## Automatic Nested Spatial Entity and Spatial Relation Extraction From Text for Knowledge Graph Creation: A Baseline Approach and a Benchmark Dataset

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#### Why extract spatial entities and spatial relations from text?<sup>2</sup>

- Textual sources
  - Unstructured spatial knowledge
  - Current or historical
  - Examples: travel guides, historical documents, social media posts, etc.
  - Spatial knowledge
    - Alternative names
    - Additional features
    - Unknown spatial entities
    - Geographic location information

#### Why store spatial knowledge in a knowledge graph?

- Heterogeneous spatial knowledge
  - Different authors
  - Different points of view
  - Different levels of detail
  - Vagueness
- Geospatial knowledge graphs
  - Queries
  - Spatial reasoning
  - Links to other sources

#### Why extract *nested* spatial entities from text?

- Flat spatial entity extraction
  - Port of Hamburg: geographic name
- Nested spatial entity extraction
  - Port of Hamburg: geographic name
  - Port: geographic feature
  - Hamburg: name

entity class assigned automatically

Port of Hamburg

indication of geographic location

### Why extract *nested* spatial entities from text?

- Flat spatial entity extraction
  - Robben Island Lighthouse: geographic name
- Nested spatial entity extraction
  - Robben Island: geographic name
  - Island: geographic feature
  - Robben: name
  - Robben Island Lighthouse: geographic name
  - Lighthouse: geographic feature

Robben Island Lighthouse automatically

indication of \_\_\_\_\_ geographic location

### Why extract spatial relations from text?

- Help disambiguation of entities
- Locate unknown entities
- Verify coherence of spatial knowledge
- Indirect spatial references

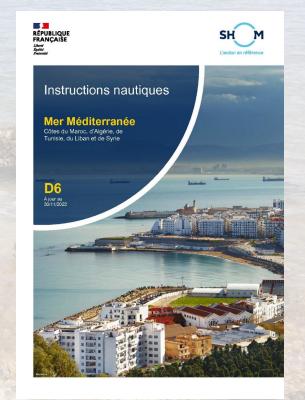
#### Context

- Structure geographic information from text as knowledge graph
  - Define ontology
  - Extract geographic information
  - Structure and disambiguate
- Application to the Instructions nautiques
  - Coastal navigation instructions
  - Coastal environment descriptions

25 À 1,9 M au SSW du phare d'Alger, un monument (36° 44,7' N – 3° 04,2' E) haut de 80 m est remarquable. Le monument et les pylônes environnants portent des feux d'obstacle aérien. À 1 M au SE du monument, le petit dôme blanc de l'ancien séminaire de Kouba (36° 44,1' N – 3° 05,3' E) est visible de toute la baie.

31 Le tronçon Nord de la jetée détachée est remarquable par les grands réservoirs qu'il porte.





#### Method

- Princeton University Relation Extraction system (PURE) [Zhong and Chen 2021]
  - Prepare annotated training dataset
    - Flat entities
    - Binary relations
  - Train two pretrained deep language models
    - Flat entity extraction
    - Binary relation extraction
- Our approach: PURE with nested spatial entities and binary spatial relations
  - Context window size?
  - Monolingual vs multilingual models?

#### **Dataset Preparation**

- Instruction nautiques extracts
  - Worldwide coverage
  - ~101,000 tokens
  - ~17,000 entity labels
  - ~3,000 relation labels
- Manual annotation
  - brat rapid annotation tool

#### **Annotation Scheme**

- Nested spatial entity annotations
  - geographic name
  - geographic feature
  - o name
- Binary spatial relation annotations
  - Topological: "is off the coast of", "is marked by", "is an element of"
  - Absolute directional: 16 cardinal directions

Un port de pêche est établi à 5,7 M à l'ENE de Ras Magroua.

#### is ENE of

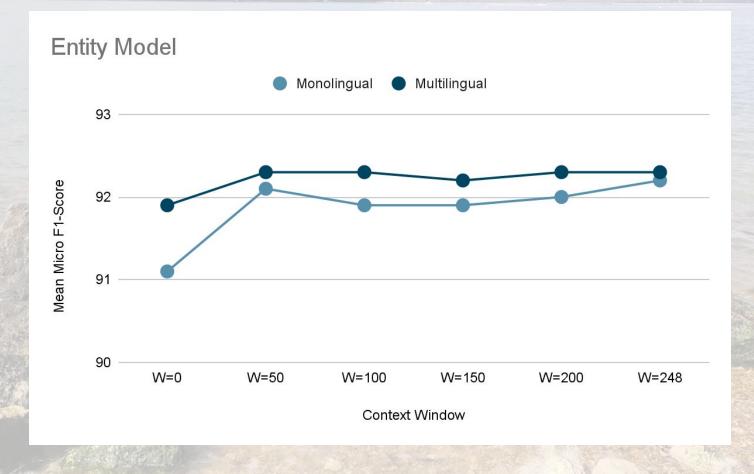
### Model Training

- Pretrained models
  - Monolingual: bert-base-french-europeana-cased
  - Multilingual: bert-base-multilingual-cased
- Context windows
  - Entity model: 0, 50, 100, 150, 200, 248
  - Relation model: 0, 50, 100

Hyperparameter	Entity Model	Relation Model
learning rate	1e-5	2e-5
task learning rate	5e-4	
train batch size	16	32
training epochs	100	10



#### **Results: Context Window**

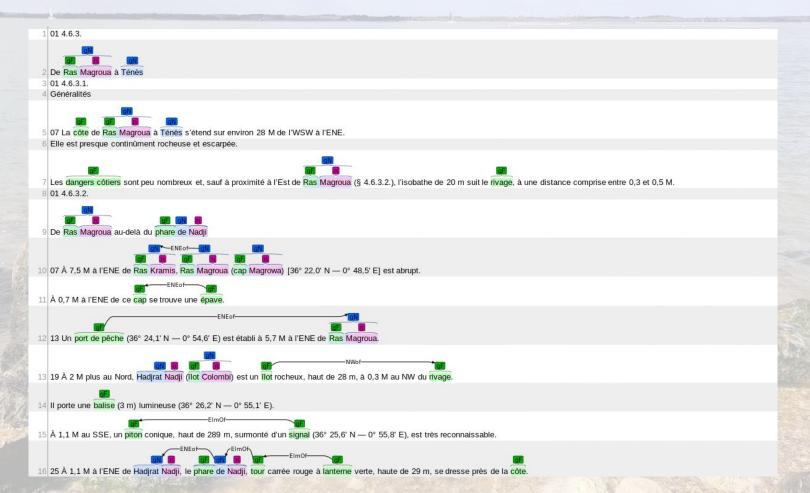


#### **Results: Context Window**

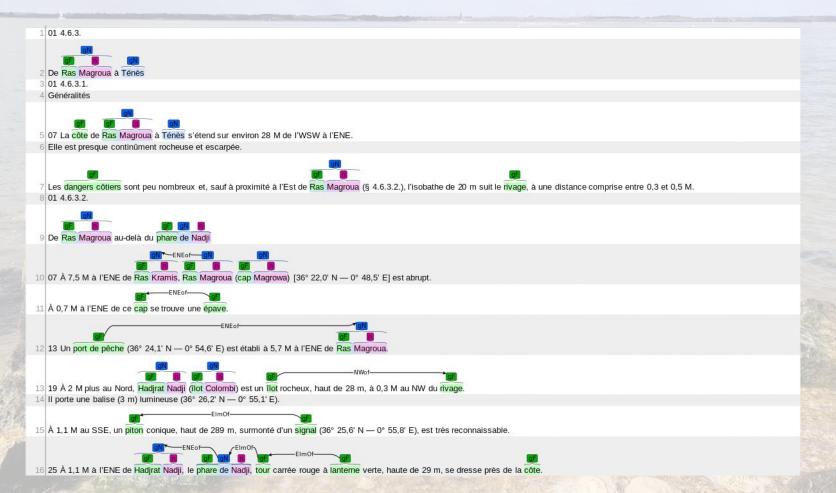


	F1-Score	
	Monolingual	Multilingual
Entity	92.2	92.3
Relation	64.2	63.2
Relation (e2e)	63.9	63.2

#### **Results: Monolingual Example**



#### **Results: Multilingual Example**



#### Conclusion

- PURE [Zhong and Chen 2021] → spatial entities, spatial relations
  - Nested entity extraction approach
- New French-language dataset
  - <u>https://github.com/umrlastig/atlantis-dataset</u> (from 16/11)
  - o https://www.kaggle.com/competitions/defi-textmine-2024/
- Benchmark results

#### Future Work

- Reducing annotation time
  - Smaller dataset + unsupervised learning
  - Machine-assisted annotation
  - Synthetic data
- Extending extraction scope
  - N-ary relations
  - Distance spatial relations
  - Intrinsic and relative directional spatial relations
  - Entity characteristics

# Thank you!

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