

# UOM-FJ at the NTCIR-15 SHINRA2020-ML Task

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## Summary



- We participated in 28 subtasks of the SHINRA2020-ML Task: mapping Wikipedia entities into Extended Named Entity (ENE) categories.
- Our model was trained to capture multiple aspects of Wikipedia articles: text, structured knowledge, images, page layout and the ENE class hierarchy.
- Our system ranked first in four languages, achieving an F1-score of 82.73 on the English subtask.

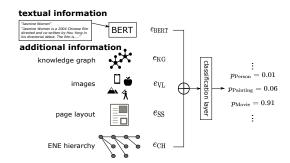
## Our System Overview



**Document representation**:  $e = FFNN(e_{BERT} \oplus e_{KG} \oplus e_{VL} \oplus e_{SS} \oplus e_{CH})$ 

- BERT encoder (Devlin et al., 2019) for pure textual information ( $e_{\rm BERT}$ )
- A set of separately-trained document representations that encodes different aspects of a given document: knowledge graph features ( $e_{\rm KG}$ ), text and images ( $e_{\rm VL}$ ), page screenshot layout ( $e_{\rm SS}$ ), and ENE class hierarchy ( $e_{\rm CH}$ )

**Label probability**:  $p(c, e) = \sigma(w_c^{\mathsf{T}} e + b_c)$ 



## Multi-aspect Document Representations (1/4)



### Knowledge graph ( $e_{\rm KG}$ )

- Pre-trained embeddings of **Wikidata graph** (Lerer et al., 2019)
- wikibase\_item field of the Wikipedia dump is used to identify the Wikidata entity corresponding to a Wikipedia article
- 98.3% of English Wikipedia articles have corresponding Wikidata entries



https://www.wikidata.org/wiki/Q1490

## Multi-aspect Document Representations (2/4)



### Text-image representation ( $e_{ m VL}$ )

- VL-BERT-based (Su et al., 2020) encoding of text and images in a given Wikipedia article
- Multiple images are rescaled and concatenated to compose a single large image; individual images are treated as regions-of-interest (ROIs)
- The VL-BERT model is fine-tuned on the SHINRA2020-ML task



## Multi-aspect Document Representations (3/4)



### Page screenshot layout ( $e_{\rm SS}$ )

- We obtain visual renderings of Wikipedia articles from a Wikipedia dump to generate their screenshots
- The screenshots are resized to a fixed size and fed into INCEPTION (Inception V3 with different convolution filters) (Szegedy et al., 2016) to obtain visual representations



## Multi-aspect Document Representations (4/4)



#### ENE class hierarchy ( $e_{CH}$ )

- We employ a hierarchy-aware global model (HiGAM) (Zhou et al., 2020) to capture the label hierarchy and correlations between ENE categories
- Construct hierarchy graph: node = ENE category, edge = hierarchical relational information or correlation information
- The encoder is trained with binary cross-entropy loss over the hierarchical label space



#### Submissions



We examined three ways to generate the final outputs:

- jointrep: output the categories whose estimated probability exceeds the threshold  $\theta=0.5$
- jointrepPostprocess: jointrep + assign the label CONCEPT if the probability scores of all candidate categories are below the threshold
- jointrepUnionPostprocess: take the union of different predictions made by five models trained on different subsets of the training data, and then apply the post-processing step as in jointrepPostprocess

### Main Results



### Official evaluation results (English)

| Submission name                  | $\mathcal P$ | $\mathcal R$ | $\mathcal{F}_1$ | Rank |
|----------------------------------|--------------|--------------|-----------------|------|
| jointrep                         | 81.77        | 83.71        | 82.73           | 1    |
| ${	t jointrepPostprocess}$       | 81.46        | 83.71        | 82.57           | 3    |
| ${\tt jointrepUnionPostprocess}$ | 80.66        | 84.80        | 82.68           | 2    |
| Other teams best                 | 79.65        | 85.00        | 82.23           |      |

### Other languages

- Non-English results are based on VL-BERT model, i.e. using only text-image representation
- Ranked first on Spanish, Italy and Catalan as well
- Relatively low performance on Arabic, Hindi and Thai

## **Ablation Study**



### leaderboard results, jointrep, English

| Model                             | ${\cal P}$ | $\mathcal R$ | $\mathcal{F}_1$ |
|-----------------------------------|------------|--------------|-----------------|
| Full                              | 75.3       | 76.4         | 75.7            |
| <ul><li>knowledge graph</li></ul> | 74.8       | 75.8         | 75.2            |
| <ul><li>text-image</li></ul>      | 74.5       | 75.5         | 74.8            |
| <ul><li>page layout</li></ul>     | 75.5       | 77.2         | 76.0            |
| <ul><li>class hierarchy</li></ul> | 74.4       | 76.4         | 75.1            |
| BERT + knowledge graph            | 70.8       | 71.3         | 71.0            |
| BERT + text-image                 | 73.5       | 74.8         | 73.9            |
| BERT + page layout                | 70.5       | 71.6         | 70.9            |
| BERT + class hierarchy            | 74.2       | 75.2         | 74.5            |

# Error examples



| Page ID                | Title                | Opening text   | Predicted ENEs                     | Gold ENEs         |
|------------------------|----------------------|--|------------------------------------|-------------------|
|                        |                      | 1 0  | 1.7.21.8:Plan                      | 0:CONCEPT         |
| 54866853 Hedi (Policy) |                      | Hedi was an economic policy of the imperial China. It was the state purchase of food supplies from farmers. As a means to control the price of grains and foods, it is an early example of Government procurement. The policy was adopted in the year of 488 by Emperor Xiaowen of Northern Wei as a counter measure of drought. The state purchases | 1.7.21.8:Plan                      | 0:CONCEPT         |
| 299259                 | Roman cur-<br>rency  | food supplies and stock them  Roman currency for most of Roman history consisted of gold, silver, bronze, orichalcum and copper coinage (see Roman metallurov) From  | 1.7.25.1:Currency                  | 9:IGNORED         |
|                        | ,                    | its introduction to the Republic, during t Confusion betw  | een CONCEP  other classes          | *                 |
| 788538                 | Azamino              | debasement and replacement of coins over the centuries<br>Azamino (あざみ野) is a bedroom community of Tokyo and Yokohama,<br>located in Aoba-ku, Yokohama, Kanagawa Prefecture, Japan. The area is<br>20 minutes from Shibuya Station on the Tokyo Den-en-toshi Line and 27   | 1.5.0:Location<br>Other            | 1.5.1.1:City      |
|                        |                      | minutes by Known as a refer to the Japanese Wikipedia articl   | •                                  |                   |
| 22786903               | Hiro H1H             | years. It is located next to the trendy famile practice.  The Hiro HI4 (or Navy Type 15) was a 1920s Japanese bomber or reconnaissance biplane flying boat developed from the Felixstowe F.5 by the Hiro Naval Arsenal for the Imperial Japanese Navy. The aircraft were built by Hiro. the Yokosuka Naval Arsenal and Aich.                         | 1.7.6:Weapon,<br>1.7.17.3:Aircraft | 1.7.17.3:Aircraft |
| 586540                 | Tailor               | were built by rino, the tokosuka Navara Arsenai and Alcin. A tailor is a person who makes, repairs, or alters clothing professionally, especially suits and men's clothing. Although the term dates to the   | 1.7.23.1:Position_<br>Vocation     | - 0:CONCEPT       |
|                        | edirect<br>Tailoring | thirter Page redirect to different entity onto century, and now recess to make so men a may women a sum, coats, trousers, and similar garments, usually of wool, linen, or silk  |                                    | Tailoring         |

## Summary (recap)



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