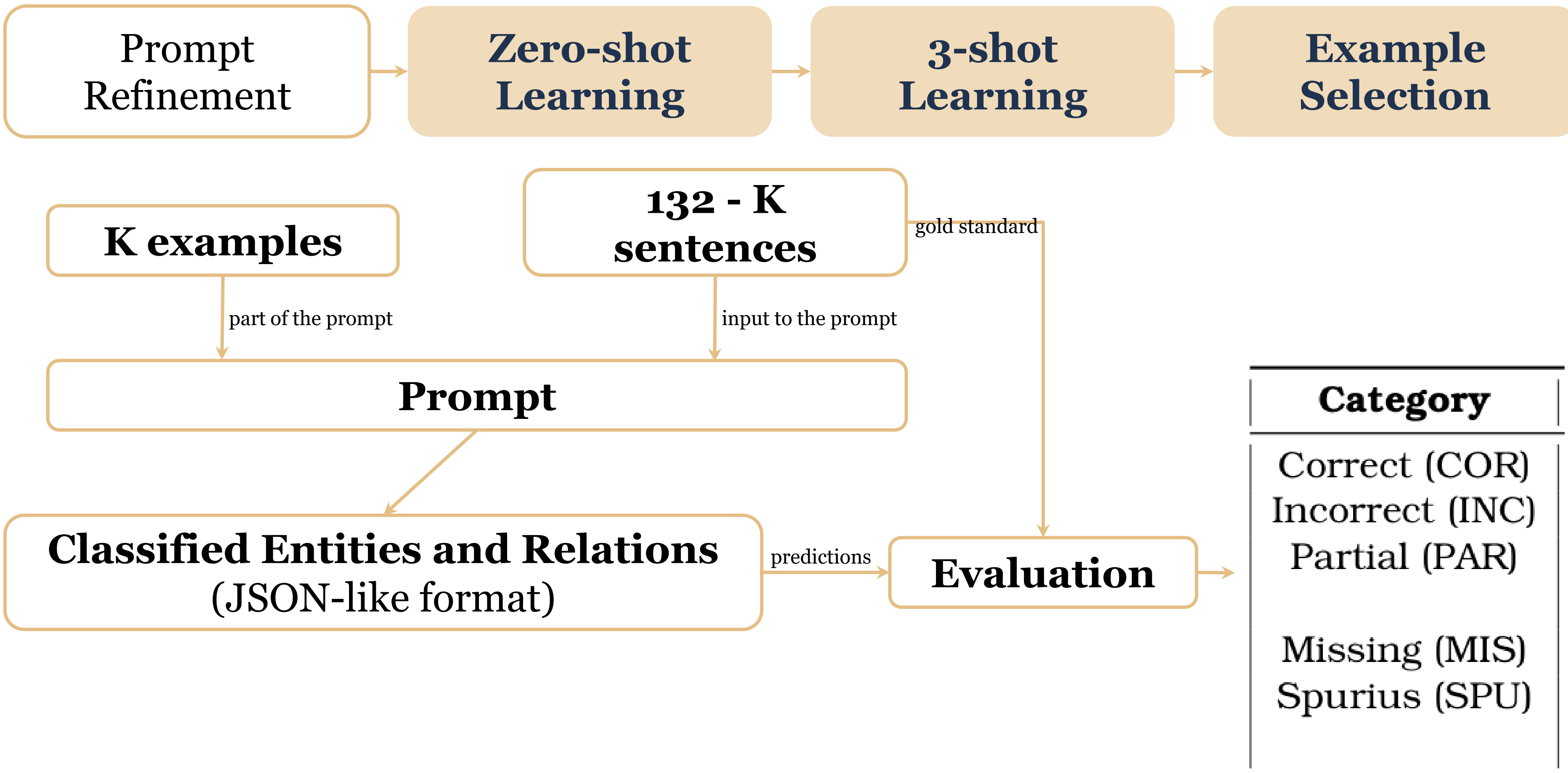
1. Separate sentences by newline delimiter
2. Extract subject, object and trigger entities using provided definitions
3. Structure the output in a JSON-like manner

Unclear instructions to recognize special cases

Instructions for argument and relations classification

2. Add complement extraction
3. Classify subject entity according to definitions
4. Classify object entity according to definitions
5. Classify legal relation according to definitions
6. Structure the output in a JSON-like manner

Experimental Results - In-Context Learning Methodology



N. Chinchor (1989) Seventh Message Understanding Conference (MUC-7):

Prompt: entity extraction and role assignment

````
Given a large set of sentences in Spanish from the legal domain, written between triple backticks, your
objective is to develop a Spanish event extraction task.
The steps to achieve it are the following:
1. Identify each sentence in the corpus separated for new lines.
2. In each sentence, detect a subject entity, an object entity, and an event trigger, usually in the form
of a verb. A sentence may relate more than one object entity with the same subject and event trigger. The
sentences can contain entities and phrases that do not correspond to any classification. Also, the object
can be separated from the subject and event trigger by complements. The definitions of each category are
the following:
• event trigger: It refers to the action enforced by the legal text. It can be in a negative form.
• subject entity: It refers to the entity doing the action of the event trigger.
• object entity: It refers to the entity that is the receptor of the action. In the legal domain, it can
be, for example, a right, a beneficiary from the action, an institution, a non-right, etc.
3. The output of the task should be a list of dictionaries.
Each dictionary contains the following keys:
• sentence: the sentence
• subject: the subject entity
• object: the object entity
• event: the event trigger
Note that it can be repeated sentences because of the different subject-event-object combinations.
The set of sentences in Spanish to use is the following:
```<sentences> ```
````

This will be the baseline!
````

Experiments

Evaluation criteria: categories

- Categories of success. Types of match:
  - **Strict**: Exact entity's text match and entity type.
  - **Exact**: Exact match over the entity's text, regardless of the type.
  - **Partial**: Partial boundary match over the entity's text, regardless of the type.
  - **Type**: Some overlap between the system-tagged entity and the gold annotation is required.

I. Segura-Bedmar, P. Martínez, M. Herrero (2013) "Extraction of drug-drug interactions from biomedical texts". In: ACL Conf.

Experimental Results

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Prompt Refinement → **Zero-shot Learning** → 3-shot Learning → Example Selection

87 incorrect exact match subjects

Extraction of articles with the entity

True: *"empresario" (entrepreneur)*
*Pred: "**el** empresario" (**the** entrepreneur)*

19 subject exact matches changed to incorrect

Spanish subtleties are not recognized

True: *"empresario" (entrepreneur)*
Legal Agent
Pred: "empresario" (entrepreneur)
Legal Entity

1 complement recovered in partial match

High variation in complement entities' between golden standard and predictions

True: *"contratos" (contracts)*
*Pred: "contratos **realizados de acuerdo…**" (contracts **made in accordance with …**)*

Compare:
0.47 (*Revenko et Martín-Chozas, 2022*)
vs.
0.32 (this work)

Experimental Results

Prompt Refinement → Zero-shot Learning → **3-shot Learning** → Example Selection

Entity and Role Detection

Exact Match

Trigger: **Metric**	**0-shot**	**3-shot**
Precision	**0.27**	**0.63**
Recall	**0.35**	**0.80**
F1 Score	**0.30**	**0.70**

Examples lead the model to better answers

0-shot: *"realizar" (work)*
vs.
*3-shot: "**no podrán** realizar" (**may not** work)*

Partial Match

Less partial matches, because of **better** exact matches

8 trigger entities not recovered

Prepositional phrase not recognized

True: *"tienen derecho **a participar**" (have the right **to participate**)*
vs.
Pred: "tienen derecho" (have the right)

Experimental Results

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Prompt Refinement → Zero-shot Learning → **3-shot Learning** → Example Selection

Entity and Relation Classification

Strict Match		Type Match		
8 subjects entities misclassified	**4** object entities misclassified	Increase of correct type classification metrics **+0.33-0.39**		
Reduction of incorrectly classified entities		**0.24** vs. **0.58** subject	**0.14** vs. **0.47** object	**0.21** vs. **0.60** Hohfeld

Experimental Results

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Prompt Refinement → Zero-shot Learning → **3-shot Learning** → Example Selection

Entity and Relation Classification

Strict Match

8 subjects entities misclassified

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Type Match

Increase of correct type classification metrics **+0.33-0.39**

0.24 vs. **0.58** subject

0.14 vs. **0.47** object

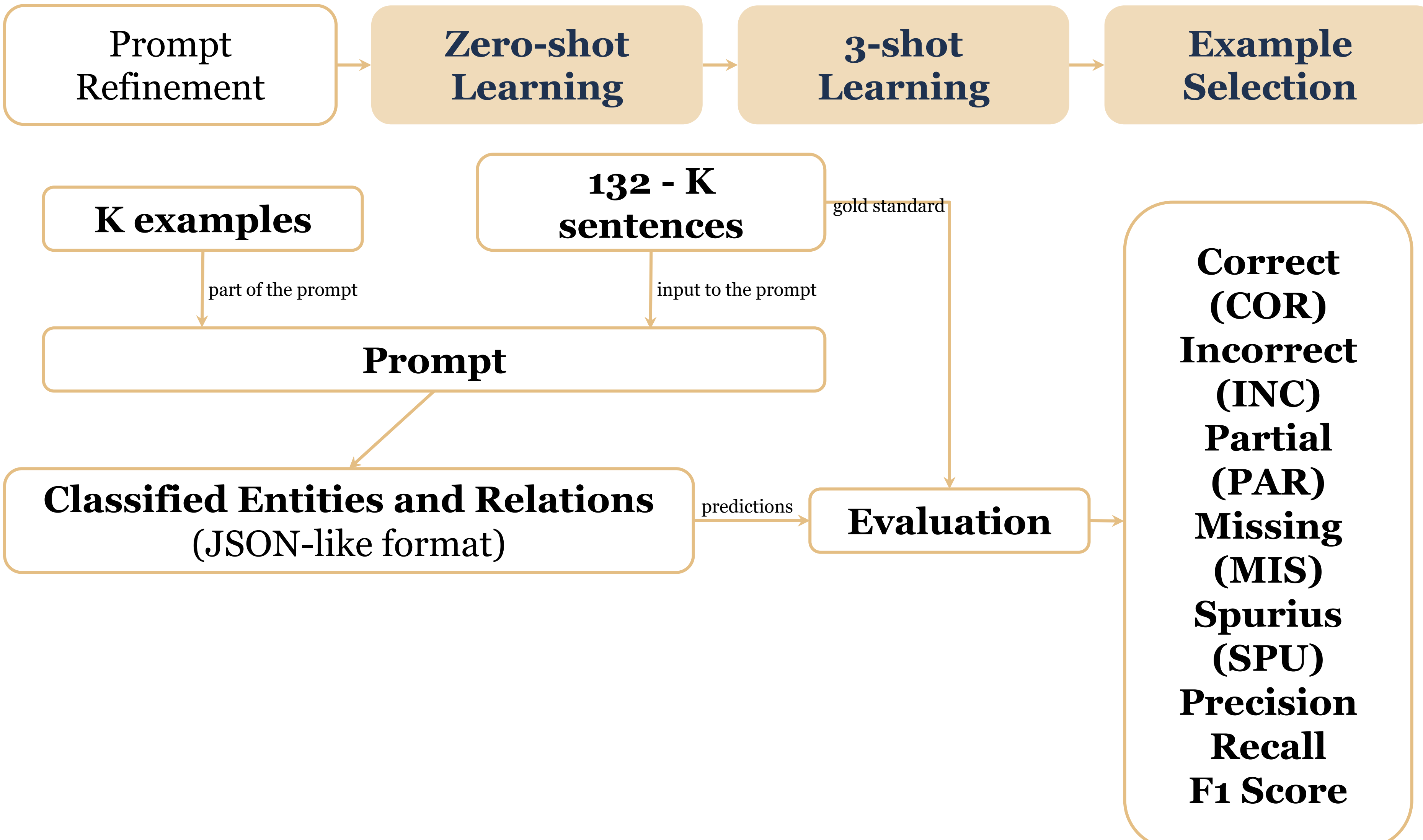
0.21 vs. **0.60** Hohfeld

Key Takeaways

Adding examples improves scores w.r.t. 0-shot

Representative examples sample is important

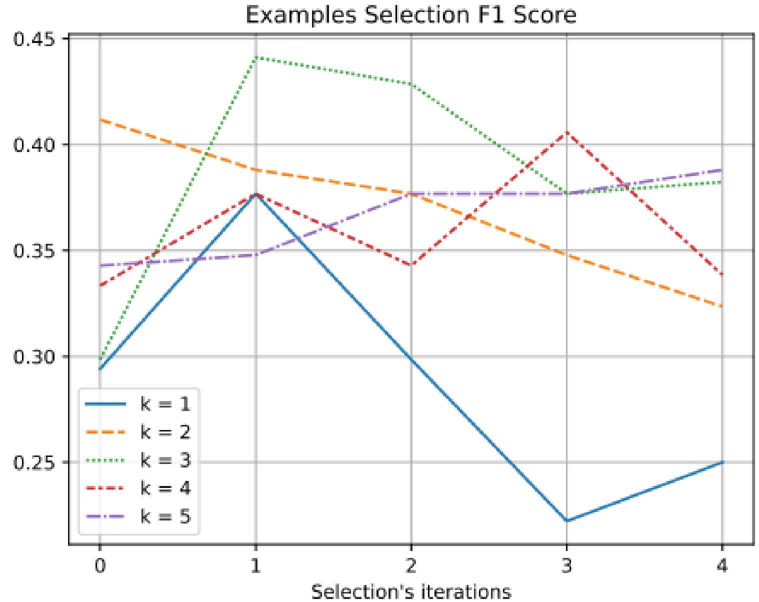
Side-contribution # 1: Example Selection Methodology

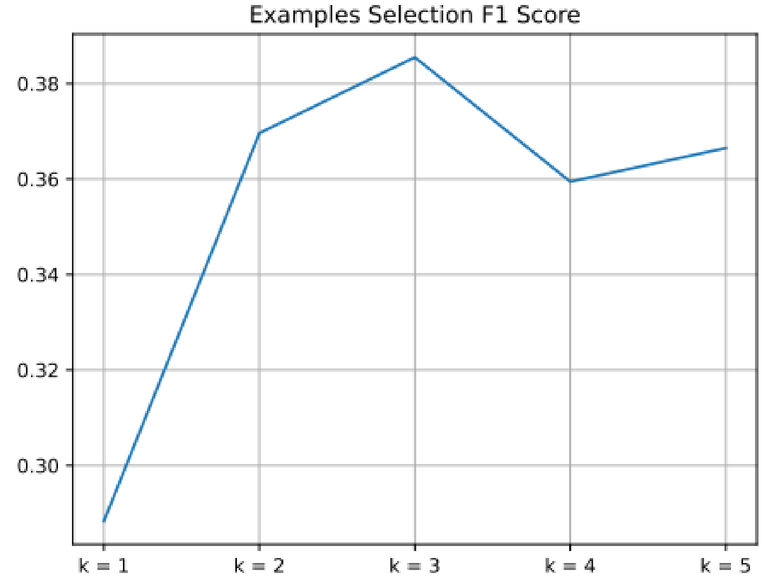


Side-contribution # 1: Example Selection Methodology

Prompt Refinement → Zero-shot Learning → 3-shot Learning → **Example Selection**

***K* = 5, *i* = 5, strict F1 score**





Experimental Results

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Prompt Refinement → Zero-shot Learning → 3-shot Learning → **Example Selection**

K = 5, i = 5, strict F1 score

Entity and Role Detection

		Exact		Partial	
	Metric	**3-shot**	**5-shot**	**3-shot**	**5-shot**
Total	Precision	0.59	0.69	0.61	0.72
	Recall	0.55	0.56	0.58	0.58
	F1 Score	0.57	0.62	0.60	0.65

Increase in overall results for all metrics, especially in precision (+0.1)

Experimental Results

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Prompt Refinement → Zero-shot Learning → 3-shot Learning → **Example Selection**

K = 5, i = 5, strict F1 score

Entity and Role Detection

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	F1 Score	**0.57**	**0.62**	**0.60**	**0.65**

Increase in overall results for all metrics, especially in precision (**+0.1**)

Entity and Relation Classification

Worsened overall type classification performance (**<0.58**)

Annotated examples may contain inconsistencies

Examples not representative of special cases

True: "empresa" (*enterprise*) derivatives
Legal Agent
vs.
Pred: "empresa" (*enterprise*) derivatives (**34%**) *Legal Entity*

Experimental Results - Partial Conclusions

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	Experiment	Precision	Recall	F1 Score
Exact	3-shot	0.59	0.55	0.57
	5-shot	**0.69**	**0.56**	**0.62**
Partial	3-shot	0.61	**0.58**	0.60
	5-shot	**0.72**	**0.58**	**0.65**
Strict	3-shot	**0.58**	**0.58**	**0.58**
	5-shot	0.57	0.55	0.56
Type	3-shot	**0.55**	**0.55**	**0.55**
	5-shot	0.52	0.52	0.52

Zero-shot learning allow to define a baseline

5-shot learning is **significantly better** at delimiting entities and assigning roles

3-shot learning is **better** at classifying entities and relations

Trade-off: delimitation or classification

Experimental Results - Partial Conclusions

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	5-shot	0.52	0.52	0.52

Zero-shot learning allow to define a baseline

5-shot learning is **significantly better** at delimiting entities and assigning roles

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Trade-off: delimitation or classification

5-shot learning with selected examples

Processing Methodology

Data Normalization → **Event Extraction** → **Semantic Representation**

Side-contribution # 2: Spanish Workers' Statute Normalization

Data Normalization → Event Extraction → Semantic Representation

Separate Statute's Parts → **Form Sentences** → **Clean Sentences**

Use regular expressions to delimit text

Unfinished ideas due to items and subitems

"Se excluyen del ámbito regulado por esta ley:"
"Las prestaciones personales obligatorias."

Join subsections headers with items

"Se excluyen del ámbito regulado por esta ley Las prestaciones personales obligatorias."

Meaningless and non-atomic sentences

"Ref. BOE-A-2009-15958Disposición transitoria octava."...

Remove phrases without verb

↓

642 sentences

↓

1. Separate phrases by punctuation
2. Add subject to subjectless sentences if possible

↓

1479 sentences

↓

Manually review syntax

↓

1235 sentences

Event Extraction from Spanish Workers' Statutes

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Data Normalization → **Event Extraction** → Semantic Representation

	Entities and Types	Count
Roles	Subjects	1141
	Objects	232
	Triggers	1158
	Complements	491
Roles' Type	Legal Agent	476
	Legal Entity	246
	Legal Concept	648
Relations' Type	Duty	586
	Right	203
	No Right	152
	Privilege	103
	No Relation	191

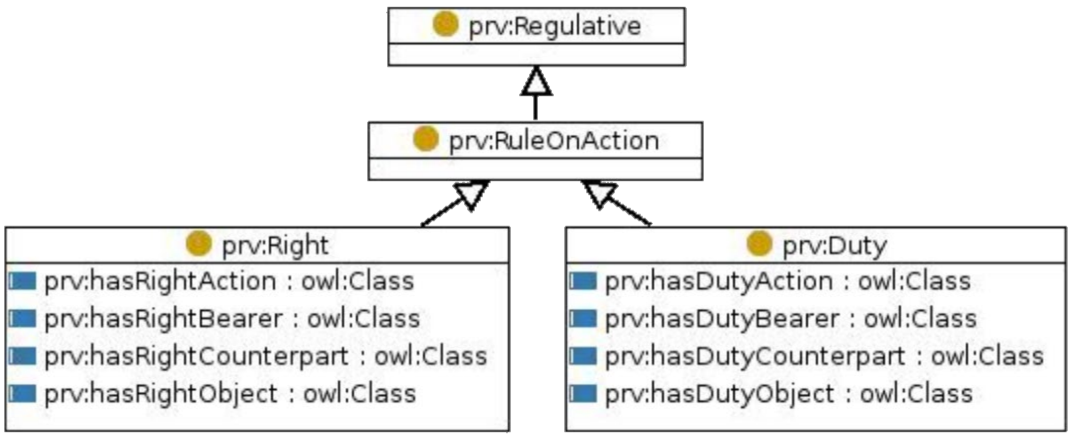
	Entities and Types	Count
Roles	Subjects	535
	Objects	139
	Triggers	713
	Complements	432
	Total	1714
Roles' Type	Legal Agent	140
	Legal Entity	107
	Legal Concept	426

56% of the Statute are duties

More than half of entities duplicated

Representation

Existing models

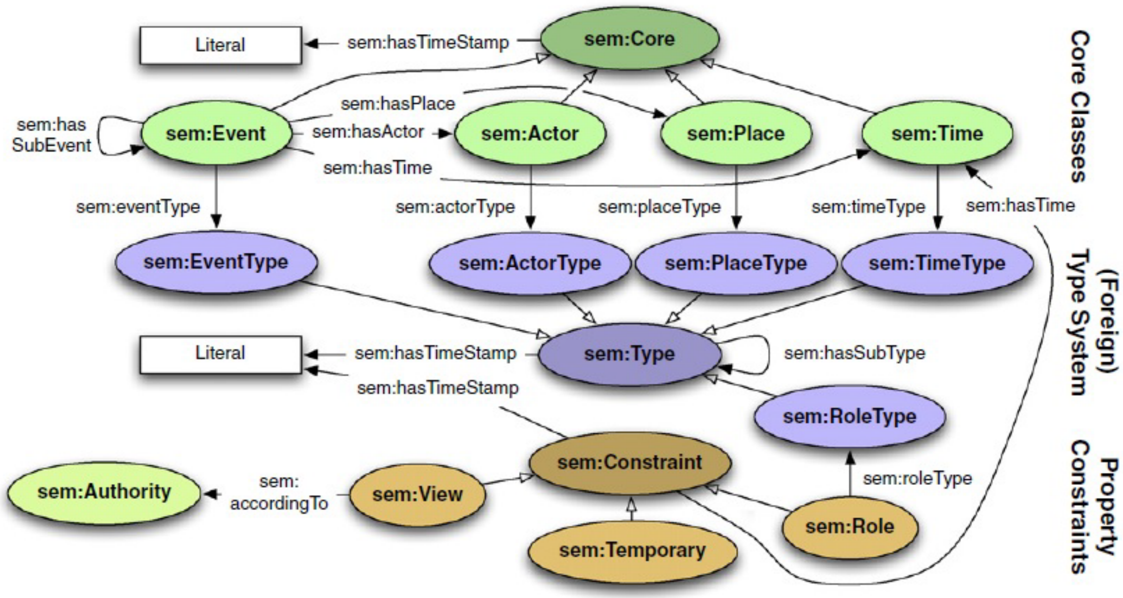


Provision Model

Enrico Francesconi (2016) "Semantic model for legal resources: Annotation and reasoning over normative provisions"

Simple Event Model

Van Hage, W. R., Malaisé, V., Segers, R., Hollink, L., & Schreiber, G. (2011). Design and use of the Simple Event Model (SEM)..



Provision Model

Hohfeld's Deontic Relations	LegalRuleML	Provision Model
Right	`lrml:Right`	`prv:Right`
Duty	`lrml:Obligation`	`prv:Duty`
No-right	`lrml:Prohibition`	`prv:Prohibition`
Privilege	`lrml:Permission`	`prv:Permission`

Enrico Francesconi. Semantic model for legal resources: Annotation and reasoning over normative provisions. In: Semantic Web 7.3 (2016), pp. 255–265.
Athan, T., Governatori, G., Palmirani, M., Paschke, A., & Wyner, A. (2015). LegalRuleML: Design principles and foundations. In Reasoning Web Int. Summer School. Springer, Cham

Semantic Representation Methodology

Semantic Representation

Hohfeld Relations

Provision Model

- Hohfeld classes: `prv:Right`, `prv:Duty`, `prv:Prohibition`, and `prv:Permission`
- Argument roles: Bearer, Counterpart and Object for Subject, Object and Complement, respectively
- Event trigger: Use of the action properties: `prv:hasDutyAction`, `prv:hasRightAction`, `prv:hasProhibitionAction` and `prv:hasPermissionAction`

Arguments and Trigger

SEM

- subject and object: `sem:Actor`
- subject and object type: `sem:ActorType` linked with `sem:actorType` property

SKOS

complement: `skos:Concept`

Schema

trigger: `schema:Action`

RDFS

entities text: `rdfs:label`

Semantic Representation Methodology

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Data Normalization → Event Extraction → **Semantic Representation**

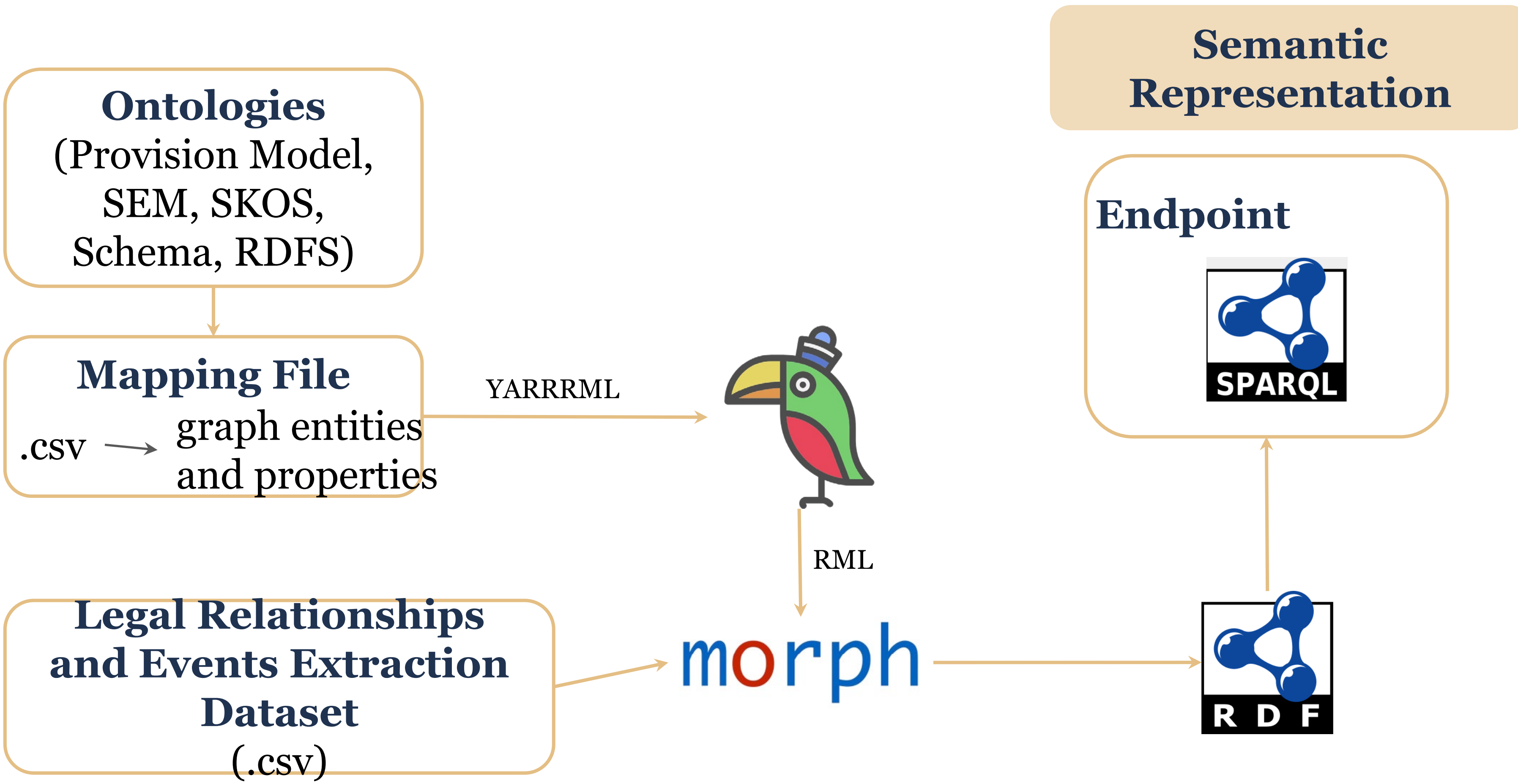
Resource Naming Strategy

Domain	Path	Ontology / Resource	Class or Property / Individual
`http://spanish-laws.es/`	+ `sws/`	+ `ontology/`	+ `[ontologyName]#[classOrPropertyName]`
		+ `resource/`	+ `[className]/[identifier]`

Class names for the individuals' resources: *Relation, EventArgument, EventTrigger, and ActorType*

http://spanish-laws.es/sws/resource/ActorType/LegalAgent
http://spanish-laws.es/sws/resource/EventArgument/argument0001

Semantic Representation of Spanish Workers' Statutes



Semantic Representation Methodology

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Data Normalization

Event Extraction

Semantic Representation

Expert Legal Systems - Question & Answering Example

As an employer, what are the ways that I have to pay my workers?

Semantic Representation Methodology

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Data Normalization → Event Extraction → **Semantic Representation**

Expert Legal Systems - Question & Answering Example

*As an **employer**, what are the **ways that I have to pay** my workers?*

```
SELECT ?rightAction ?rightComplement
  WHERE {{
    ?subject a sem:Actor .
    ?subject rdfs:label "empresario" .
    ?rightRelation a prv:Right .
    ?rightRelation prv:hasRightBearer ?subject .
    ?rightRelation prv:hasRightCounterpart ?object .
    ?object rdfs:label "salario" .
    ?rightRelation ns2:hasRightAction ?action .
    ?action rdfs:label ?rightAction .
    ?rightRelation prv:hasRightObject ?complement .
    ?complement rdfs:label ?rightComplement .
}}
```

"podrá efectuarlo" en "moneda de curso legal"
"podrá efectuarlo" en "cheque"
"podrá efectuarlo" en "modalidad de pago similar"
"podrá efectuarlo" en "entidades de crédito"
"podrá efectuarlo" en "informe al comité de empresa"
"podrá efectuarlo" en "delegados de personal"

Conclusions

Conclusions: contributions

To extract **structured event information** from the **Spanish Workers' Statute** and to link this information into a **semantic graph representation**.

Zero- and few-shot learning was evaluated with the annotated data from *Revenko et t Martín-Chozas (2022)*
Side-contribution #1: Automatic example selection strategy to improve model performance
Compare with *Revenko et Martín-Chozas (2022)* the overall results increased from **0.47** to **0.62** F1 score

Side-contribution #2: Normalization of the Spanish Workers' Statute raw text
Applied few-shot learning to the normalized text and extracted the events

Semantic graph construction after the information extracted

Limitations

GPT-3.5 model is not robust enough

Inconsistent examples from dataset used as a reference

High dependency of the few-shot learning approach on the quality of demonstrations

Presence of different resources representing the same entity (in plural and singular form)

Limitation of cross-reference detection in the event extraction task

Future Work Strategies

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GPT-3.5 model is not robust enough Inconsistent examples from dataset used as a reference High dependency of the few-shot learning approach on the quality of demonstrations	**Data quality check of the dataset before being used**
Presence of different resources representing the same entity (in plural and singular form)	**Add processing instructions to the prompt or post-process the output**
Limitation of cross-reference detection in the event extraction task	**Event extraction at paragraph level or post-process strategy**

Future Work

Test a reinforcement learning approach through the chatting interface of GPT-3.5

Linked RDF entities with existing resources in other ontologies and graphs

Research the possibility of feeding the LLM with legal resources from the Semantic Web

Analyzed the suitability and compliance of the resource naming strategy defined with the "Technical Interoperability Standard for the Reuse of Information Resources"

Research Results

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Code

https://github.com/gabyarte/event-extraction-small-corpus

zenodo

Spanish Workers' Statute Sentence Dataset

https://doi.org/10.5281/zenodo.8143596

zenodo

Spanish Workers' Statute Legal Relations and RDF

https://doi.org/10.5281/zenodo.8147616

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