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Reproducibility companion paper: Knowledge enhanced neural fashion trend forecasting

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Reproducibility Companion Paper: Knowledge Enhanced Neural Fashion Trend Forecasting

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ABSTRACT

This companion paper supports the replication of the fashion trend forecasting experiments with the KERN (Knowledge Enhanced Recurrent Network) method that we presented in the ICMR 2020. We provide an artifact that allows the replication of the experiments using a Python implementation. The artifact is easy to deploy with simple installation, training and evaluation. We reproduce the experiments conducted in the original paper and obtain similar performance as previously reported. The replication results of the experiments support the main claims in the original paper.

CCS CONCEPTS

- Information systems → Specialized information retrieval.

KEYWORDS

Fashion Trend Forecasting; Fashion Analysis; Time Series Forecasting

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1 INTRODUCTION

In the original paper [1], we presented the KERN model for addressing the fashion trend forecasting problem. The problem aims

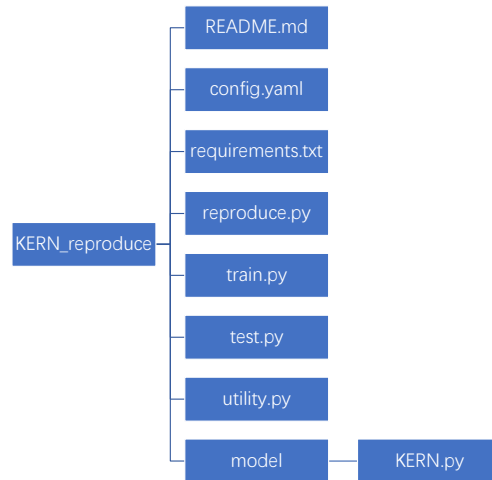


Figure 1: The structure of KERN_reproduce artifact.

to take a period of historical fashion trend records as input, and predict a period of following trends in the future. It is formulated as a multi-horizon time-series forecasting task. Our KERN method utilizes a deep learning-based framework, *i.e.*, LSTM encoder-decoder, and further incorporates both internal and external knowledge to enhance the forecasting performance. In this companion paper, we present a replication artifact that provides a complete re-implementation of the model as well as the required experimental facilities used in the original paper.

The artifact *KERN_reproduce* is available at https://github.com/mysbupt/KERN_reproduce. The dataset is accessible at https://drive.google.com/file/d/1E_gPmh6lIHxEX3IRDWWKvm_8op5B82t/view?usp=sharing. We also pack and upload the code and dataset to the platform Zenodo, and the URL is <https://zenodo.org/record/4774766#.YKdfH6LnhhE>. This artifact includes a detailed README file which specifies the environmental requirements, code structures and implement instructions. It also includes the code to train



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Table 1: Dataset setting

Dataset	Input length (year)	Output length (year)	#training sample	#test sample
GeoStyle	1	0.5	80,960	2,024
FIT	2	0.5	422,784	8,808
	2	1	211,392	8,808

and evaluate the KERN model for fashion trend forecasting. The experimental settings are easy to configure by a unified configuration file in the artifact. The file structure of the artifacts is shown in Figure 1.

2 DATASET

In the original paper, two datasets, *i.e.* FIT [1] and GeoStyle [2], are involved to evaluate the effectiveness of the presented method. In our replication, we use the exactly same datasets. Both of the two datasets consist of considerable number of specific fashion trend time-series. Each time-series denotes the evolving process of a specific type of fashion element among a certain group of people. In comparison, FIT has longer fashion trend sequences, includes more fine-grained fashion elements, and considers more user attributes than GeoStyle. The detailed settings and statistics of the two datasets in our experiments are shown in Table 1. The datasets which are directly applied in our experiments can be downloaded according to the instruction in the README file in the artifacts. The original GeoStyle dataset is also provided, along with the pre-processing code in the script.

3 EXPERIMENTAL SETUP

The code is purely written with Python and the required modules for using the artifact are listed in the file of *requirements.txt*. In particular, we use the PyTorch (1.6.0 or higher version) framework to implement the model. In addition, we have tested the code on servers which have the OS of Ubuntu 16.04/18.04 and are equipped with Nvidia TiTan X/V/Xp/V100 GPUs.

The KERN model is an end-to-end neural network model, which can be easily trained and evaluated by the proposed artifact. Here we describe the utility of each script in the artifact.

- **reproduce.py** The auxiliary script to reproduce all the experimental results reported in Table 3 and Table 4.
- **train.py** The script to train the KERN method following the default settings defined in the configure file (*./config.yaml*).
- **test.py** The script to generate the testing result for the saved models.
- **utility.py** The code for preparing data, including both dataset preprocessing and data loader. It generates training and testing samples which are fed into the model during training.
- **model/KERN.py** The code defines the model of KERN.

4 PARAMETERS

We provide the *config.yaml* file for users to adjust the hyper-parameters needed to reproduce the experiments. We list all the configured settings and hyper-parameters used in the experiments in Table 2, as

well as the detailed descriptions and the default values. Note that some parameters are set differently for different experimental settings, such as *triplet_lambda* and *epoch*. Parameters for model training, including *lr*, *epoch* and *batch_size*, are chosen based on empirical observations of the training process considering both convergence and stability, which we suggest users keep the default values for these settings in order to generate fair results. *input_len* and *output_len* are set differently for two datasets, resulting in three settings: *FIT output_len 12*, *FIT output_len 24*, *GeoStyle output_len 26*. *feat_size* and *rnn_hidden_size* are model hyper-parameters, which are kept the same with the original paper. By adjusting *ext_kg* and *int_kg*, users can conduct various ablation studies to verify the effectiveness of introducing external knowledge and internal knowledge individually or collaboratively. We tune *triplet_lambda* (corresponds to λ in equation (9) of the original paper) and *sample_range* for the KERN model and the ablated model with internal knowledge only to achieve the best performance. Specifically, the hyper-parameter *sample_range* is used to control the sampling of p and q in terms of a certain k , the smaller the *sample_range*, p and q will be more closer with each other.

5 EXPERIMENTAL RESULTS

We reproduce the experiments on two datasets for all settings applied in the original paper. The overall performance of the KERN model, both in the original paper and our replication, are reported in Table 3. From the table, we can see that the replication results are not identical but quite similar with the original reported results. We carefully go through all the scripts used for the experiment, and find the reason might be the randomness introduced during the initialization of the deep learning model’s parameters.

We also reproduce the ablation experiments and report the original and replicated results in Table 4. Specific settings for two hyper-parameters *triplet_lambda* and *sample_range* are: [KERN/KERN-I, GeoStyle]: [0.002, 50], [KERN-I, FIT-half year]: [0.0001, 500], [KERN, FIT-half year]: [0.001, 500], [KERN-I, FIT-one year]: [0.01, 1000], [KERN, FIT-one year]: [0.0002, 100]. Users can also find the detailed settings for various experiments in the *config.yaml* file that we provide in the artifact. From the table, we can see that our replicated results are overall similar with the original reported ones. Although the results are not identical, most of our claims in the original paper still hold with the replicated results. For FIT, the external knowledge is helpful in improving the performance for both experimental settings. However, the internal knowledge is not consistent helpful in all settings. Based on our replicated results, when predicting the FIT for half year, adding the internal knowledge upon the external knowledge-involved model slightly degrades the final performance. All the results and conclusions obtained are consistent with those in the original paper. By the way, we find a presentation typo in the original paper, where the KERN-I result of GeoStyle in Table 2 should be 0.0137. In this paper, we fix this typo.

6 REPRODUCIBILITY EFFORTS

The last two co-authors of this paper are the reviewers of this companion paper. Through some corrections and improvements, we have successfully installed necessary libraries and execute source codes from scratch. Moreover, we have reproduced results that are

Table 2: Introduction of Parameters

Parameter	description	Default value	
		FIT	GeoStyle
input_len	the length of input fashion trend sequence (for encoder)	48	52
output_len	the length of the fashion trend sequence to predict (for decoder)	12/24	26
ext_kg	whether to apply the external knowledge	true	true
int_kg	whether to apply the internal knowledge	true	true
triplet_lambda	coefficient for the triplet loss (chosen from [0.0001,0.0002,0.001,0.002,0.01,0.02])	0.002	0.002
sample_range	the range to sample similar and dissimilar sequence(choose from [50,100,500,1000])	500	500
feat_size	the embedding dimension for the element and user features	10	10
rnn_hidden_size	the dimension of the LSTM hidden state	50	50
lr	the initialized learning rate	0.001	0.001
lr_decay	whether to decay the learning rate during the training	true	true
lr_decay_interval	after how many epochs to decay the learning rate	10	15
lr_decay_gamma	the learning rate decay rate	0.1	0.1
epoch	the number of total training epochs	15	20
batch_size	the batch size	400	400

Table 3: The original and the replication performance of KERN

Dataset	GeoStyle		FIT			
	Half year		Half year		One year	
Method	MAE	MAPE	MAE	MAPE	MAE	MAPE
Original	0.0134	14.24	0.083	30.02	0.094	33.45
Replication	0.0129	14.77	0.082	29.40	0.093	32.56

Table 4: Comparison of the results of ablation study. (KERN-I: w/o internal knowledge, KERN-E:w/o external knowledge, KERN-IE:w/o both)

Dataset	GeoStyle		FIT			
	Half year		Half year		One year	
Prediction	original	replication	original	replication	original	replication
KERN-IE	0.0137	0.0130	0.0840	0.0824	0.0966	0.0940
KERN-E	-	-	0.0835	0.0827	0.0953	0.0941
KERN-I	0.0137	0.0130	0.0831	0.0824	0.0942	0.0940
KERN	0.0134	0.0129	0.0836	0.0823	0.0939	0.0931

quite close to ones from the original paper [1]. We deeply appreciate the active efforts of the authors of the original paper to improve the reproducibility of this companion paper, which benefit the future research.

During the reviewing process, we focused on corrections and improvements on the user-friendly installation and execution that enable other researchers to obtain the reproduced results without struggling in the trial-and-error process. First, we provide additional explicit information on CUDA version and all necessary

python libraries with their specific versions, which are described in *requirements.txt*. Second, we add an auxiliary script of *reproduce.py* that runs all the testing together to easily reproduce and check all the results. Finally, we separate testing codes from training codes (*train.py*) to provide better development environment to other researchers for additional training and testing beyond reproducing the described results. We save the best model derived from the *train.py* and add an additional script *test.py* to load the model and do the test.

In conclusion, we worked together as a team for this reproducibility companion paper. With dedication from both the original authors and reviewers, we finally obtained the improved paper and materials. We hope this paper would be very helpful for other researchers to utilize this paper.

7 CONCLUSION

In this paper, we document the replication of the original KERN method for fashion trend forecasting proposed in ICMR 2020. The replication shows that the experimental results are not strictly identical but quite similar with those reported in the original paper.

Therefore, it supports the main claims in the original paper that KERN method outperforms all compared methods and the technical contributions are demonstrated to be valid.

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