Next Product Title Generation in E-commerce: Rule-based Methods and Autoencoder Model

10th Place Solution for Task 3 in Amazon KDD Cup 2023

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Who we are?

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HAKUHODO is the 9th largest ad agency group in the world.
We are the people experts.

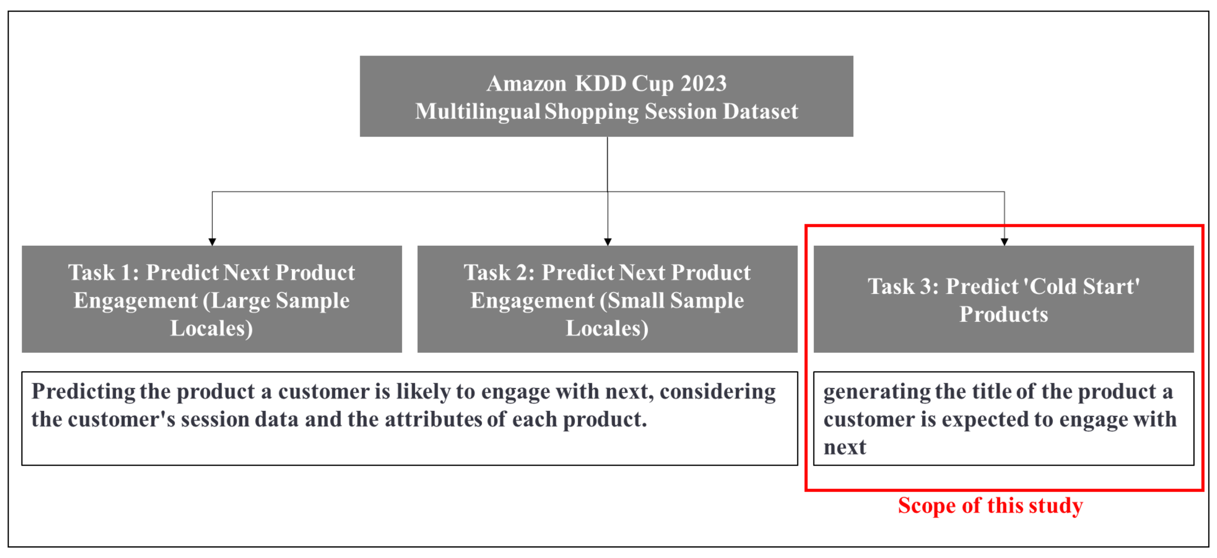
Data Science Boutique

Data Science Boutique is the professional organization for data science in HAKUHODO.
We are the members of Data Science Boutique.

Introduction

Background

- Our team secured the 10th place in Task 3 of the Amazon KDD Cup 2023.
- The competition's goal was to create multilingual recommendation systems using a "Multilingual Shopping Session Dataset" collected from six different locales.
- Task 3 posed a unique challenge of predicting "cold start" products by generating the title of the next product a customer is likely to engage with.
- The absence of a ground truth in Task 3 made it particularly challenging and different from traditional product prediction tasks.



Methodology

Overview

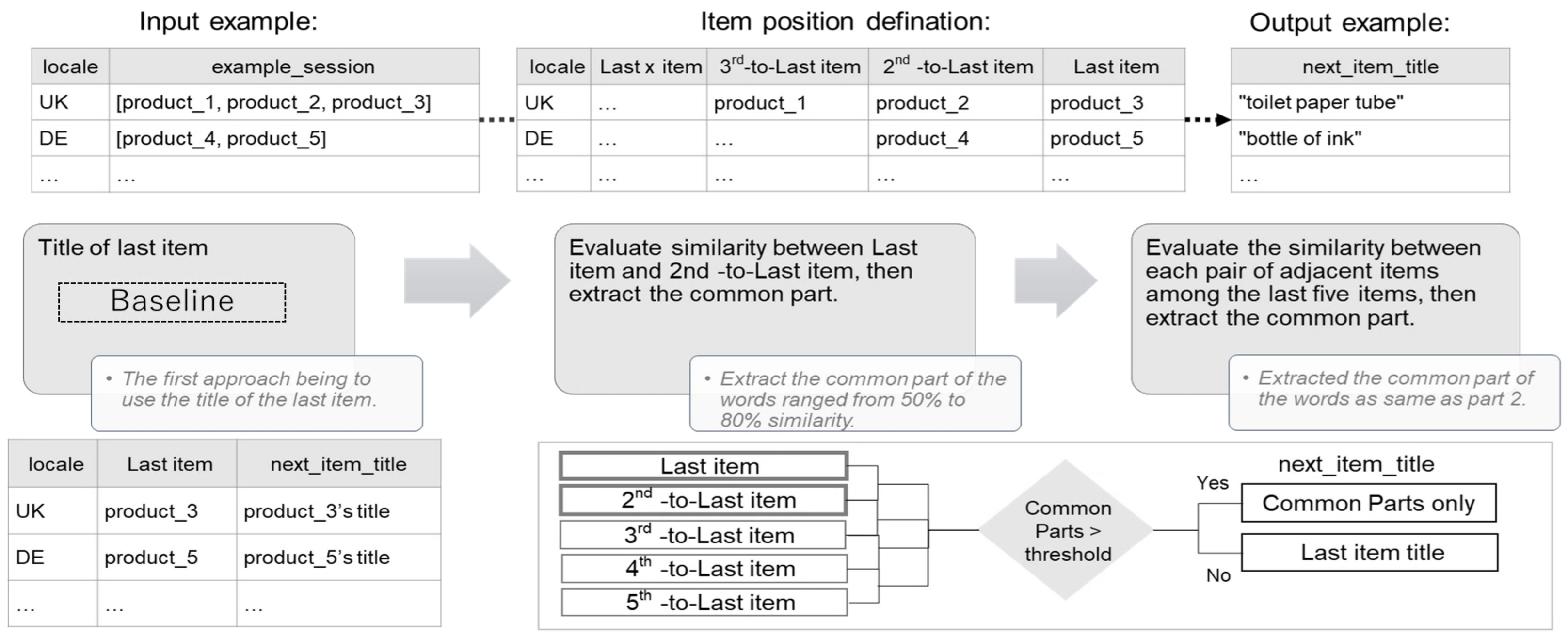
- The evaluation metric for this task is the BLEU score, which ranges from 0 to 1 and assesses the quality of natural language generation.
- A higher BLEU score indicates higher performance and more accurate predictions.
- Our approach first establishes a baseline using the title of the last item in each customer's session.
- We explore a rule-based method to generate the next product title.
- Additionally, we apply an LSTM-trained autoencoder model to generate product titles that align with customer preferences.

Baseline

Established a baseline score using the title of the last product in a customer's session as the generated product title, based on high correlation found between adjacent products in the training dataset.

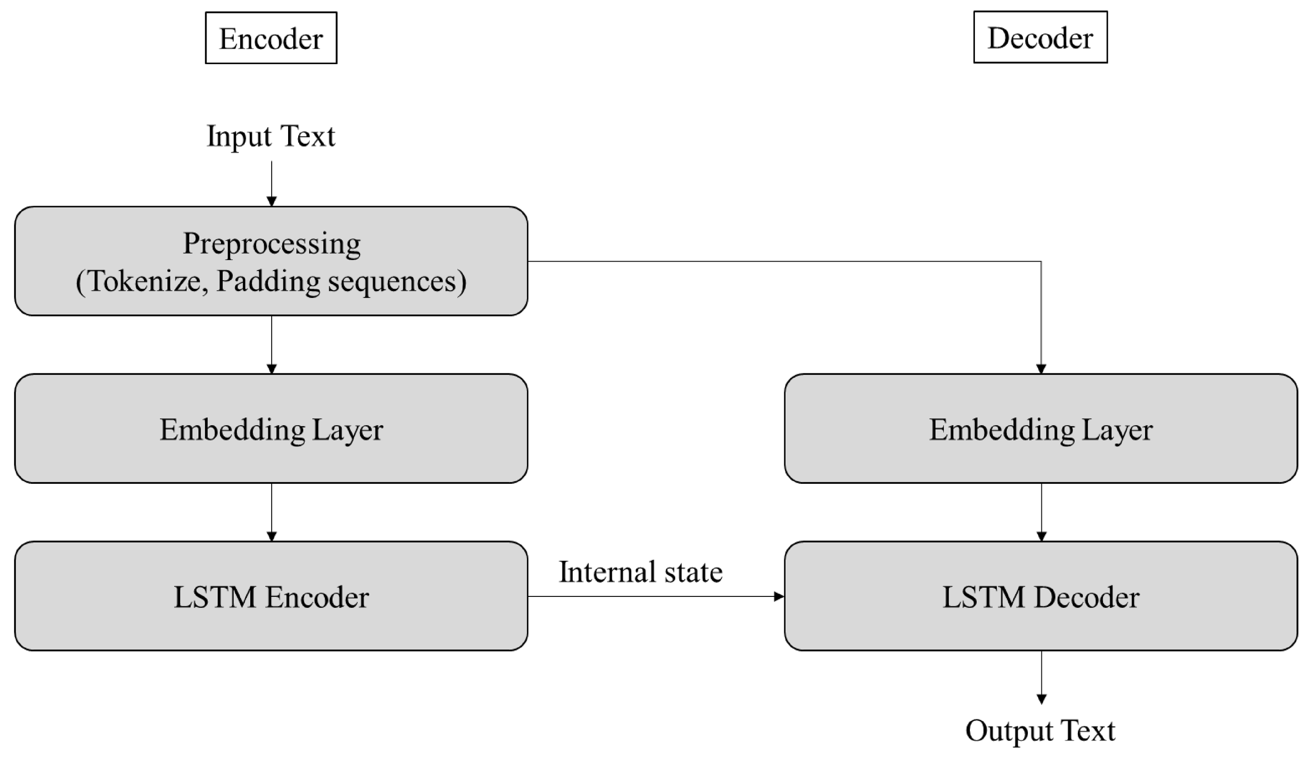
Rule Base Approach

- If the last and penultimate product titles are similar, the next product's title is generated using their common elements.
- If the products are dissimilar, the last product's title is used as the next product's recommendation.
- Similarity is determined by dividing titles into four-word units and setting a similarity threshold.
- Initial evaluation was based on the last and second-to-last items, with thresholds of 50%, 60%, 70%, and 80% for title generation.
- Further analysis considered the last product and the preceding five products, generating titles if any similar items were found.
- The similarity threshold was set based on the value that yielded the highest score.



Autoencoder Approach

To enhance our proposed rule-based approach, we implemented an Auto-Encoder model [1], composed of an embedding layer and an LSTM [2] layer, to reproduce the last product title of the session. The model processes preprocessed text sequences and generates product titles. This process was applied only to sessions that have a certain level of similarity between the last and second-to-last products.



Result and Discussion

Result

- The best score, 0.26787, was achieved when the match rate of words in the last and penultimate products was over 70%.
- Generating titles based on a product similar to the last product of the session and any of the previous five products did not improve accuracy.
- The Auto-Encoder approach improved accuracy against the baseline but did not reach the best score (BLEU=0.26696).

Discussion

- The generation of symbols was potentially unsuccessful in the Auto-Encoder approach.
- Tuning the decoder hyperparameters could potentially improve the Auto-Encoder approach in future work.

Approaches	BLEU Score	Brevity Penalty
Baseline: Last Item's titles Only	0.26553	1.00000
Rule Base1: 50% common	0.26019	0.96430
Rule Base2: 60% common	0.26497	0.98584
Rule Base3: 70% common	0.26787	1.00000
Rule Base4: 80% common	0.26695	1.00000
Rule Base5: Last5Session common	0.24915	0.99195
Encoder-decoder generation based on Rule Base3	0.26696	0.99676

Best Score

References

[1] Hinton GE, Salakhutdinov RR. 2006. Reducing the Dimensionality of Data with Neural Networks. Science, 313(5786), 504-507. DOI: https://doi.org/10.1126/science.1127647

[2] Sepp Hochreiter, Jurgen Schmidhuber. 1997. Long Short-Term Memory. Neural Computation, 9(8), 1735-1780. DOI: https://doi.org/10.1162/neco.1997.9.8.1735