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)



- 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 the external data and gained significant benefits.



Este sófi cama doble es una excelente solución para personas con espacio limitado. Proporciona espacio para dormir para dos personas, al tiempo que maximiza el espacio disponible en el suelo. La cama de abajo se estina suavemente, por lo que se puede convertir fácilmente en un sofá durante el día y en una cama cómoda por la noche. Además, la cama inferior está equipada con una tabla lateral que evitará que el usuario se caiga mientras duerme. Toda la estructura de la cama tineu na construcción de madera robusta, lo que la hace muy duradera y adecuada para el uso díario. El montaje es bastante fácil.Tenga en cuenta que la entrega incluye la estructura de la cama solamente, los colchones no está in incluidos:

Color: Blanco
 Material: Estructura de madera de pino + listones de madera contrachapada
 Dimensiones cama superior: 205 x 97,5 x 66 cm (largo x ancho x alto)
 Dimensiones cama inferior: 200 x 90,5 x 19 cm (largo x ancho x alto)
 Tamaño adecuado del colchón: 200 x 90 cm (ancho x profundo) (colchones no incluido
 Cama inferior equipada con 4 ruedas

Las dos camas se pueden usar por separado
 Eácil montaie

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 :

$$\begin{split} Input &= [CLS] + Query + [SEP] + product_id + [SEP] + product_brand + [SEP] \\ &+ product_color + [SEP] + product_title_name + [SEP] + product_bullet_point + [SEP] \\ &+ product_description + [SEP] \end{split}$$

- 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

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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

ACKNOWLEDGMENTS

- We thank both KDD organizers as well as Amazon for holding such a great competition.
- This study is supported by the National Natural Science Foundation of China (Grant No.41931183). The numerical calculation in this work were carried out on the SunRising-1 computing platform.
- This study is also supported by National Natural Science Foundation of China (Grant No: 62106221)