Automatic Text Summarization Based on Graph Convolutional Networks and Abstract Meaning Representation

Program Riset PPMI STEI Pandita Utama Institut Teknologi Bandung

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Introduction

Text summarization addresses information overload by generating concise summaries that capture essential information from a source text.

Graph Convolutional Network (GCN)-based summarization represents the source text as a graph and updates each node with document context through message passing. The resulting representations are used to select sentences (extractive) or as decoder input (abstractive). Unlike Pre-trained Language Models (PLMs), GCNs are not limited by a maximum input length.

Abstract Meaning Representation (AMR) encodes the meaning of a sentence as a graph. Existing AMR-based summarizers either select subgraphs with Integer Linear Programming (ILP) or linearize the graph for Seq2Seq models. To our knowledge, no prior study has used Smatch similarity between AMR graphs to build the sentence graph for GCN-based summarization.

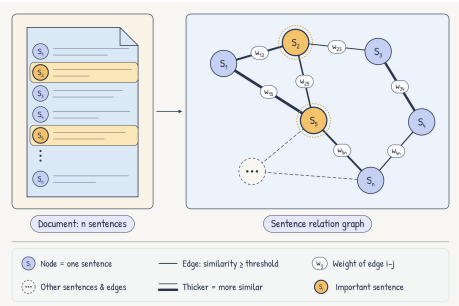
Keywords: Text Summarization, GCN, AMR, Fine-tuning, PLM.

Research Objective

This research developed GCN-based extractive and abstractive summarization models for Indonesian texts, using Smatch similarity between the sentences' AMR graphs to define semantic relations between sentences.

Methods

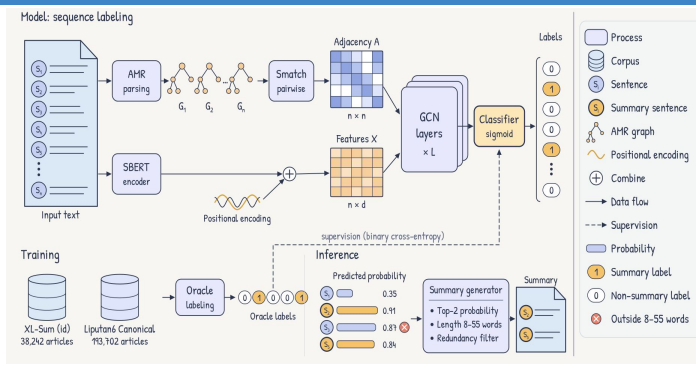
Two pipelines were developed: AMR-GCNExt (extractive) and AMR-GCNAbs (abstractive). Both use a GCN over a Smatch-weighted sentence graph and are evaluated on Liputan6 Canonical and XL-Sum Indonesia against variants without AMR (IndoSBERT-GCN, IndoT5-GCN) and baselines without a GCN (BERTSumExt, IndoT5 seq2seq). In the sentence graph, nodes are sentences and edge weights are inter-sentence similarities.



Each sentence is parsed into an AMR graph. The sentence-level graph of the input text is represented as an adjacency matrix, with edge weights defined by Smatch (*semantic match*) scores measuring the semantic similarity between sentence-level AMR graphs. In addition, the feature matrix consists of IndoSBERT embeddings and positional encodings.

Extractive Summarization

Extractive summarization is formulated as a *sequence labeling* task. The input is a sequence of sentences, and the output is a sequence of binary labels indicating whether each sentence is selected for the summary. The model architecture consists of multiple GCN layers and a classification head.

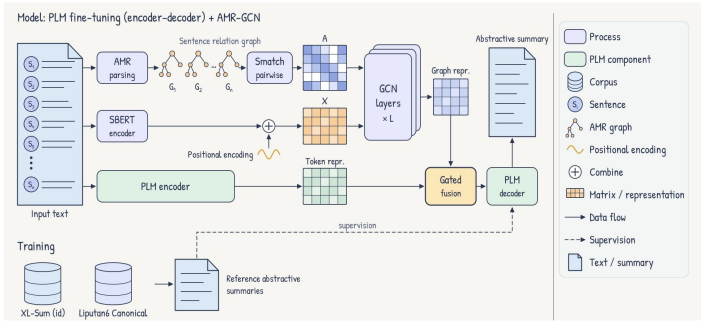


The AMR-GCNExt model is trained on an oracle-labeled corpus using Binary Cross-Entropy (BCE) loss. The summary is generated by selecting the top two sentences with the highest predicted probabilities, each 8–55 words long, after a redundancy filter.

Abstractive Summarization

As in extractive summarization, the input text is preprocessed into a sentence-level graph. However, abstractive summarization adopts a Pre-trained Language Model (PLM) fine-tuning paradigm using an encoder–decoder architecture.

A Gated Fusion mechanism integrates representations from the encoder and GCN, and the fused representations serve as input to the decoder. The AMR-GCNAbs model is trained on the reference summaries of XL-Sum (id) and Liputan6 Canonical.



Model Performance

AMR improves extractive R1/R2 on Liputan6 and gives the best abstractive results on both datasets, though the margin is very small. On XL-Sum, abstractive models clearly outperform extractive ones.

Model	Approach	R1	R2	RL
Corpus: Liputan6 Canonical				
BERTSumExt	Extractive	0.3803	0.2072	**0.3507**
IndoSBERT-GCN	Extractive	0.3781	0.2083	0.3067
AMR-GCNExt	**Extractive**	**0.3882**	**0.2147**	0.3147
IndoT5-GCNAbs	Abstractive	0.4069	0.2279	0.3413
AMR-GCNAbs	**Abstractive**	**0.4071**	**0.2283**	**0.3414**
Corpus: XL-Sum Indonesia				
IndoSBERT-GCN	Extractive	0.2369	0.0746	0.1769
AMR-GCNExt	Extractive	0.2335	0.0727	0.1747
IndoT5 (seq2seq)	Abstractive	0.3714	0.1711	0.3088
IndoT5-GCNExt	**Extractive**	**0.2402**	**0.0775**	**0.1801**
IndoT5-GCNAbs	Abstractive	0.3720	0.1743	0.3094
AMR-GCNAbs	**Abstractive**	**0.3737**	**0.1746**	**0.3108**

Example summaries on XL-Sum Indonesia. The extractive summary misses the main event, but the abstractive summary captures it.

Article ID: 150709_dunia_india_ujian
Gold Summary: Mahkamah Agung India telah memerintahkan penyelidikan terhadap skandal ujian masuk sekolah kedokteran di negara bagian Madya Pradesh.
Extractive Summary (IndoT5-GCNExt): Oposisi memprotes partai penguasa di Madya Pradesh sehubungan dengan skandal yang melibatkan ribuan orang ini. Vyapam merupakan singkatan dalam bahasa Hindi untuk kantor penyelenggara ujian masuk untuk pegawai negeri dan sekolah kedokteran di Madya Pradesh.
Abstractive Summary (AMR-GCNAbs): Mahkamah Agung India memerintahkan penyelidikan terhadap skandal ujian masuk sekolah kedokteran di negara bagian Madya Pradesh.

Research Output

L. M. Harahap, M. L. Khodra. IndoSBERTSumExt: Fine Tuning Sentence Representation Model IndoSBERT for Extractive Summarisation (under review at *Journal of Information and Communication Technology*)