

Online Chinese News Classification System based on Python Reptile and Convolutional Neural Network

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Abstract: With the advent of the era of big data, the amount of data has shown an exponential growth. A series of news retrieval platforms represented by Netease News have new content all the time. In order to allow users to more directly understand the current hot spots, the system uses THUCNews data sets for training, including a total of 14 categories, 830,000 articles. Using TensorFlow to train a character-level convolutional neural network with a single convolutional layer, a 92.24% accuracy rate was achieved on the validation set. Combined with the Python crawler, it eventually achieved automatic crawling and classification of news information, presented to the user in a concise manner.

Keywords: Crawler; Convolutional neural network; Python

1. Introduction

In the current era of information explosion, various kinds of information are uploaded daily from various media. In order to allow users to more intuitively understand the current hot news in the society, people have used crawlers to crawl and display news titles and content, but the news leaderboard only gives the news headlines, and does not give specific news categories. Even the classification of news content pages is classified by people subjectivity. There is also an article corresponding to multiple categories, so how to objectively carry out the news correctly classification becomes an important research issue in natural language processing. Therefore, it was can't achieved that use the simple adoption of crawler technology, so this paper regularly uses crawler technology to crawl the top 20 hits with the highest click rate from the Netease news rankings, put them into a trained neural network, these news will be classified and stored in the database by the neural network.

2. Related Research Work

Kim[1] used CNN[2][3] to classify sentences based on word2vec[4], and conducted comparative experiments on seven sets of datasets to prove a single layer of convolutional nerves. CNN is effective in text categorization tasks, it also shows that using unsupervised learning methods to pre-train word vectors is an important part of natural language processing (NLP). Xiang Zhang, Junbo Zhao, and Yann LeCun[5] provided empirical research on text classification for character-level convolutional neural networks. Using some large-scale datasets, the

traditional model and the deep learning model were compared to find that the character-level convolutional neural network is an effective method for text classification.

This paper uses THUCNews[6][7] to construct vocabulary based on the training set and then converts the input text into a fixed-length id sequence by using the word2id operation. These a fixed-length id sequence as neural networks' input. It was adopted that character-level convolutional neural network model. The model achieves good results by adjusting different hyperparameters.

3. System Design and Implementation

In order to realize news online classification, this paper uses crawler technology to automatically crawl and store the required data, and these data are input into the neural network after preprocessing, and then the results are stored in the database, and displayed on the front-end of the website by friendly means.

3.1. Model design

The crawler is an automated program that requests websites and extracts data. This paper analyzes and compares the rankings of various news portals, and finally selects the Netease News rankings with regular contents, less bad information, and fewer advertisements. Crawl every hour and select the top 20 hot news with the highest click rate, as shown in Figure 1.

Analyzing the landing page: http://news.163.com/special/0001386F/rank_news.html, the page leaderboard is not dynamically generated by JavaScript, so the page can be processed directly after crawling, using the BeautifulSoup + requests library can be achieved, crawler process show

n in Figure 2. After the above steps, a simple Netease news crawler is implemented.

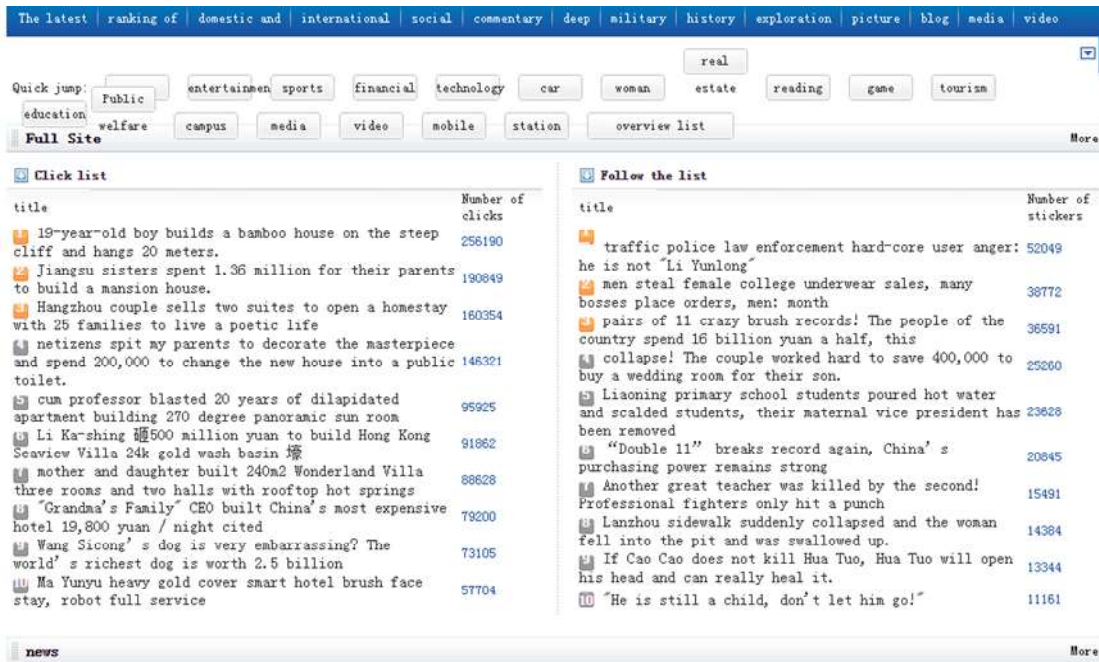


Figure 1. Netease news ranking

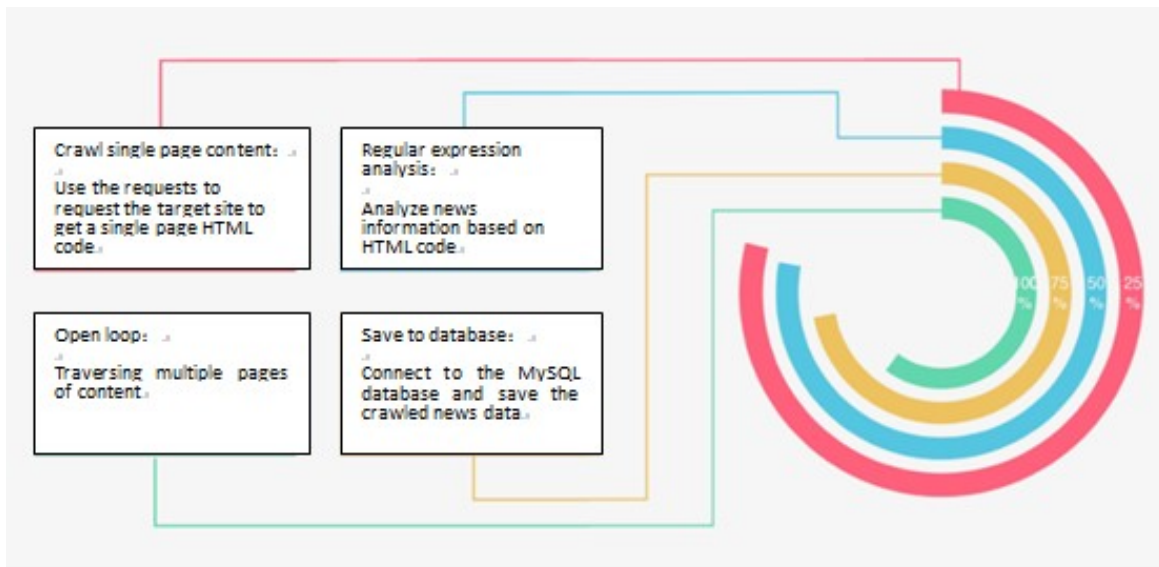


Figure 2. Crawler process

The model architecture adopted in this paper is shown in Figure 3. The first-layer word embedding layer (Embedding) [8] converts a one-dimensional sequence into a two-dimensional vector, and accesses a convolutional layer composed of multiple filters. The convolutional layer is used as a feature extraction. The extraction layer extracts local features through filters and generates feature maps through convolution kernel function operations

and outputs them to Max Pooling. The max pooling layer belongs to the feature mapping layer, which samples the feature maps generated by the convolutional layer and outputs the local optimal features. Immediately after the Fully Connected layer, the layer is added with dropout[9] regularization and relu activation functions. The last full connection layer and Softmax layer are used as classifiers,

and finally map the output of multiple neurons to within the (0,1) interval, multiple classifications are performed.

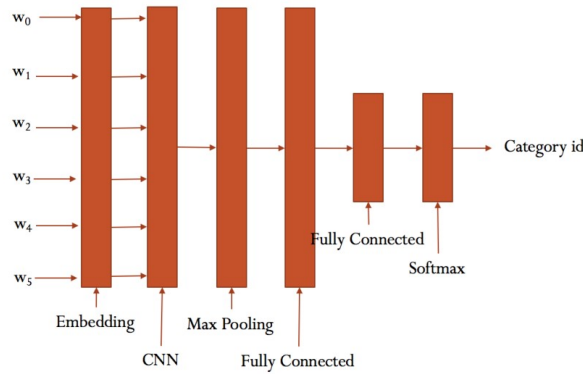


Figure 3. Model architecture

3.2. Data preprocessing and model training

This paper selects the THUCNews data sets generated by the Natural Language Processing Laboratory of Tsinghua University according to the historical data of the Sina News RSS subscription channel from 2005 to 2011. The data sets contains about 830,000 news documents (2.19 GB) and 14 candidate classification categories: Finance, lottery, real estate, stocks, home, education, technology,

society, fashion, politics, sports, constellations, games, entertainment.

First,preprocessing the data sets, and 830,000 independent documents are integrated into three files, which are training set, verification set and test set. The proportion of the data sets is 70%, 15%, 15%. The specific division is shown in Table 2 After preprocessing, the data in the format of Table 1 is obtained.

Table 1. Pre-processed Data

Data	Shape	Data	Shape
x_train	[585247, 600]	y_train	[585247, 14]
x_val	[125403, 600]	y_val	[125403, 14]
x_test	[125425, 600]	y_test	[125425, 14]

Table 2. Data Set Partitioning

Data set partition				
Classification	Training set	Verification set	Test set	Total
Finance	25968	5564	5566	37098
Stock	108078	23159	23161	154398
Technology	114050	24439	24440	162929
Society	33594	7627	7628	50849
Game	17061	3655	3657	24373
Constellation	2504	536	538	3578
Politics	44160	9462	9464	63086
Fashion	9357	2005	2006	13368
Education	29355	6290	6291	41936
Property	14035	3007	3008	20050
Lottery ticket	5311	1138	1139	7588
Household	22810	4887	4889	32586
Entertainment	64842	13894	13896	92632
Sports	92122	19740	19742	131604

Total	585247	125403	125425	836075
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The 10-fold cross-validation method was used during the time of training. Set the training to be suspended in advance if the model does not improve over 10,000 rounds. After continuous improvement, the following parameters are finally selected.

embedding_dim = 64 #Word vector dimension
 seq_length = 600 #Sequence length
 num_classes = 14 #Number of categories
 num_filters = 512 #Number of convolution kernels
 kernel_size = 9 #Convolution kernel size
 vocab_size = 6000 #Glossary size
 hidden_dim = 128 #Fully connected neurons

dropout_keep_prob = 0.6 #dropoutRetention ratio
 learning_rate = 1e-3 #Learning rate
 batch_size = 128 #Training size per batch
 num_epochs = 10 #Total iteration round
 print_per_batch = 1000 #Output results every few rounds
 save_per_batch = 10 #How much of each round into tensorboard

The experimental results are shown in Figure 4 The highest accuracy of 85.23% was achieved on the verification set and stopped only after 6 rounds.

```
totalMemory: 15.91618 freeMemory: 15.98618
2018-04-06 22:01:57.578111: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1021] Adding visible gpu devices: 0
2018-04-06 22:01:57.578284: I tensorflow/core/common_runtime/gpu/gpu_device.cc:911] Device interconnect StreamExecutor with strength 1 edge matrix:
2018-04-06 22:01:57.578480: I tensorflow/core/common_runtime/gpu/gpu_device.cc:937] 0
2018-04-06 22:01:57.578619: I tensorflow/core/common_runtime/gpu/gpu_device.cc:938] 0
2018-04-06 22:01:57.591139: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1043] Created TensorFlow device (/job:localhost/replica:0/task:0/device:GPU:0 with 15839 MB memory) -> physical_device_id: 0, name: Tesla P40-PCI-E-16GB, pci bus id: 0000:00:08:0, compute capability: 6.0
Training and evaluating...
Epoch: 1
Iter: 0, Train Loss: 2.0, Train Acc: 16.80%, Val Loss: 2.0, Val Acc: 21.40%, Time: 0:00:20 *
Iter: 1000, Train Loss: 0.25, Train Acc: 91.41%, Val Loss: 0.57, Val Acc: 81.44%, Time: 0:01:13 *
Iter: 2000, Train Loss: 0.33, Train Acc: 92.07%, Val Loss: 0.68, Val Acc: 81.11%, Time: 0:02:00 *
Iter: 3000, Train Loss: 0.18, Train Acc: 96.80%, Val Loss: 0.56, Val Acc: 80.75%, Time: 0:02:50 *
Iter: 4000, Train Loss: 0.19, Train Acc: 92.07%, Val Loss: 0.51, Val Acc: 84.40%, Time: 0:03:42 *
Epoch: 2
Iter: 5000, Train Loss: 0.807, Train Acc: 96.80%, Val Loss: 0.52, Val Acc: 81.91%, Time: 0:04:36 *
Iter: 6000, Train Loss: 0.14, Train Acc: 96.80%, Val Loss: 0.52, Val Acc: 81.21%, Time: 0:05:30 *
Iter: 7000, Train Loss: 0.29, Train Acc: 92.07%, Val Loss: 0.51, Val Acc: 81.60%, Time: 0:06:32 *
Iter: 8000, Train Loss: 0.11, Train Acc: 96.80%, Val Loss: 0.56, Val Acc: 84.60%, Time: 0:07:24 *
Iter: 9000, Train Loss: 0.16, Train Acc: 95.31%, Val Loss: 0.52, Val Acc: 84.90%, Time: 0:08:17 *
Epoch: 3
Iter: 10000, Train Loss: 0.12, Train Acc: 96.80%, Val Loss: 0.57, Val Acc: 83.91%, Time: 0:09:11 *
Iter: 11000, Train Loss: 0.802, Train Acc: 97.60%, Val Loss: 0.56, Val Acc: 84.50%, Time: 0:10:04 *
Iter: 12000, Train Loss: 0.12, Train Acc: 95.31%, Val Loss: 0.56, Val Acc: 84.67%, Time: 0:11:00 *
Iter: 13000, Train Loss: 0.14, Train Acc: 95.31%, Val Loss: 0.56, Val Acc: 86.90%, Time: 0:12:00 *
Epoch: 4
Iter: 14000, Train Loss: 0.11, Train Acc: 95.31%, Val Loss: 0.59, Val Acc: 85.23%, Time: 0:13:00 *
Iter: 15000, Train Loss: 0.12, Train Acc: 96.31%, Val Loss: 0.56, Val Acc: 84.60%, Time: 0:14:00 *
Iter: 16000, Train Loss: 0.11, Train Acc: 96.80%, Val Loss: 0.64, Val Acc: 83.83%, Time: 0:15:00 *
Iter: 17000, Train Loss: 0.11, Train Acc: 94.31%, Val Loss: 0.62, Val Acc: 84.15%, Time: 0:16:00 *
Iter: 18000, Train Loss: 0.054, Train Acc: 99.25%, Val Loss: 0.62, Val Acc: 84.60%, Time: 0:17:00 *
Epoch: 5
Iter: 19000, Train Loss: 0.076, Train Acc: 98.40%, Val Loss: 0.69, Val Acc: 84.41%, Time: 0:18:00 *
Iter: 20000, Train Loss: 0.002, Train Acc: 96.80%, Val Loss: 0.79, Val Acc: 84.30%, Time: 0:19:00 *
Iter: 21000, Train Loss: 0.11, Train Acc: 97.60%, Val Loss: 0.71, Val Acc: 83.62%, Time: 0:20:00 *
Iter: 22000, Train Loss: 0.15, Train Acc: 93.75%, Val Loss: 0.65, Val Acc: 83.90%, Time: 0:21:00 *
Epoch: 6
Iter: 23000, Train Loss: 0.059, Train Acc: 96.80%, Val Loss: 0.79, Val Acc: 84.11%, Time: 0:22:00 *
Iter: 24000, Train Loss: 0.071, Train Acc: 97.60%, Val Loss: 0.75, Val Acc: 83.90%, Time: 0:23:00 *
No optimization for a long time, auto-stopping...
```

Figure 4. Training results

3.3. Test of the model

By testing on the test sets, the following results were obtained: Test Loss: 0.28, Test Acc: 92.24%

The classification effect is shown in Table3.

Table 3. Classification Results

Classification	Precision	Recall	F1-score	Support
Sports	0.98	0.99	0.99	19741
Finance	0.83	0.77	0.8	5565
Property	1	1	1	3007
Household	0.94	0.93	0.94	4888
Education	0.93	0.93	0.93	6290
Technology	0.91	0.97	0.94	24439
Fashion	0.88	0.91	0.89	2005
Politics	0.84	0.93	0.88	9463
Game	0.9	0.87	0.88	3656
Entertainment	0.95	0.94	0.94	13895
Stock	0.93	0.87	0.9	23160
Lottery ticket	0.97	0.85	0.91	1138
Society	0.91	0.84	0.87	7627
Constellation	0.98	0.87	0.92	537
Avg / total	0.92	0.92	0.92	125411

The confusion matrix is shown in Figure 5. The results show that the accuracy rate on the test sets reached 92.24%. Excluding the low F1-Score of finance and economics, the other classifications were all over

87%. From the confusion matrix, it can be seen that the classification effect is obvious.

3.4. System integration

Django is a large and comprehensive web application framework written in Python. This paper uses Django to integrate reptiles, convolutional neural network news classifiers, and web front ends. It sets the crawler to crawl once every whole point, the crawler runs over, and

sends the crawled results to the neural network for prediction and stores the results. The effect is shown in Table 4.

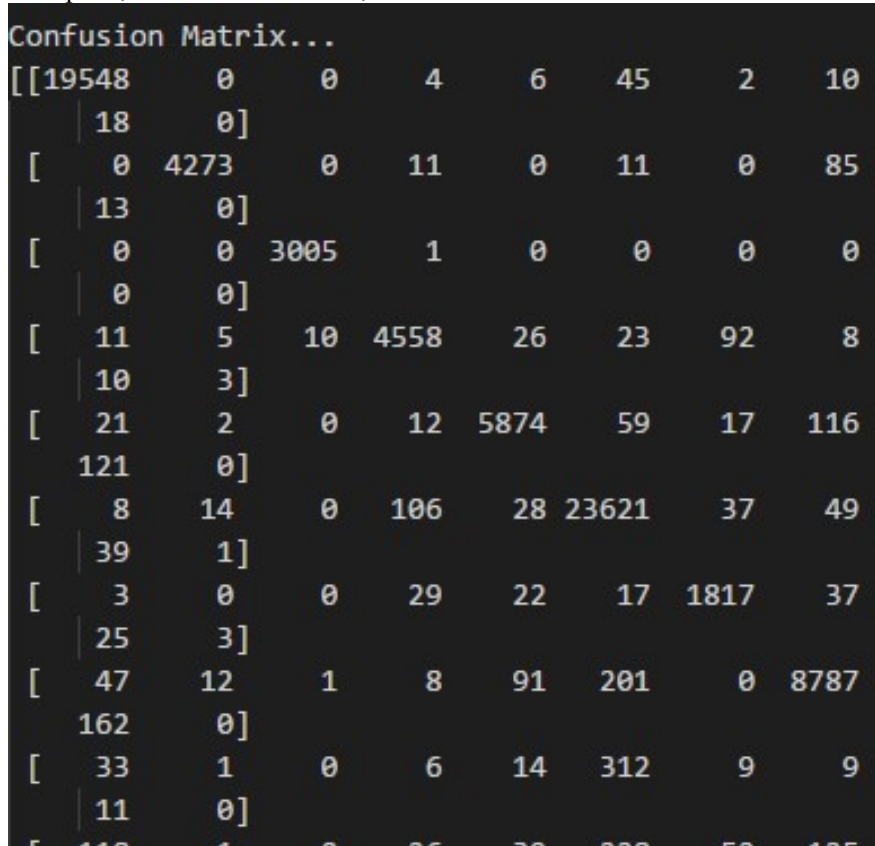


Figure 5. Result confusion matrix

Table 4. System Display

News hotspot	Classification	Time
African students are fainting in Hubei heatstroke	Fashion	2018.06.30 14:00
The first prisoner of the 18th National Congress was full of corruption	Politics	2018.06.30 14:00
The man pretending to be a captain cheated, and lied that he would be the secretary of the municipal party committee.	Society	2018.06.30 14:00
Taxation education housing expenditure can be deducted before tax	Politics	2018.06.30 14:00
The daughter of the daughter of the school will receive 19 boss gifts.	Education	2018.06.30 14:00
Trump: Didn't say that I want to withdraw from the WTO, but the WTO is really unfair to us.	Entertainment	2018.06.30 14:00

4. Conclusion

In this paper, we have achieved the online classification of Netease news clicks by Python crawler and character-level convolutional neural network, and obtained higher accuracy on the THUCNews dataset. compared with the 88.6% accuracy reached by THUCTC toolkit used the LibSVM and Liblinear classification algorithms by the Tsinghua University Natural Language Processing Laboratory, have been significantly improved. Therefore, character-level convolutional neural networks are better

than traditional linear classifiers for Chinese text classification. However, the data sets used in this paper are relatively old, and it is believed that using crawler technology to crawl according to today's news classification and using the methods proposed in this project can achieve better results.

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