Leveraging Graph Structural Knowledge to Improve Argument Relation Prediction in Political Debates

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Argument Mining aims to automatically identify argumentative structures—such as claims, premises, and the support or attack relations between them. Political debates represent a compelling yet challenging domain for AM, due to their complex, often implicit reasoning patterns. However, most existing approaches focus solely on the textual content of arguments, overlooking the structural context provided by the argumentation graph.

TRUMP: *We have 180 million people out there that have great private health care, far more than we're talking about with Obamacare.* Joe Biden is going to terminate all of those policies. These are people that love their healthcare, people that have been successful - middle income people - been successful. [...] He won't even have a choice. They want to terminate 180 million plans. *We have done an incredible job on health care.* And we're going to do even better

SUPPORT

ATTACK

BIDEN: What i'm going to do is pass Obamacare with a public option - become Bidencare. [...]. He's been talking about this for a long time. There is no - *he's never come up with a plan.* I guess we're gonna get the pre-existing condition plan the same time we get the infrastructure plan we waited since 17, 18, 19, 20. [...]

SUPPORT

📚 ElecDeb60to20

- ➔ 44 televised U.S. presidential debates (1960–2020)
- ➔ Annotated with argument components
  - ◆ *claims* and *premises*
- ➔ Annotated with argument components relations
  - ◆ *support, attack and equivalent*
- ➔ ~39K components, ~26K relations
- ➔ Imbalanced: *support* dominates, *equivalent* (e.g., a rephrasement) is rare

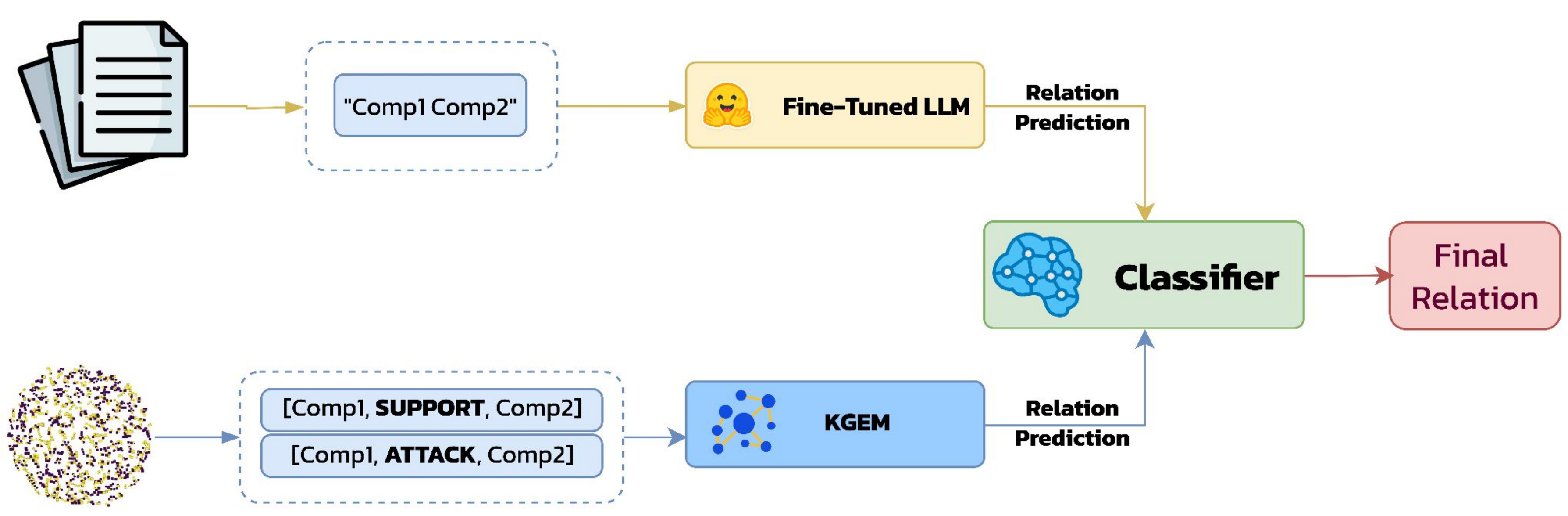
⚙️ Methodology

- ➔ **Knowledge Graph Construction:** from debate transcripts to triples *(head, relation, tail),* multiple Knowledge Graphs variants depending on the additional information contained in the original dataset (speaker, year, type of argument), enhanced embeddings with Sentence-BERT
- ➔ **Knowledge Graph Embedding Models (KGEM):** TransE (Bordes et al., 2013), DistMult (Yang et al., 2015), ConvE (Dettmers et al., 2018)
- ➔ **Language Models (LM):** RoBERTa (Liu et al., 2019), DeBERTa-V3 (He et al., 2021)
- ➔ **Evaluation Tasks:** link prediction, relation prediction, link deletion, triple classification and relation classification
- ➔ **Model Integration:** Combine KGEM and LM predictions using a binary classifier

Ref.	Dataset	#nodes	#edges	%support	%attack	%equivalent	%type	%speaker	%year
(i)	basic	29,791	26,100	80%	15%	5%	-	-	-
(ii)	+ year node	29,835	56,064	38%	7%	1%	-	-	54%
(iii)	+ speaker node	29,855	57,868	37%	7%	1%	-	55%	-
(iv)	+ type node	29,793	63,227	34%	6%	1%	59%	-	-
(v)	+ type and year nodes	29,837	93,191	23%	4%	1%	40%	-	32%
(vi)	+ type and speaker nodes	29,857	94,995	23%	4%	1%	39%	33%	-
(vii)	+ year and speaker nodes	29,899	87,832	25%	4%	1%	-	36%	34%
(viii)	+ type, year and speaker nodes	29,901	124,959	17%	3%	0.5%	30%	25.5%	24%

Ref.	Dataset	#nodes	#edges	%support	%attack	%equivalent	%type	%speaker	%year
(ix)	modified argument nodes	37,127	26,103	83%	15%	2%	-	-	-
(x)	+ speaker node	37,191	64,787	33%	6%	1%	-	60%	-
(xi)	+ year node	37,171	63,425	34%	6%	1%	-	-	59%
(xii)	+ speaker and year nodes	37,235	102,109	21%	4%	1%	-	38%	36%

📊 Results Overview



Model	Macro F1
RoBERTa *(only)*	0.603
DistMult *(only)*	0.604
RoBERTa + DistMult (Random Forest Classifier)	0.683
DeBERTa-V3 *(only)*	0.694
DeBERTa-V3 + DistMult (CNN)	**0.734**

✅ +13% improvement over standalone KGEM

✅ +4% over standalone LM

💡 Key Contributions

- Developed a hybrid approach that integrates graph **structural knowledge** through a KGEM with **contextual knowledge** provided by a LM
- Improved performance over previous models on a **challenging benchmark** for Argument Mining
- Explored the **application of multiple KGEMs** to an Argument Mining task within a political debate domain where such models had not been previously used