

# BIOMEDICAL ENTITY REPRESENTATION WITH GRAPH-AUGMENTED MULTI-OBJECTIVE TRANSFORMER

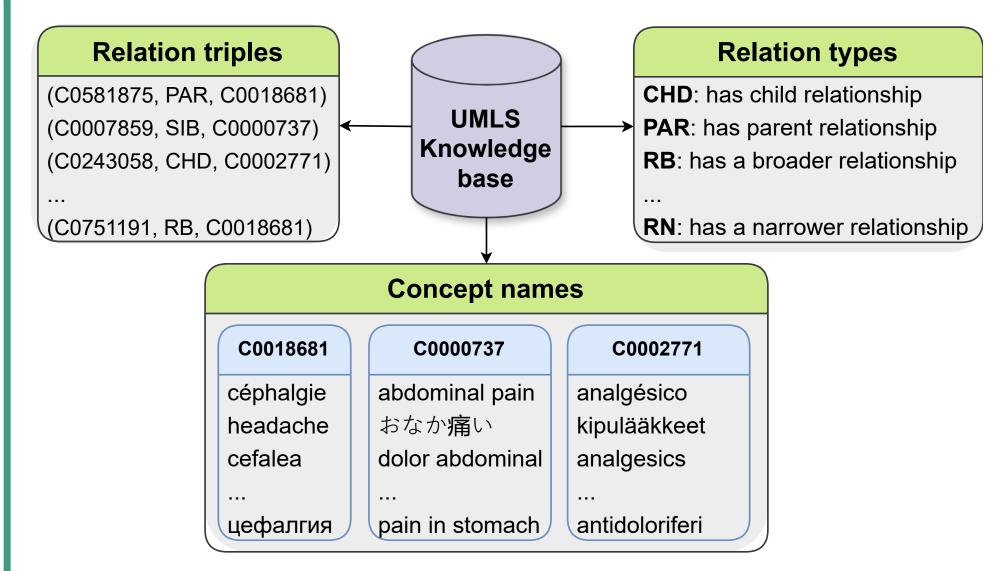
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#### **O**VERVIEW

- **Problem**: multilingual biomedical Language Models (LMs) do not fully utilize domain-specific *Unified Medical Language System* Knowledge Graph (UMLS KG);
- Idea: Simultaneously learn textual, graph-based, and intermodal objectives to enrich LM with domain knowledge from KG.
- Result: graph-enriched BERGAMOT LM achieves SoTA results on multiple zeroshot biomedical entity linking benchmarks and datasets.

## UMLS KNOWLEDGE GRAPH



- 4.36M biomedical concepts V;
- 12 relation types  $(\mathcal{R})$ ;
- Knowledge triples  $(v, r, u) \in V \times \mathcal{R} \times V$ .

## GRAPH ENCODERS

GraphSAGE (mean neighbors pooling):

$$h'_v = \sigma(W^l \cdot [h_v \parallel MEAN(N(v))])$$

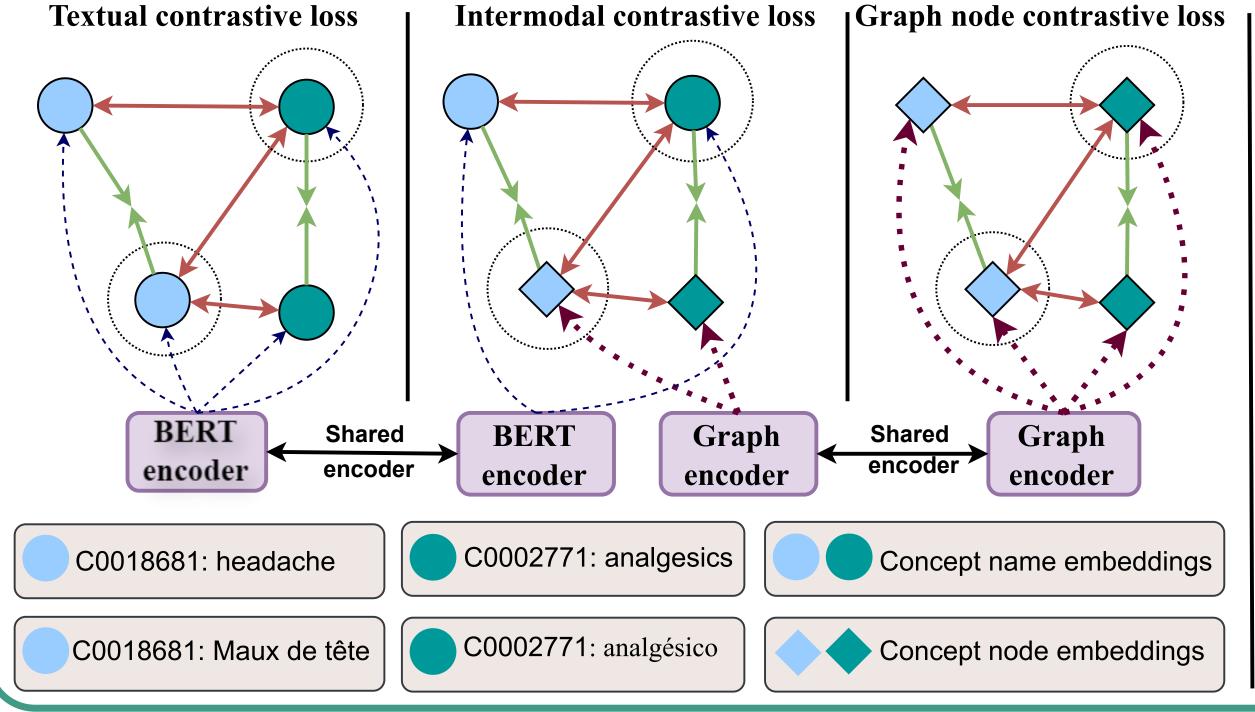
**R-GCN** (relation r-specific transformations):

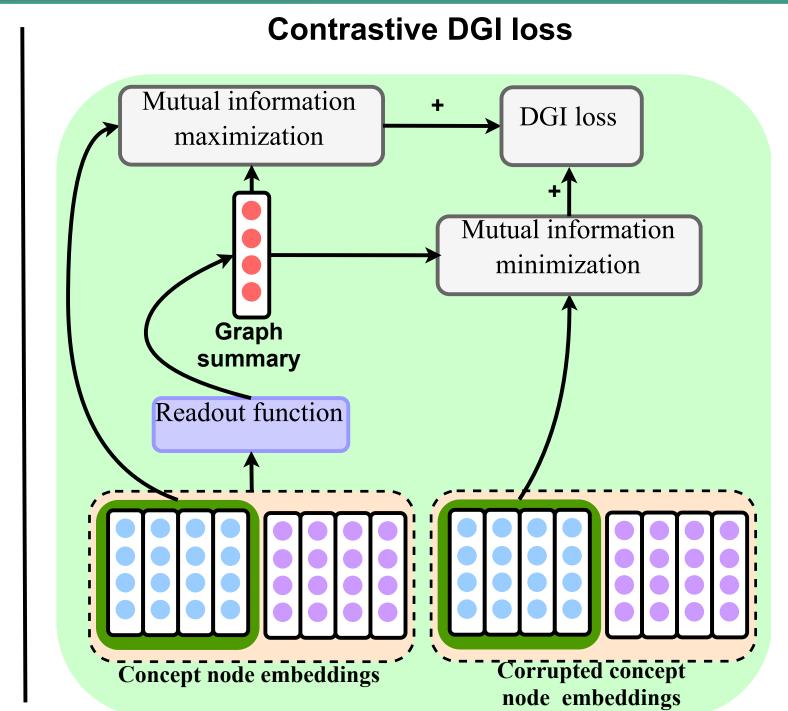
$$h'_{v} = \sigma \left( \sum_{(r,u)\in N(v)} \frac{1}{|N(v)|} (W_{r}^{l} h_{u} + W^{l} h_{v}) \right)$$

GAT (Attention-based neighbors weighing):

$$h'_{v} = \alpha_{v,v} W h_{v} + \sum_{(r,u) \in N(v)} \alpha_{v,u} W h_{u}$$

## TRAINING OBJECTIVES





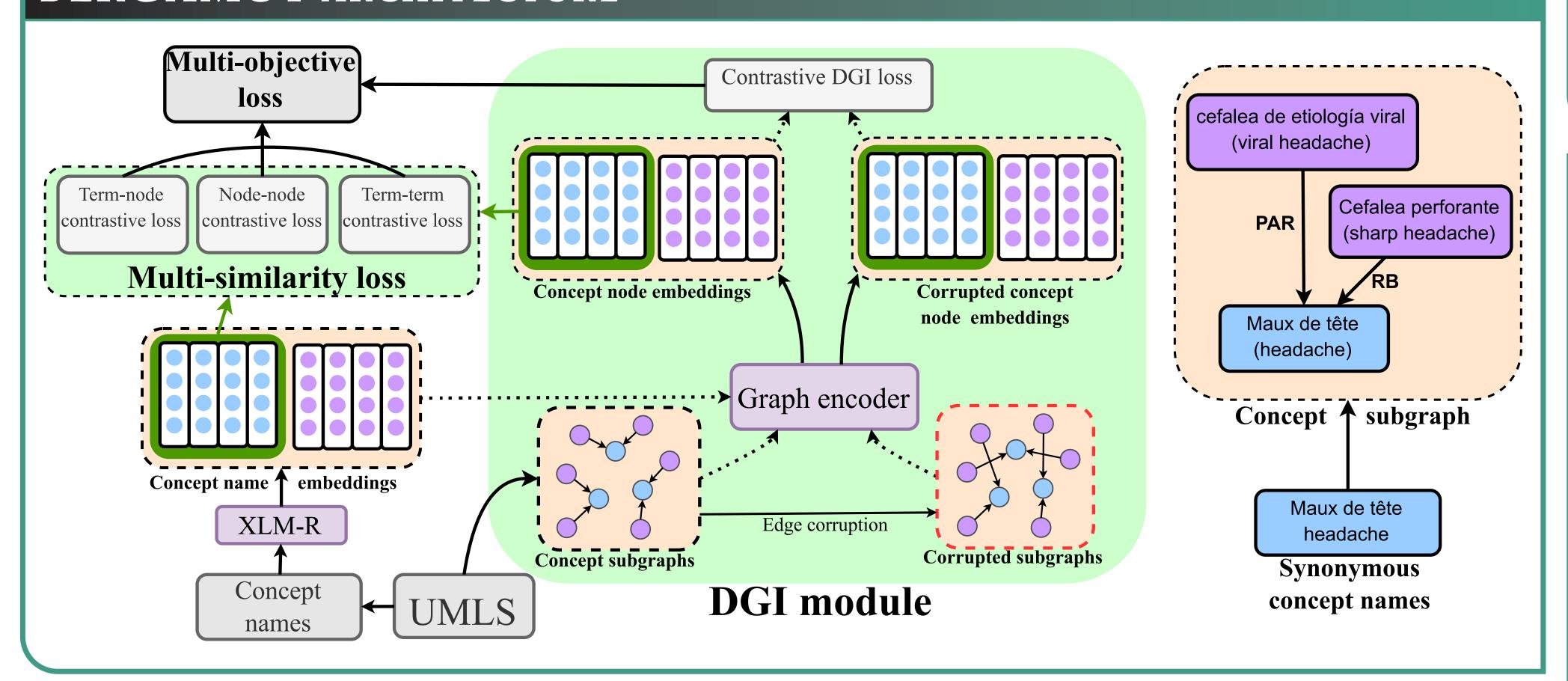
### **OBJECTIVES MOTIVATION**

- $\mathcal{L}_{sap}$  (textual): clusterizes synonymous concept names;
- $\mathcal{L}_{node}$  (node level): clusterizes concept node representations;
- $\mathcal{L}_{dgi}$  (subgraph level): enriches node embeddings with structural information;
- $\mathcal{L}_{int}$  (Intermodal): aligns two modalities to enrich LM with graph information.

#### Multi-task training objective:

$$\mathcal{L} = \mathcal{L}_{sap} + \mathcal{L}_{node} + \mathcal{L}_{int} + \lambda_{dgi} \mathcal{L}_{dgi},$$

## BERGAMOT ARCHITECTURE



#### PRETRAINING DATA

- 30.6M cross-lingual synonym pairs;
- UMLS graph: 4.4M nodes, 38M. edges;
- Batch-level neighbors shuffling corruption;

## EVALUATION & BASELINES

- Entity linking
- Mantra GSC and XL-BEL benchmarks;
- Spanish CodiEsp & CANTEMIST corpora;
- French QUAERO corpus.
- Question Answering: PubMedQA & BioASQ datasets;
- Textual entailment: MedNLI & SciTail (ST) datasets;
- Domain-specific BERT-based baselines:
- **SapBERT** [1]: pre-trained on multilingual UMLS concept names only;
- CODER [2]: pre-trained on UMLS concept names and relation triples.

#### ZERO-SHOT ENTITY LINKING

Model	QUAERO-E		QUAERO-M		CodiEsp-D		CANTEMIST		Mantra		XL-BEL	
	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5
SapBERT	32.43	41.64	39.42	51.6	45.98	61.96	52.82	61.44	73.43	86.99	34.8	39.4
CODER	33.59	40.80	40.30	50.26	35.52	49.14	48.59	58.84	75.58	86.24	31.0	34.4
GraphSAGE-BERGAMOT	35.30	41.60	40.94	51.24	46.45	59.55	51.93	61.54	73.51	86.63	_	
RGCN-BERGAMOT	33.59	39.55	40.83	50.26	46.3	62.1	52.33	60.43	74.19	87.12	_	_
GAT-BERGAMOT	35.39 <sup>†</sup>	43.92	42.94 <sup>†</sup>	53.88	48.74 <sup>†</sup>	63.61	<b>57.41</b> <sup>†</sup>	61.38	77.93	89.93	35.6	40.7

## NON-LINKING RESULTS

Model	· ·	<b>QA</b>	Entailment			
Model	<b>PMQA</b>	BioASQ	MedNLI	ST		
SapBERT	63.1	74.3	82.8	90.2		
CODER	63.1	73.3	82.4	90.9		
BERGAMOT	62.3	<b>76.4</b>	83.1	90.3		

## Conclusion

- **GAT-BERGAMOT** achieves SOTA biomedical entity linking on two multilingual two Spanish and one French corpora with decent performance on non-linking tasks;
- Our best GAT-BERGAMOT is publicly available<sup>a</sup>;
- Biomedical LMs can benefit from knowledge graph modality learnt via external graph neural network.

#### REFERENCES

[1] Fangyu Liu et al. 2021b. Learning domain-specialised representations for cross-lingual biomedical entity linking. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 565–574, Online. Association for Computational Linguistics.F

[2] Zheng Yuan et al. 2022. Coder: Knowledge-infused cross-lingual medical term embedding for term normalization. Journal of Biomedical Informatics, 126:103983.
[3] Petar Velickovic et al. 2019. Deep graph infomax. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019.

ahuggingface.co/andorei/BERGAMOT-multilingual-GAT