MDFEND:Multi-domain Fake News Detection

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Introduction

Fake news spread widely on social media in various domains, and most existing approaches focus on single-domain fake news detection (SFND). As an emerging field, multi-domain fake news detection (MFND) is incresingly attracting attention. However, data distributions, such as word frequency and propagation patterns, vary from domain to domain, namely domain shift. Facing the challenge of serious domain shift, existing fake news detection techniques perform poorly for multi-domain scenarios.

We first design a benchmark of fake news dataset for MFND with domain label annotated, and further propose an effective Multi-domain Fake News Detection Model (MDFEND) by utilizing a domain gate to aggregate multiple representations extracted by a mixture of experts.

Weibo21: A New Dataset for MFND

Data Statistics of Weibo21

Data statistics of nine domains

domain	Science	Military	Education	Disasters	Politics
real	143	121	243	185	306
fake	93	222	248	591	546
all	236	343	491	776	852
domain	**Health**	**Finance**	**Entertainment**	**Society**	**All**
real	485	959	1000	1198	4640
fake	515	362	440	1471	4488
all	1000	1321	1440	2669	9128

- **Data source**: we collect both fake and real news from Sina Weibo ranging from December 2014 to March 2021.
- **Data composition**: news content, pictures, timestamp, comments for all, and judgement information for fake news.

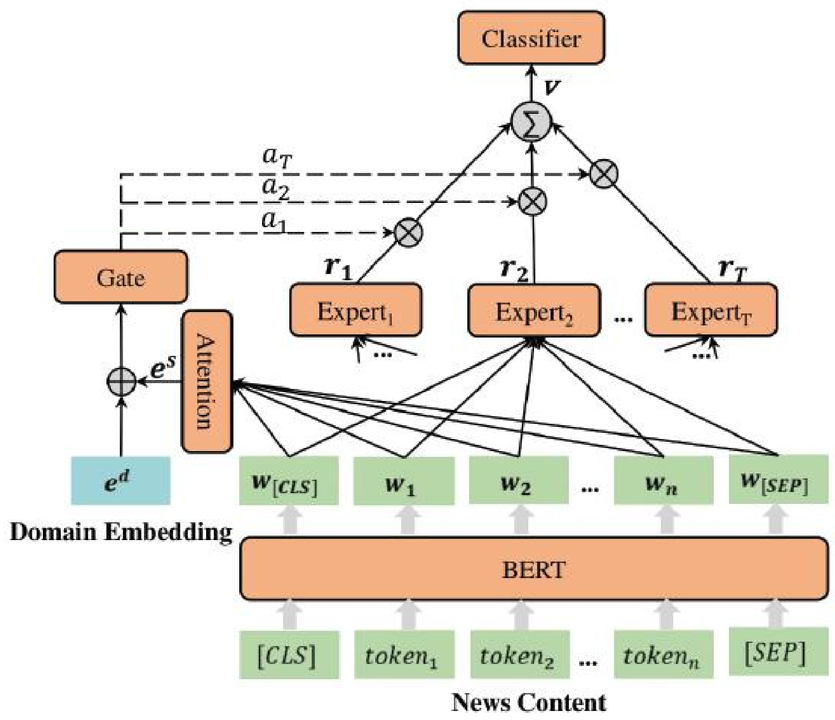
Preliminary Analysis of Weibo21

(a) health (b) military

(c) education (d) science

As the most straightforward clue, we analyze the topic distribution of news amoing different domains. We choose four domains to show off, and we can observe that different domains have different frequently used words, which illustrates the phenomenon of domain shift.

MDFEND Framework



- Expert module: $r_i = \Psi_i(W; \theta_i)$,
- Domain gate: $a = softmax(G(e^d \oplus e^s; \phi))$,
- Aggregation: $v = \sum_{i=1}^{T} a_i r_i$,
- Prediction: $\hat{y} = softmax(MLP(v))$.

Experiments

MFND performance (f1-score)

model	Science	Military	Education	Accidents	Politics
TextCNN_single	0.7470	0.778	0.8882	0.8310	0.8694
BiGRU_single	0.4876	0.7169	0.7067	0.7625	0.8477
BERT_single	0.8192	0.7795	0.8136	0.7885	0.8188
TextCNN_all	0.7254	0.8839	0.8362	0.8222	0.8561
BiGRU_all	0.7269	0.8724	0.8138	0.7935	0.8356
BERT_all	0.7777	0.9072	0.8331	0.8512	0.8366
EANN	0.8225	0.9274	0.8624	0.8666	0.8705
MMOE	**0.8755**	0.9112	0.8706	0.8770	0.8620
MOSE	0.8502	0.8858	0.8815	0.8672	0.8808
EDDFN	0.8186	0.9137	0.8676	0.8786	0.8478
MDFEND	0.8301	**0.9389**	**0.8917**	**0.9003**	**0.8865**

model	Health	Finance	Entertainment	Society	All
TextCNN_single	0.9053	0.7909	0.8591	0.8727	0.8380
BiGRU_single	0.8378	0.8109	0.8308	0.6067	0.7342
BERT_single	0.8909	0.8464	0.8638	0.8242	0.8272
TextCNN_all	0.8768	0.8638	0.8456	0.8540	0.8686
BiGRU_all	0.8868	0.8291	0.8629	0.8485	0.8595
BERT_all	0.9090	0.8735	0.8769	0.8577	0.8795
EANN	0.9150	0.8710	0.8957	0.8877	0.8975
MMOE	0.9364	0.8567	0.8886	0.8750	0.8947
MOSE	0.9179	0.8672	0.8913	0.8729	0.8939
EDDFN	0.9379	0.8636	0.8832	0.8689	0.8919
MDFEND	**0.9400**	**0.8951**	**0.9066**	**0.8980**	**0.9137**