Multiclass Product Classification Based On Multilingual Model and LightGBM (Team:Uni)

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BACKGROUND

- The primary objective of ESCI competition is to build new ranking strategies and identify interesting categories of results (i.e., substitutes) that improves customer product searching experience.
- The dataset is multilingual that includes English, Japanese, and Spanish.

- Task 1: Query-Product Ranking
- Task 2: Multiclass Product Classification
- Task 3: Product Substitute Identification

BACKGROUND

- Task 2 & Task 3 share the same training dataset with different classification targets

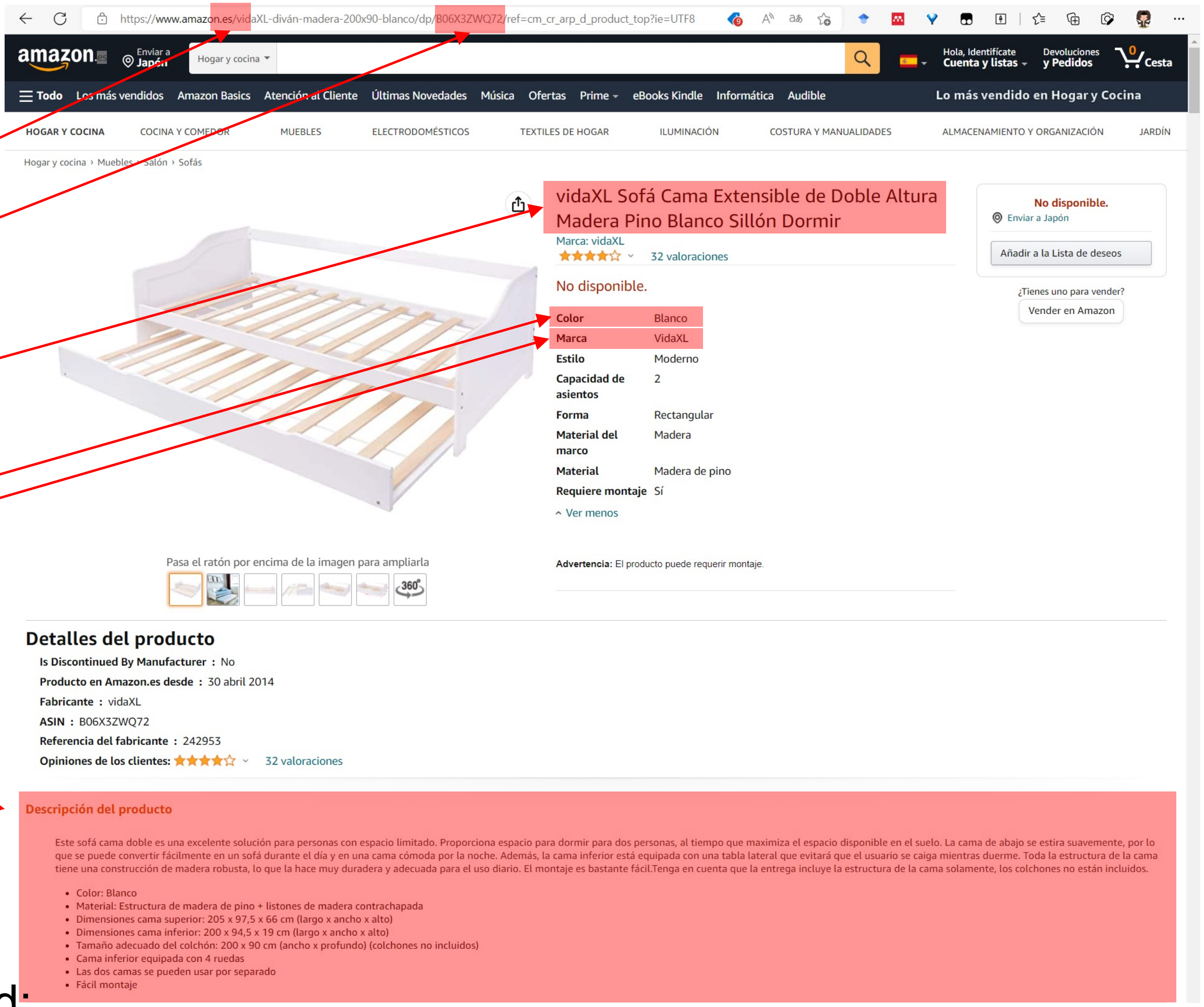
- Task 2: Multiclass Product Classification
    - Given <Query, product> pairs, predict 4 labels. (**exact, complement, irrelevant, substitute)**
- Task 3: Product Substitute Identification
    - Given <Query, product> pairs, predict 2 labels. (**no_substitute, substitute)**

- **We participated in Task 2 and Task 3. We won the 3rd place in both tasks.**

BACKGROUND

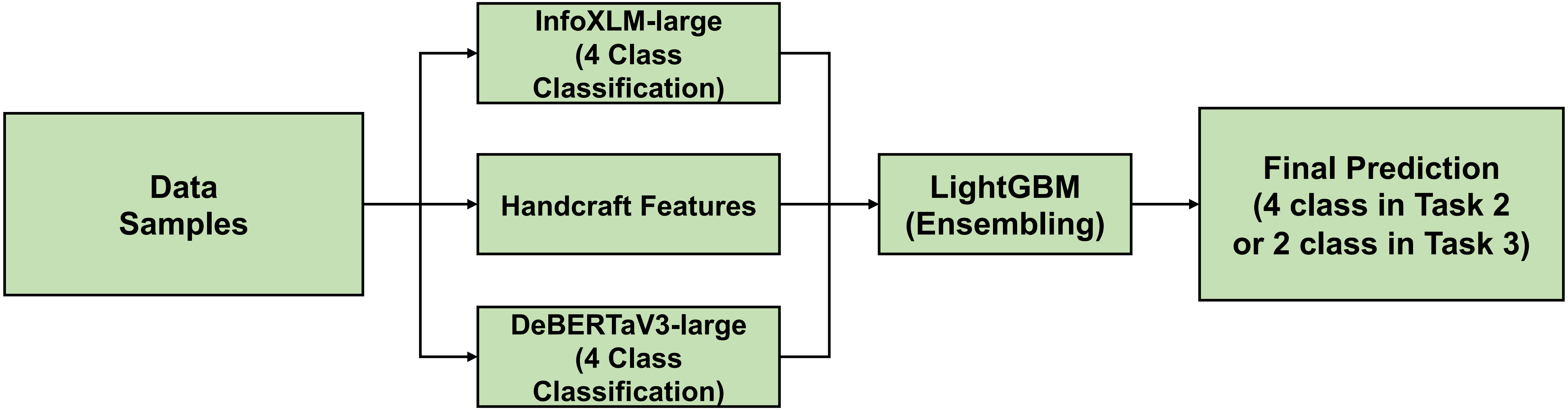
Product Information

- product_locale
- product_id
- product_title
- product_color_name
- product_brand
- product_description
- product_bullet_point (Nan)



- NONE of the following external data is used:
  - Product info pages and images crawled by web crawlers
  - Data leakage from Task 1
  - Training dataset of Task 1
- Disclaimer: We didn ‘t use any external data, but the top 2 teams all stated in their respective posts that their solutions used theexternal data and gained significant benefits.

OUR SOLUTION



OUR SOLUTION – Language Models

- InfoXLM
  - One of the most powerful cross-lingual pre-trained models
- DeBERTaV3
  - ~70% of the sample pairs are English corpus in this dataset.
  - One of the most powerful pre-trained English language models

OUR SOLUTION – Training Strategy

- Input of the Language Model：

$$
\begin{aligned}
Input = [CLS] + Query + [SEP] + product\_id + [SEP] + product\_brand + [SEP] \\
+ product\_color + [SEP] + product\_title\_name + [SEP] + product\_bullet\_point + [SEP] \\
+ product\_description + [SEP]
\end{aligned}
$$

- Take Language Model as a feature extractor and then a fully connected layer will transform the feature into the two/four class probability

- Other Useful Train Strategies:
  - FGM
  - Rdrop
  - Hard Samples Mining

OUR SOLUTION - Stacking

- We use LightGBM as the final predictor, which contains three different inputs:
    1. 4-fold cross-validation probability of InfoXLM-large
    2. 4-fold cross-validation probability of DeBERTaV3-large
    3. Handcraft Features
        - Match scores based on query term and product term, e.g. Jaccard similarity between query and product_title
        - Query_locale (tell the model which country this sample comes from)
        - Aggregation features of predicted results of all samples under the same query
        - ……

Results

Language Models	Input Length	Training Strategy	Model Ensembling (KFold)	Handcraft Features	Model Ensembling Strategy	Online F1 score
InfoXLM-large	180	-	5	-	Average	0.8142(public)
InfoXLM-large	128	Rdrop, FGM	5	-	Average	0.8163(public)
InfoXLM-large + DeBERTaV3	128	Hard-Sample-Mining, Rdrop, FGM	4	-	Average	0.8184(public)
InfoXLM-large + DeBERTaV3	128	Hard-Sample-Mining, Rdrop, FGM	4	Add	LightGBM Blending	0.8281(public)
InfoXLM-large + DeBERTaV3	128	Hard-Sample-Mining, Rdrop, FGM	4	Add	LightGBM Blending	0.8274(private)

Table 1: Performance comparison with different models

Only use Task 2 dataset and achieve 0.8274 on private dataset

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