Topic-Enhanced Argument Mining via Mutual Learning

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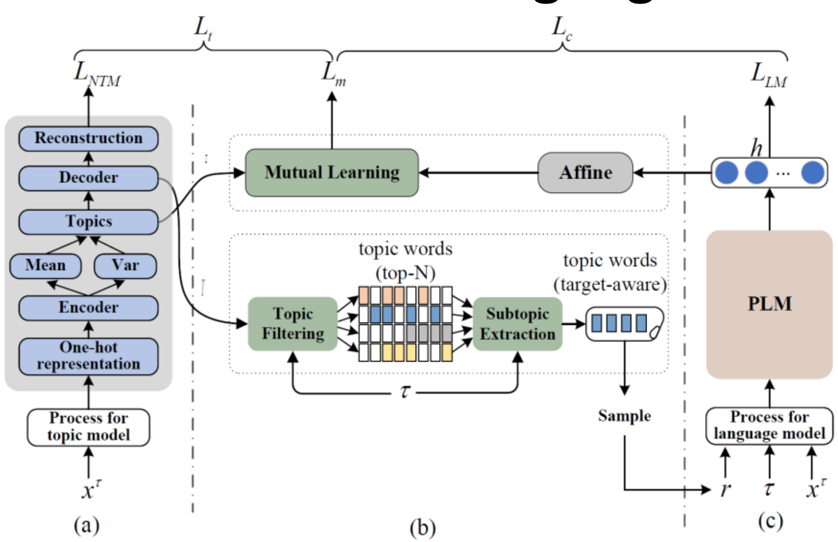
Problems & Ideas

- Problems of current argument mining methods:
  - Argument mining faces three main challenges: insufficient contextual information on targets, cross-domain adaptation across varying targets, and implicit argumentative information within the argument.
  - Current approaches mainly focus on solving the first two issues from the semantic perspective.
- Ideas: A novel topic-enhanced information-seeking argument mining approach by leveraging the mutual interaction between the neural topic model and the language model.



The architecture of the proposed TEAM model: (a) topic representation generation; (b) target-aware subtopic extraction (bottom), topic-argument mutual learning (top); (c) argument identification.

Main Contributions

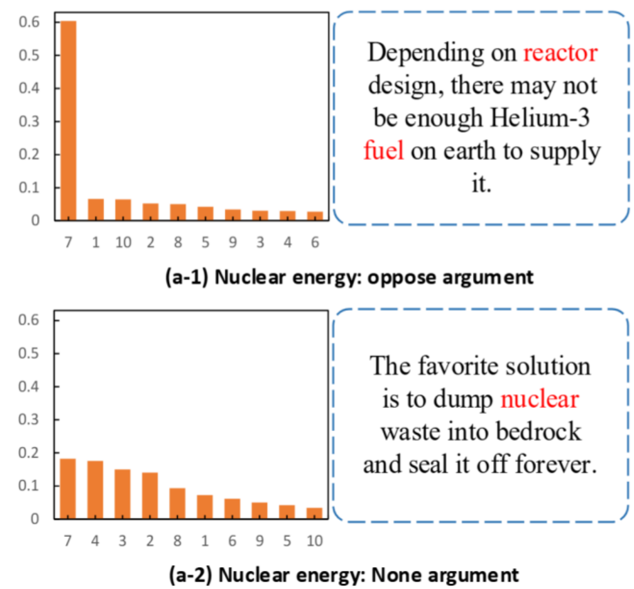
- Contributions:
  - A novel Topic-Enhanced Argument Mining model is proposed based on mutual learning to address the insufficiency of contextual information of the targets, the cross-domain adaptation across the varying targets and the implicit argumentative information within the argument;
  - Comprehensive experiments are conducted on the **UKP ArgMin** dataset in both in-domain and cross-domain scenarios to show the effectiveness of the proposed model.

Model	UKP ArgMin				
	F1	P+	P-	R+	R-
BiLSTM	.5337	.4521	.4832	.2911	.4816
BiCLSTM	.5382	.4185	.4469	.3860	.4813
ClaimLex	.5684	.4736	.5075	.3756	.5011
SentimentLex	.5718	.4937	.5125	.3590	.5240
EmotionLex	.5695	.4920	.5036	.3524	.5264
WordNet	.5788	.4846	.5191	.3724	.5235
BERT-base	.6710	.5742	.5937	.5811	.6250
BERT-large	.7008	.5954	.6426	.6568	.6637
CKD	.6876	.5154	.6795	**.7719**	.5571
TESTED	.6703	.5735	.6190	.5735	.5920
MoLE	.6950	.5998	.5934	.6195	**.7179**
TEAM	**.7243**	**.6177**	**.6814**	.6820	.6723
-ML	.7113	.6123	.6474	.6425	.7018
-TS	.7135	.6116	.6722	.6725	.6691
-TS & ML	.6815	.5813	.5976	.6137	.6354

Results of each model using **in-domain** evaluation on the test sets

Model	UKP ArgMin				
	F1	P+	P-	R+	R-
BiLSTM	.3796	.3484	.4710	.0963	.2181
Outer-att	.3873	.3651	.4696	.1042	.2381
BicLSTM	.4242	.2675	.3887	.2817	.4028
BicLSTM$_E$	.3924	.2372	.4381	.0317	.3955
BicLSTM$_B$	.4243	.3431	.4397	.1060	.4275
BERT-base	.6128	.5048	.5313	.4698	.5795
BERT-large	.6325	.5535	.5843	.5051	.5594
ChatGPT$_{t=0}$	.6418	.4397	**.7049**	.8125	.5098
ChatGPT$_{t=0.5}$	.6301	.4352	.6809	.8114	.4955
Llama2-7B	.3203	.2418	.4614	.8571	.1982
GLM4-9B	.4529	.2863	.5517	**.9643**	.3559
Baichuan2-7B	.2958	.2284	.6068	.9561	.2714
Mistral-7B	.6586	.6149	.5206	.5431	.6239
TEAM	**.6748**	**.6199**	.6063	.5296	**.6340**
-ML	.6654	.6136	.6249	.5152	.6135
-TS	.6665	.6156	.6286	.5150	.5881
-TS & ML	.6214	.5173	.5421	.4737	.5683

Results of each model using **cross-domain** eval-uation on the test sets.



The local topic distribution within the argument and argument sentences with target-aware subtopics (red) extracted by our TEAM.