Structure-Augmented Keyphrase Generation

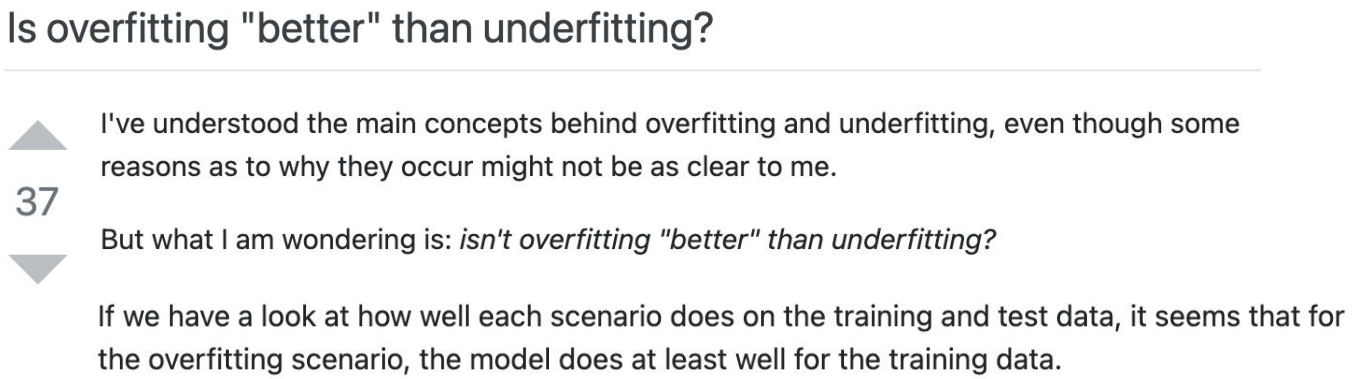
Jihyuk Kim[*] Myeongho Jeong[*] Seungtaek Choi[*] Seung-won Hwang[**]

Yonsei Univ[*] Seoul National Univ[**]

Target task: keyphrase generation

- Generating keyphrases for a given document.
  - Keyphrases provide main contents of the given document, using only a few words.

Q&A post



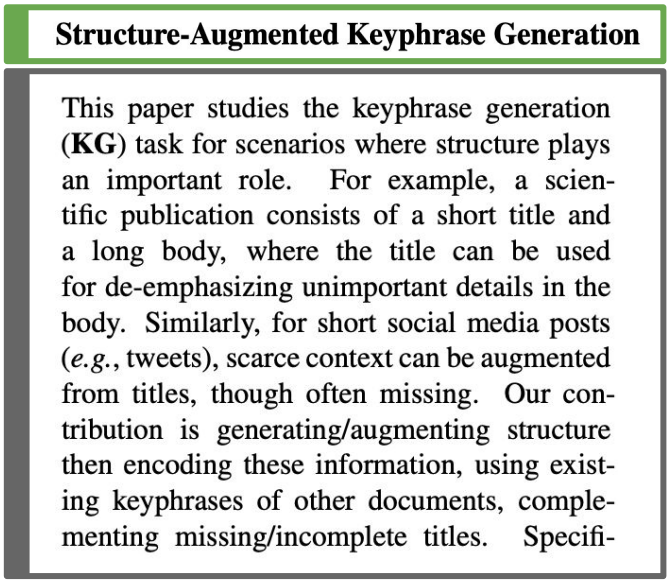
Keyphrases (or hashtags)

machine-learning | neural-networks | overfitting | bias-variance-tradeoff

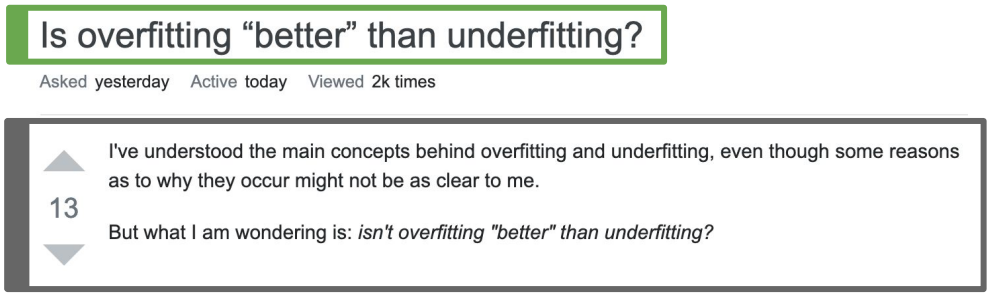
Leveraging structure

- The most standard structure: **title**-**body** structure
  - As in keyphrases, **titles** help to capture essential contents from the **main body**.

[Scientific articles]

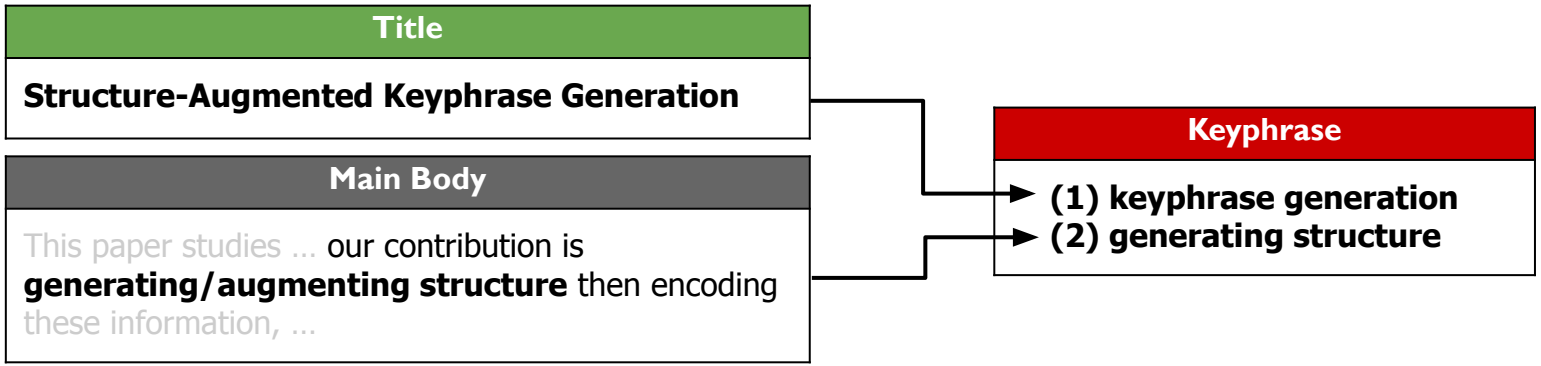


[Q&A post]



Previous work: title for KG

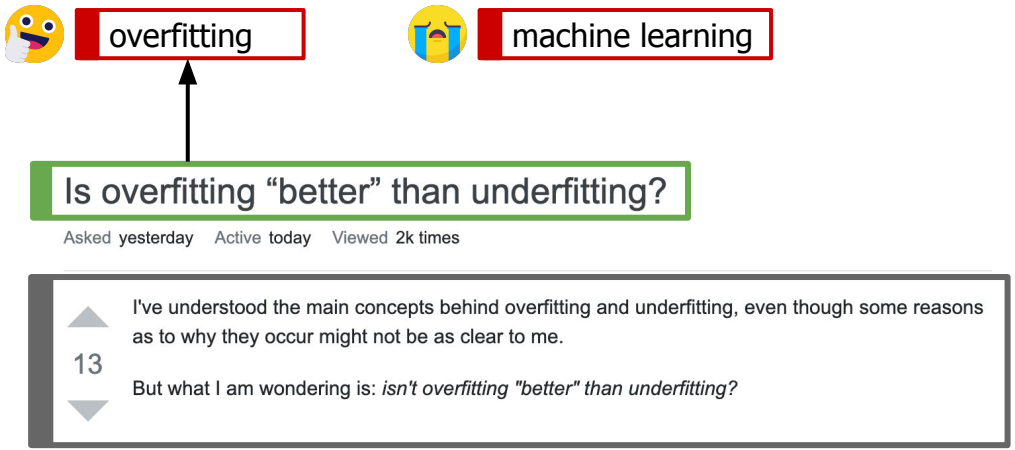
- Leveraging the title of a scientific paper [1].
  - 1) Generating **keyphrases** from the **title**.
  - 2) Generating **keyphrases** from related **body** contents to the **title**.



[1] Title-Guided Encoding for Keyphrase Generation. Chen et al., AAAI 2019

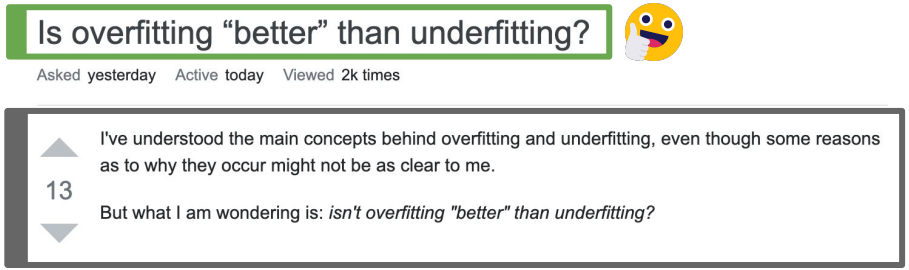
Challenge 1.

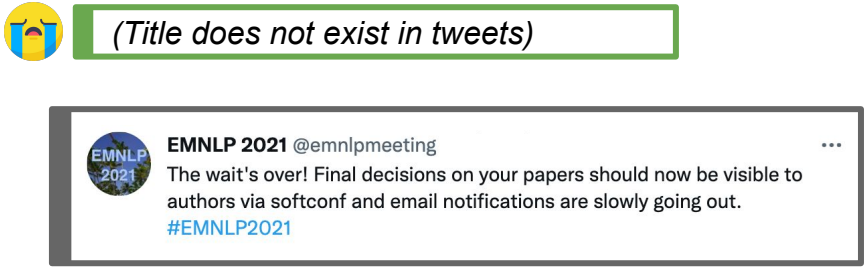
- Titles are short!



Challenge 2.

- Titles may not exist at all!





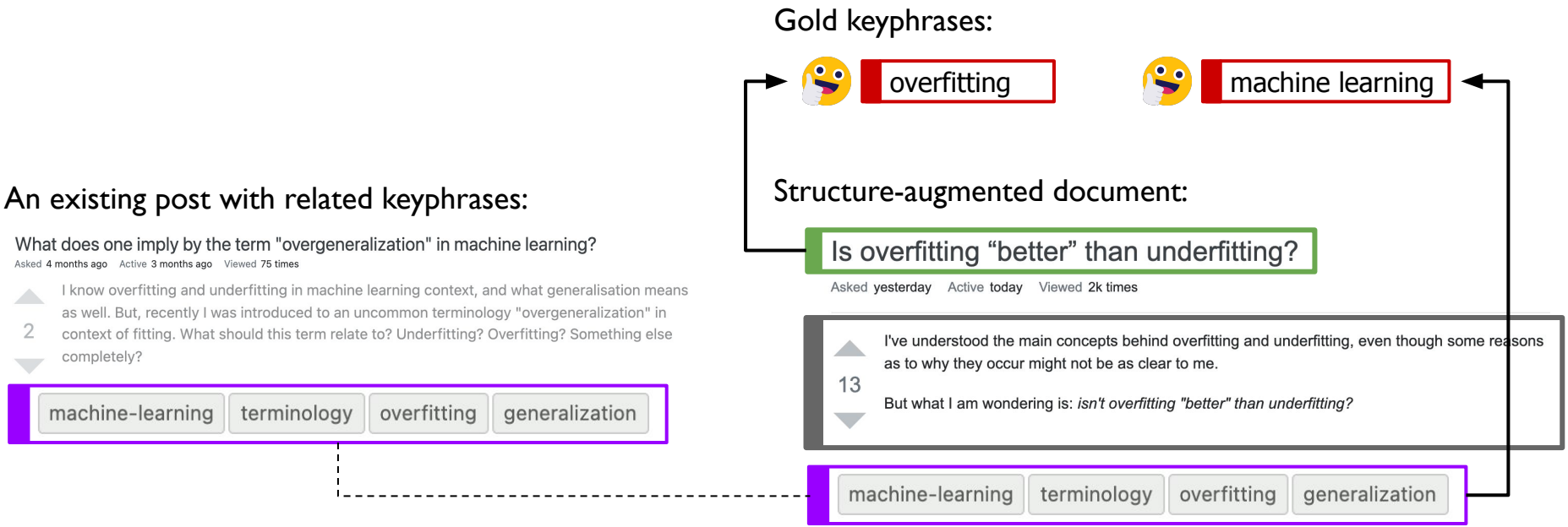
Goal

Our goal is **generating/augmenting structures** for KG.

- generating title-like structures when titles are not available,
- and augmenting structures to complement incomplete titles.

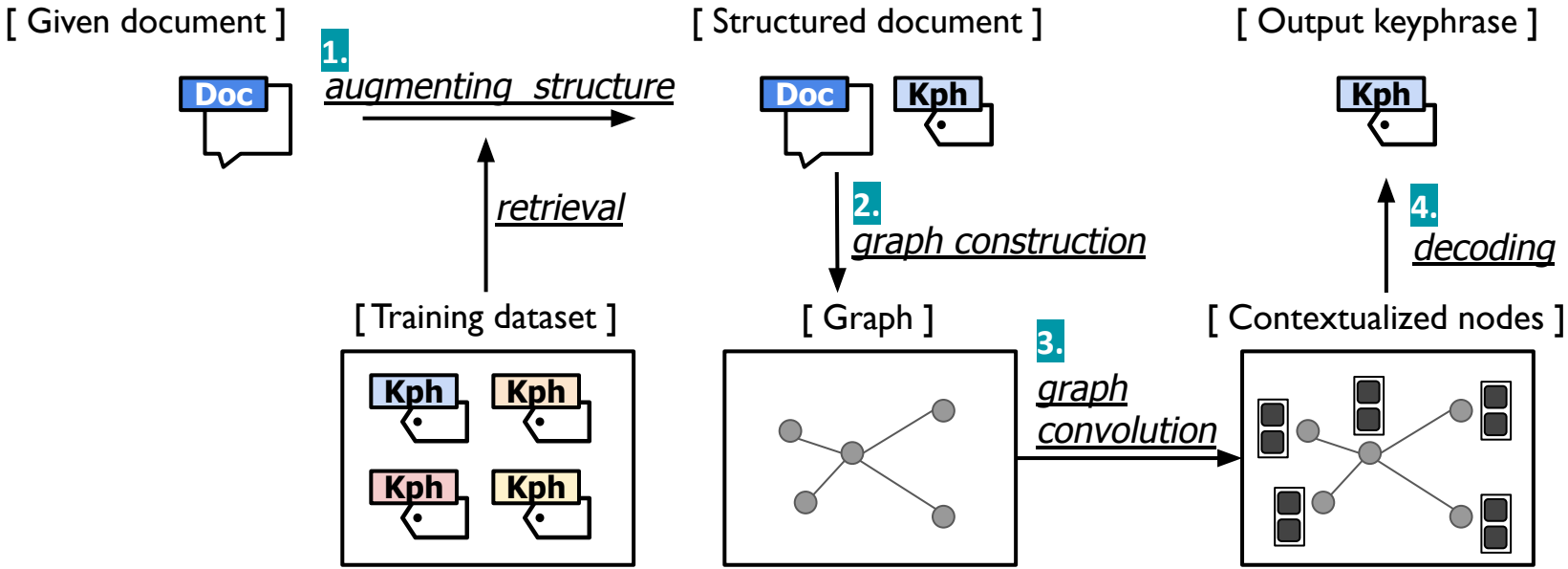
Proposal: leveraging existing keyphrases

- Augmenting structures, using **existing keyphrases**.



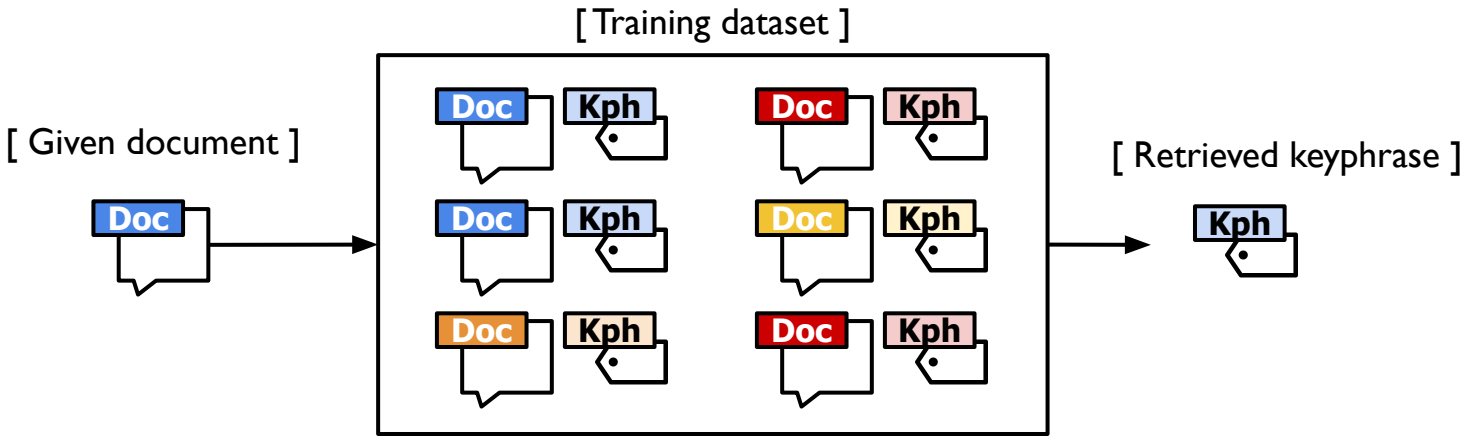
Overall process

- Structure-augmented keyphrase generation.



Retrieving relevant keyphrases

- Motivation: “Similar documents tend to have similar keyphrases.”
  - We retrieve keyphrases of similar documents from training dataset.



Closed/open set scenarios

Closed set
(e.g., social media posts)

: Trending hashtags are frequently reused.

Open set
(e.g., scientific publications)

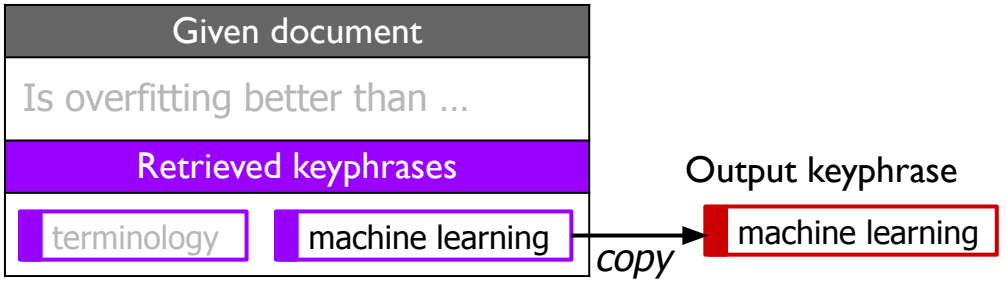
: New terms are introduced continuously.

Dataset	% of unobserved kph
social media posts	4.1% (95.9% kphs are reused)
sci-publications	18.1% (18.1% kphs are newly introduced)

Closed/open set scenarios

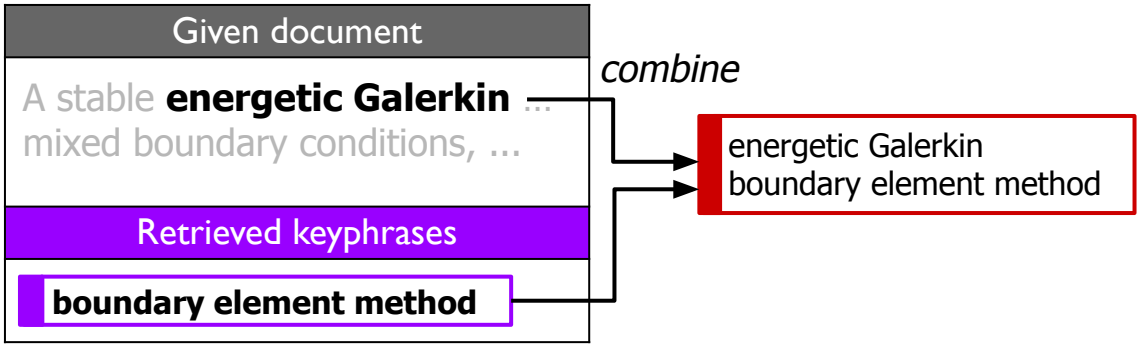
Closed set
(e.g., social media posts)

: Trending hashtags are frequently reused.



Open set
(e.g., scientific publications)

: New terms are introduced continuously.



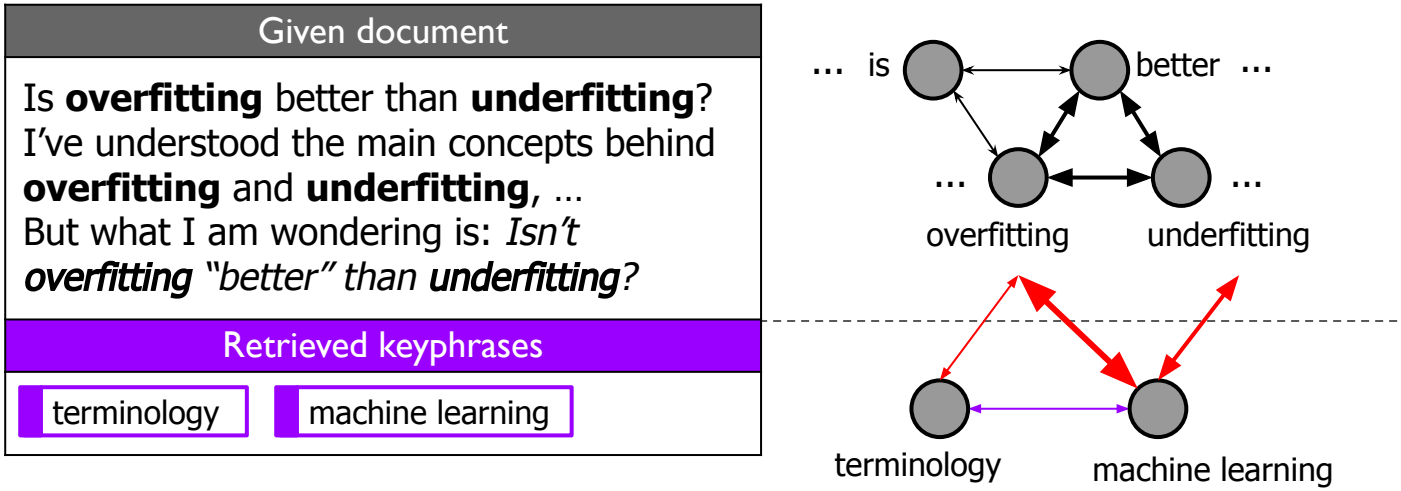
Graph construction

- **Two principles for graph construction**

1. Relevant nodes should be merged or connected with each other, and irrelevant nodes should be disconnected.
2. Relevant contexts between the given document and the retrieved keyphrases should be exchanged to each other.

Structure-aware graph for closed set

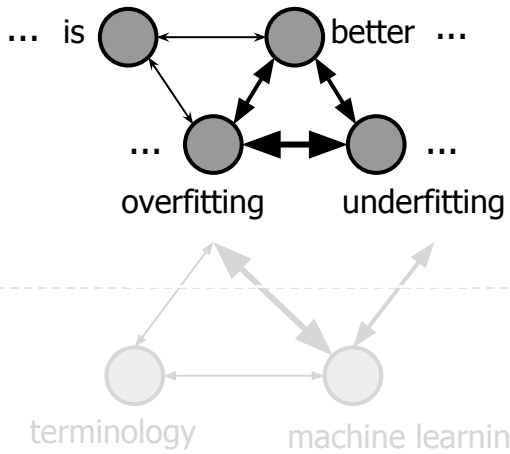
- **Connecting** the two graphs, using inter-field edges:
  - 1. graph for the given document.
  - 2. graph for the retrieved keyphrases.



Structure-aware graph for closed set

- Graph for the given document:

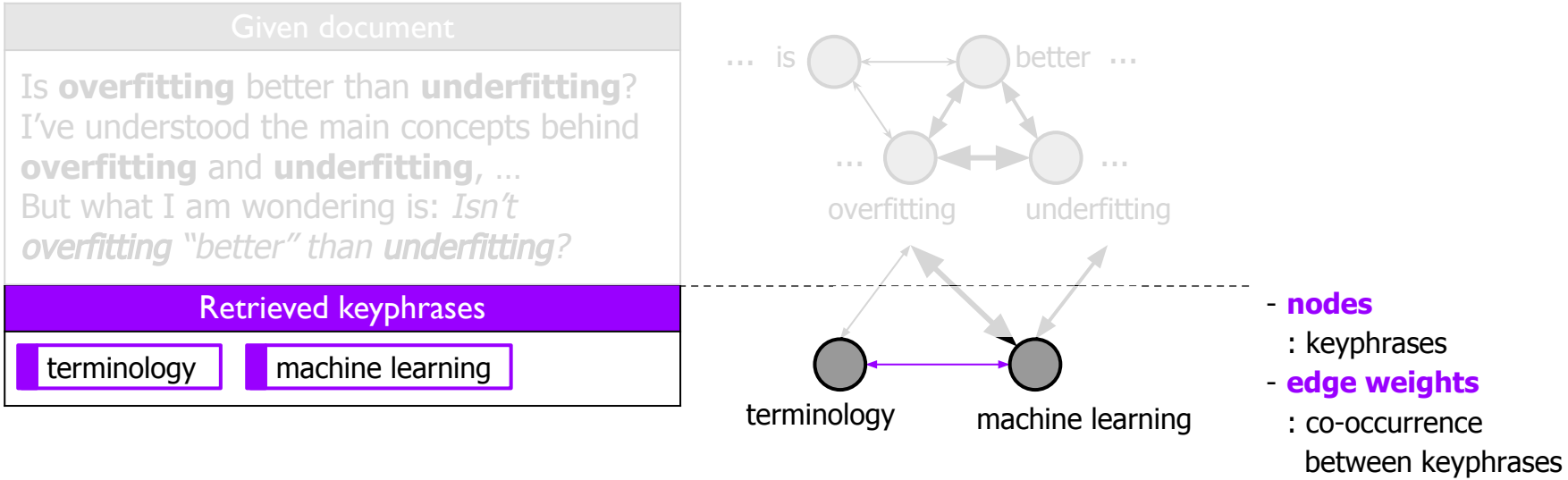
Given document
Is **overfitting** better than **underfitting**? I've understood the main concepts behind **overfitting** and **underfitting**, … But what I am wondering is: *Isn't* ***overfitting*** *"better" than* ***underfitting****?*
Retrieved keyphrases
terminology machine learning



- **nodes**
  : words in doc
- **edge weights**
  : reciprocal of distance (position-based)

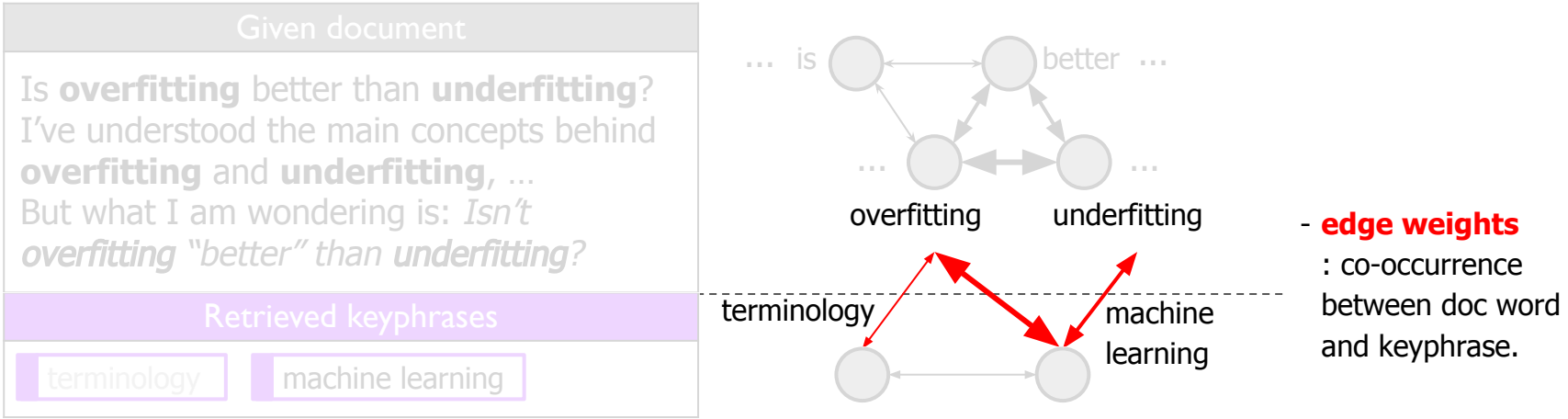
Structure-aware graph for closed set

- Graph for the retrieved keyphrases:



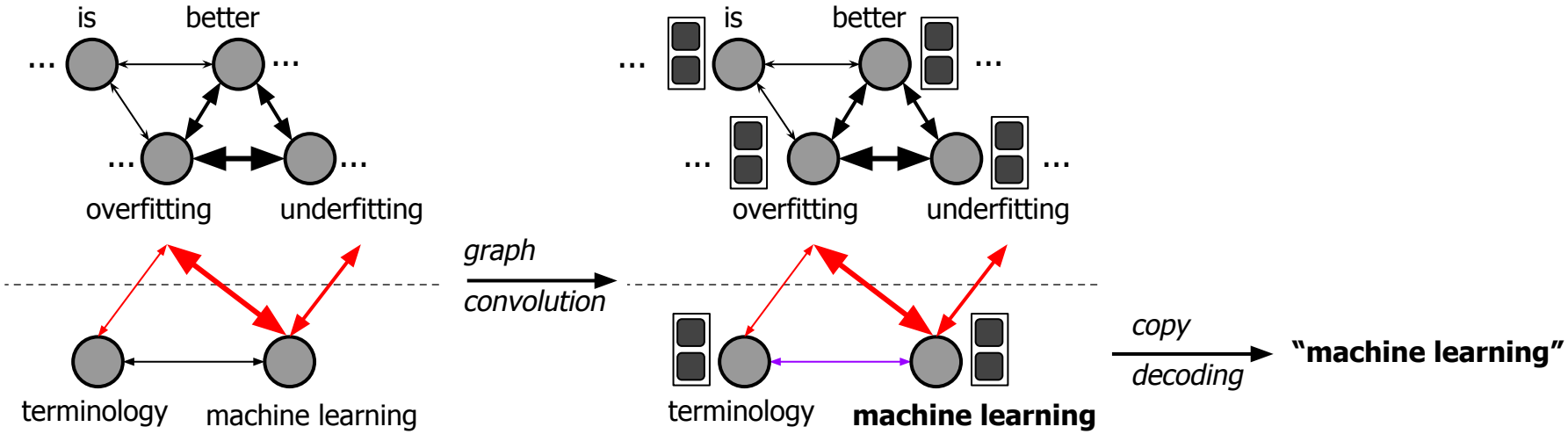
Structure-aware graph for closed set

- Connecting edges between nodes in the two graph:



Decoding for closed set

- Copying keyphrases based on keyphrase node representations.



Structure-aware graph for open set

- **Merging** the two graphs,
  using the same word nodes with different edges (i.e., multi-graph):

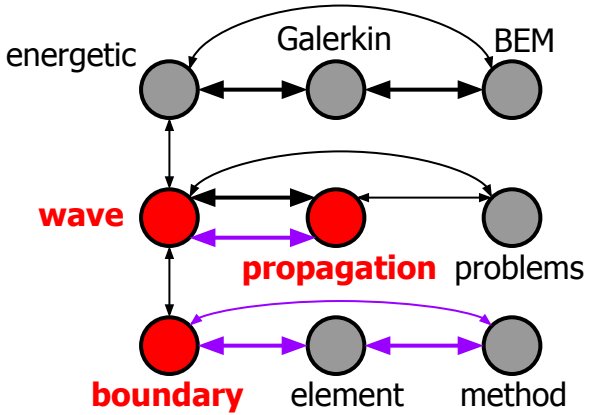
Given document

A stable 3D energetic Galerkin BEM approach for **wave propagation** problems. … mixed **boundary** conditions, … **boundary** integral …

Retrieved keyphrases

wave propagation

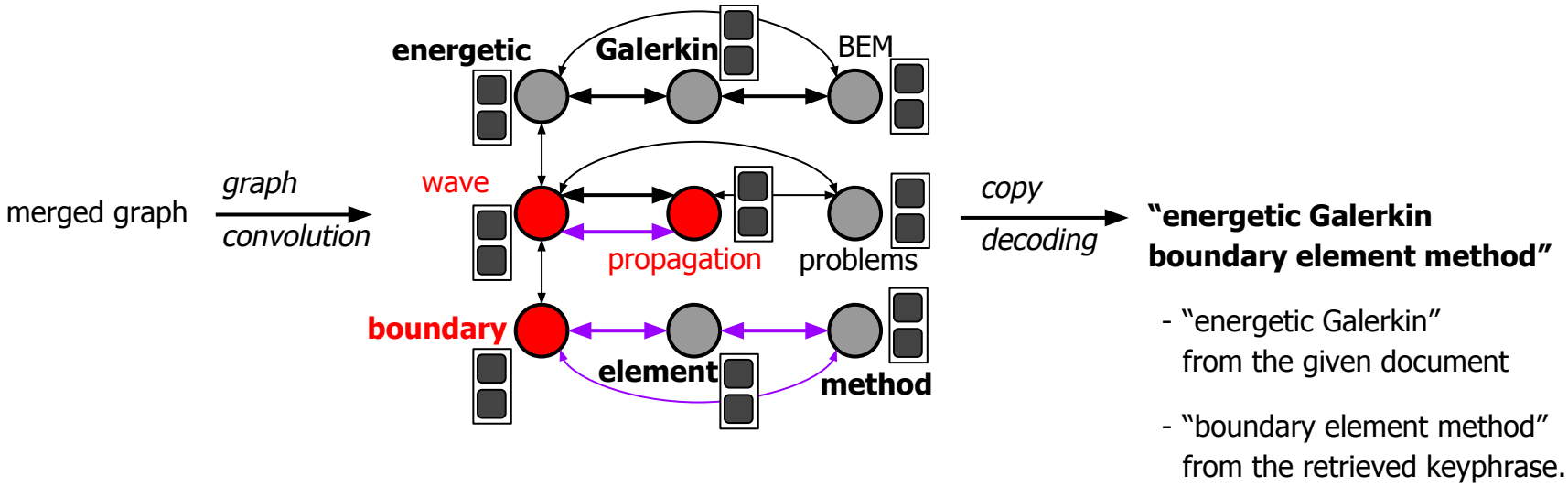
boundary element method



- **nodes**
  : words in doc
  and words in kph
  (the same word nodes are merged)
- **edges from doc**
  and **edges from kph**
  : reciprocal of distance
  (position-based)

Decoding for open set

- Combining keywords from the given document and the retrieved keyphrases.



Experiments

- Dataset.
  - StackExchange (social Q&A posts) for closed set scenario.
  - KP20k (scientific publication) for open set scenario.

[StackExchange; social Q&A post]

title

Is overfitting “better” than underfitting?

body

13

I've understood the main concepts behind overfitting and underfitting, even though some reasons as to why they occur might not be as clear to me.

But what I am wondering is: *isn't overfitting "better" than underfitting?*

keyphrase (annotated by the author)

machine-learning | neural-networks | overfitting | bias-variance-tradeoff

[KP20k; scientific publications]

title

A stable 3D energetic Galerkin BEM approach for wave propagation interior problems

body

ABSTRACT

We consider 3D interior wave propagation problems with vanishing initial and mixed boundary conditions, reformulated as a system of two boundary integral equations with retarded potentials. These latter are then set in a weak form, based on a natural energy identity satisfied by the solution of the differential problem, and discretized by the energetic Galerkin boundary element method. Numerical results are presented and discussed in order to show the stability and accuracy of the proposed technique.

keyphrase (annotated by the authors)

Keywords:
Wave propagation
Boundary integral equation
Energetic Galerkin boundary element method

Experiments

- Baselines:
  - CopyRNN[1]: using plain texts without structures.
  - TGNet[2]: using title-body structures.

[1] Deep Keyphrase Generation. Meng et al., ACL 2017
[2] Title-Guided Encoding for Keyphrase Generation. Chen et al., AAAI 2019

Experiments

- Evaluation metrics: ***F1 score on top-k keyphrase predictions***.

Prediction = top-k keyphrases, regarding likelihood.

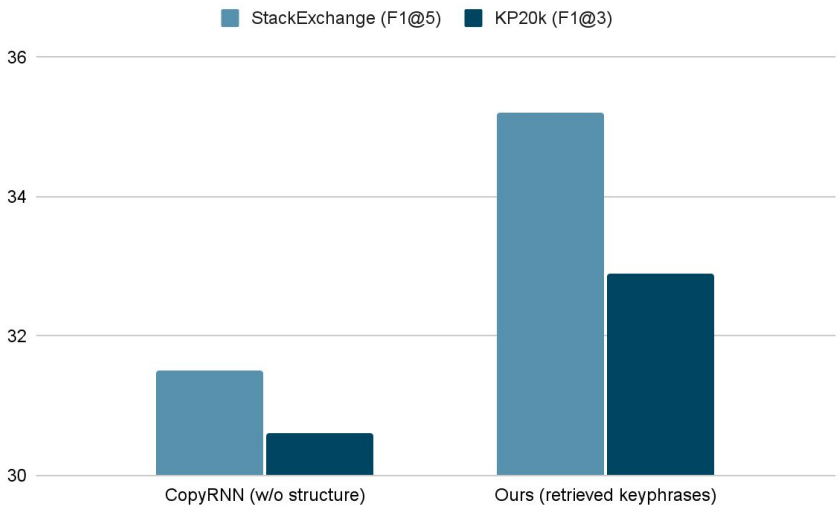
Precision@k = # of correct predictions / k

Recall@k = # of correct predictions / # of author-annotated keyphrases

F1@k = **(2 x precision@k x recall@k) / (precision@k + recall@k)**

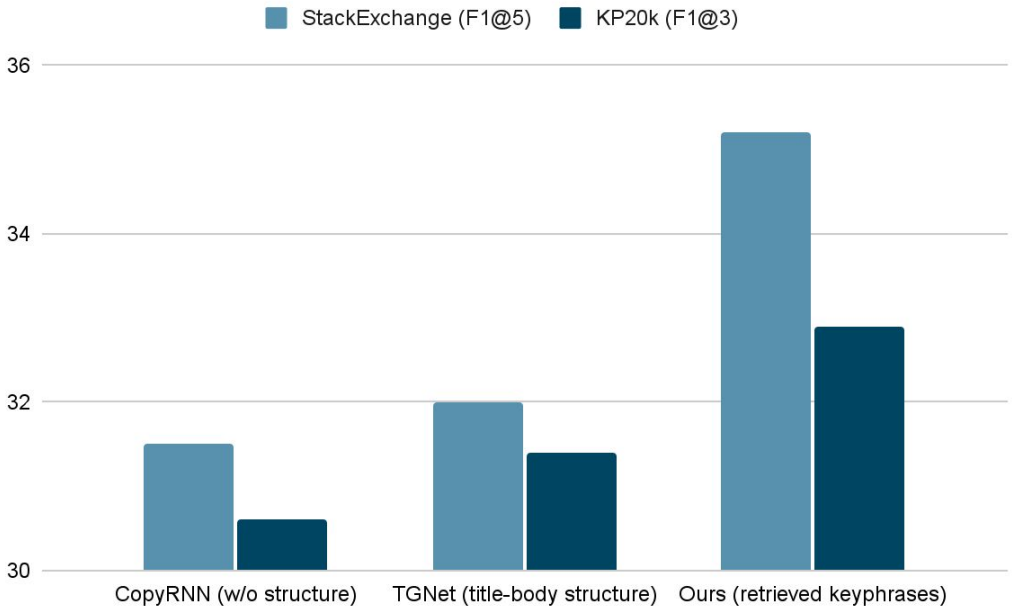
RQ 1.

- Whether leveraging existing keyphrases as structures improves performance.
  - CopyRNN w/o structures < Ours w/ augmented structures.



RQ 2.

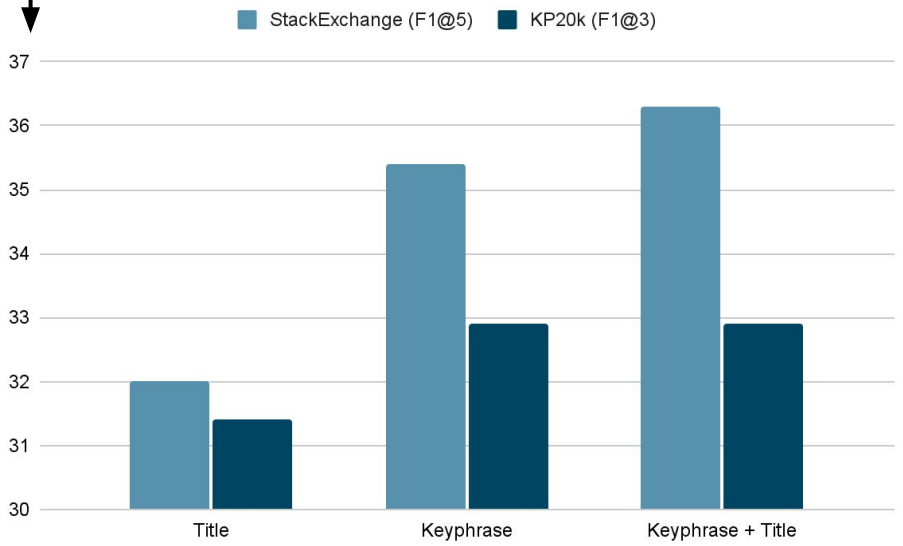
- Whether retrieved keyphrases are better than given titles.
  - TGNet using given titles < Ours using retrieved keyphrases.



RQ 3.

- Whether titles and retrieved keyphrases are complementary to each other.
  - When retrieved keyphrases are less relevant (e.g., StackExchange), titles complement the retrieved keyphrases.

Dataset	F1 of retrieved keyphrases
StackExchange	11.5
KP20k	22.3



Conclusion

- We studied augmenting structure for keyphrase generation task.
- We leverage existing keyphrases to augment or generate structures.
- Our proposed methods work for both closed/open set scenarios.