

# Medical Entity Disambiguation with Medical Mention Relation and Fine-grained Entity Knowledge

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# MED (Medical Entity Disambiguation)

- **Insulinum** is an important factor in the treatment of **DM**.

Medical Entity Disambiguation (MED) refers to the task of mapping medical mentions in medical text documents to their corresponding entities in a knowledge base (KB).

# Challenge 1:

## Neglect more knowledge information in KBs

Existing medical entity disambiguation methods primarily rely on a single type of knowledge and do not effectively integrate the knowledge embedded within medical KBs, which inadequately models the semantic representation of medical mentions and the semantic representation of candidate entities.

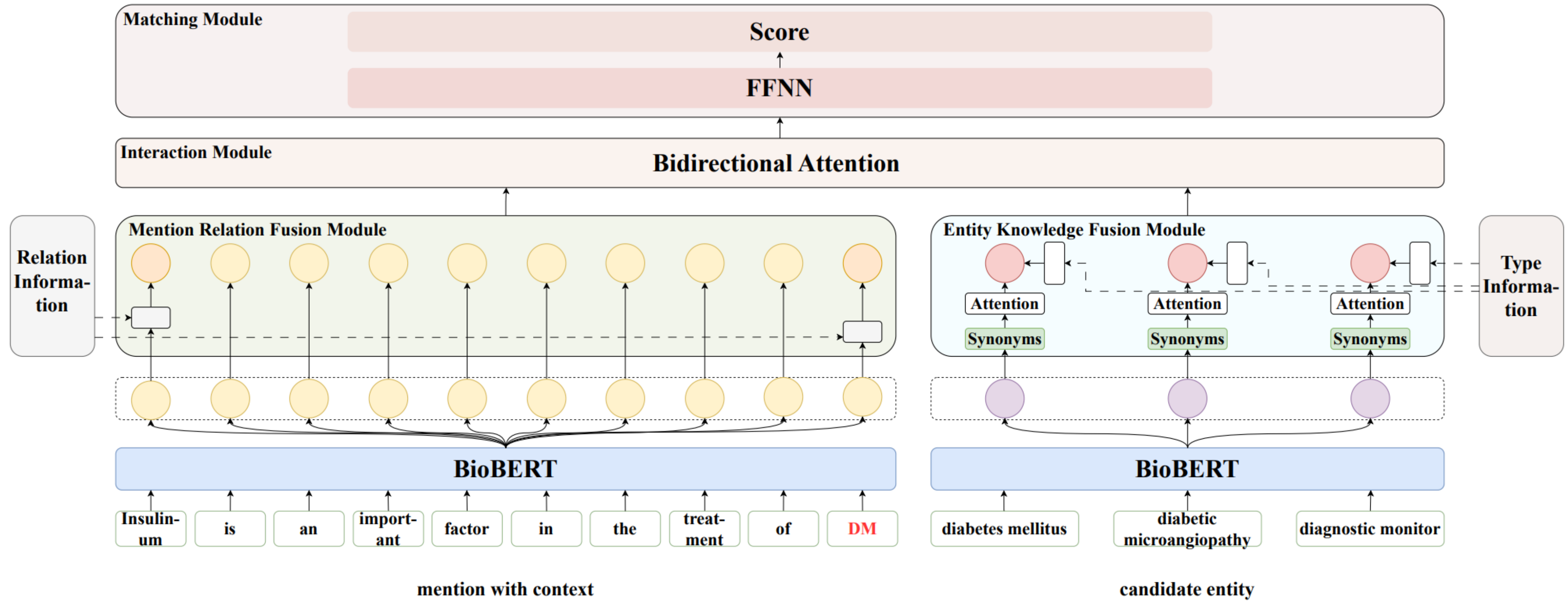
## Challenge 2: Overlook essential interactions

Existing medical entity disambiguation methods overlook essential interactions between medical mentions and candidate entities.

# Contribution

We propose a novel approach for medical entity disambiguation with medical mention relation and fine-grained entity knowledge (MMR-FEK). In contrast to existing works, our approach mines more additional relation knowledge between mentions and more fine-grained entity knowledge to enhance their representations, and captures more interactions between mentions and entities.

# Model



# Datasets

**MedMentions** is the most popular and largest biomedical entity disambiguation dataset, which consists of 4,392 abstracts from PubMed, with over 350,000 mentions linked to UMLS concepts.

**BC5CDR** consists of 1,500 articles from PubMed, with 4,409 annotated chemicals and 5,818 diseases. It contains over 28,000 mentions linked to MeSH concept, which are mapped to UMLS ones by us.

<b>Dataset</b>	<b>Statistics</b>	<b>Train</b>	<b>Dev</b>	<b>Test</b>
MedMentions	#Documents	2,635	878	879
	#Mentions	211,029	71,062	70,405
	#Entities	20,830	6,941	6,953
BC5CDR	#Documents	900	300	300
	#Mentions	17,135	5,710	5,714
	#Entities	5,489	1,830	1,830

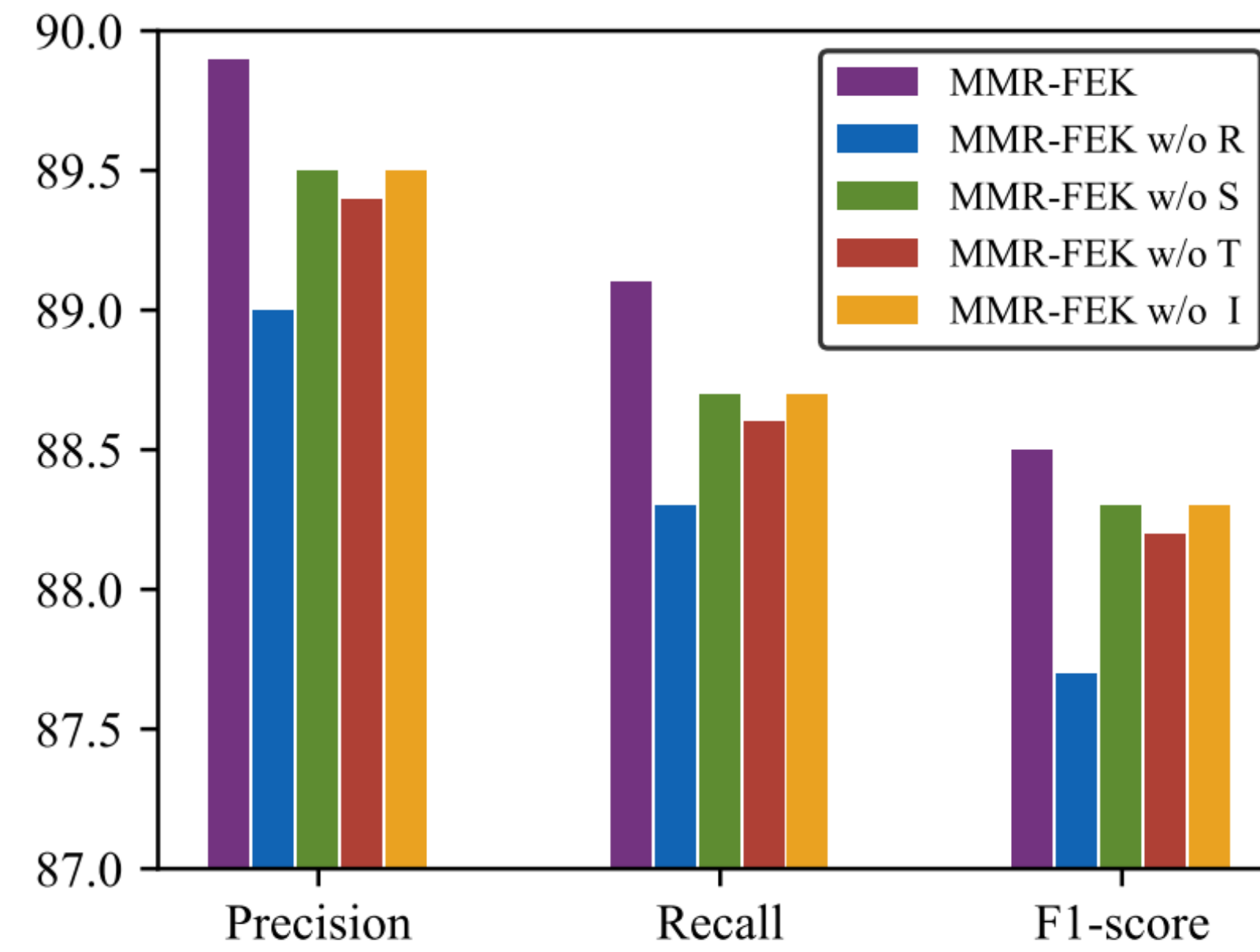
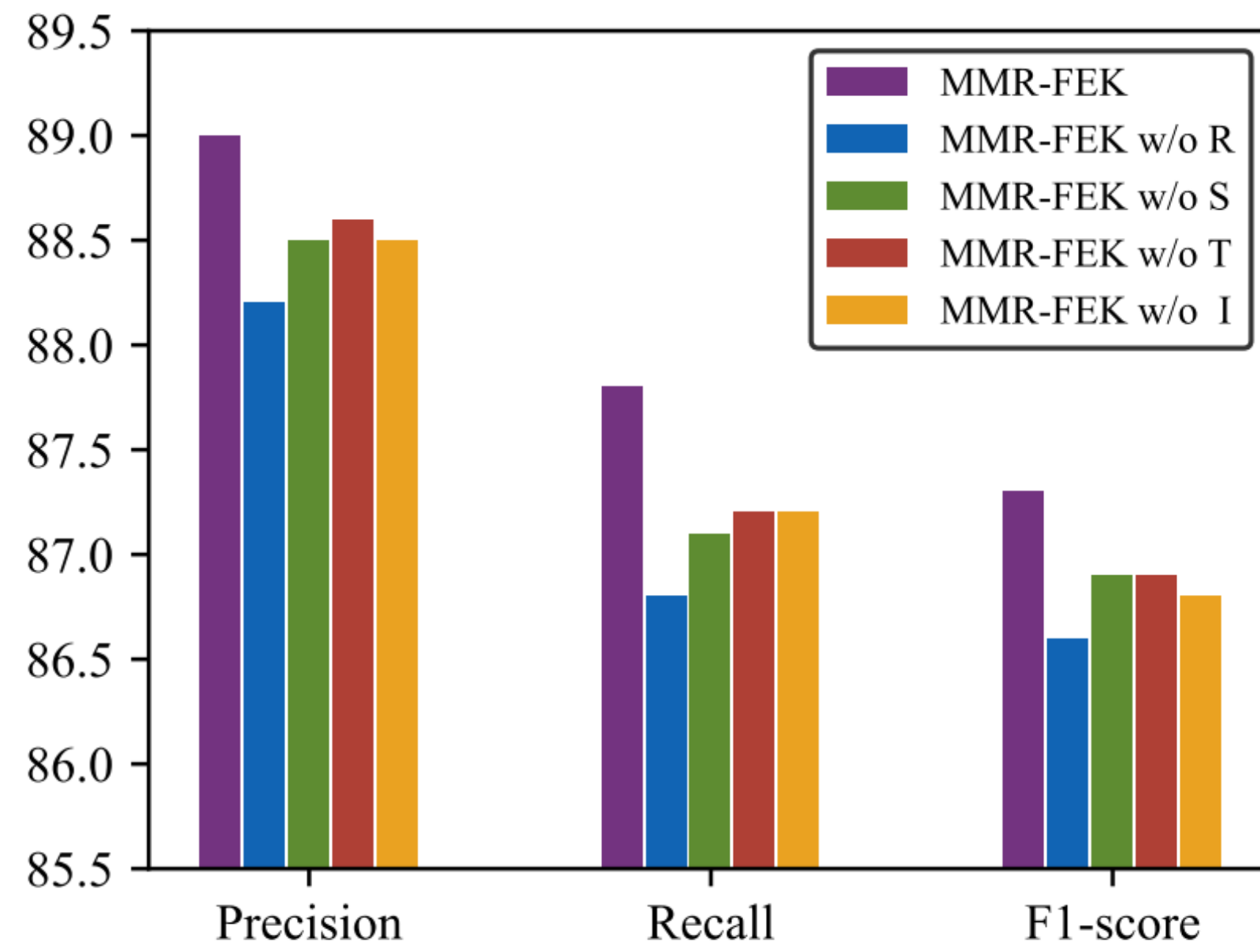
Table 1: Statistics of datasets.

# Experiment Result

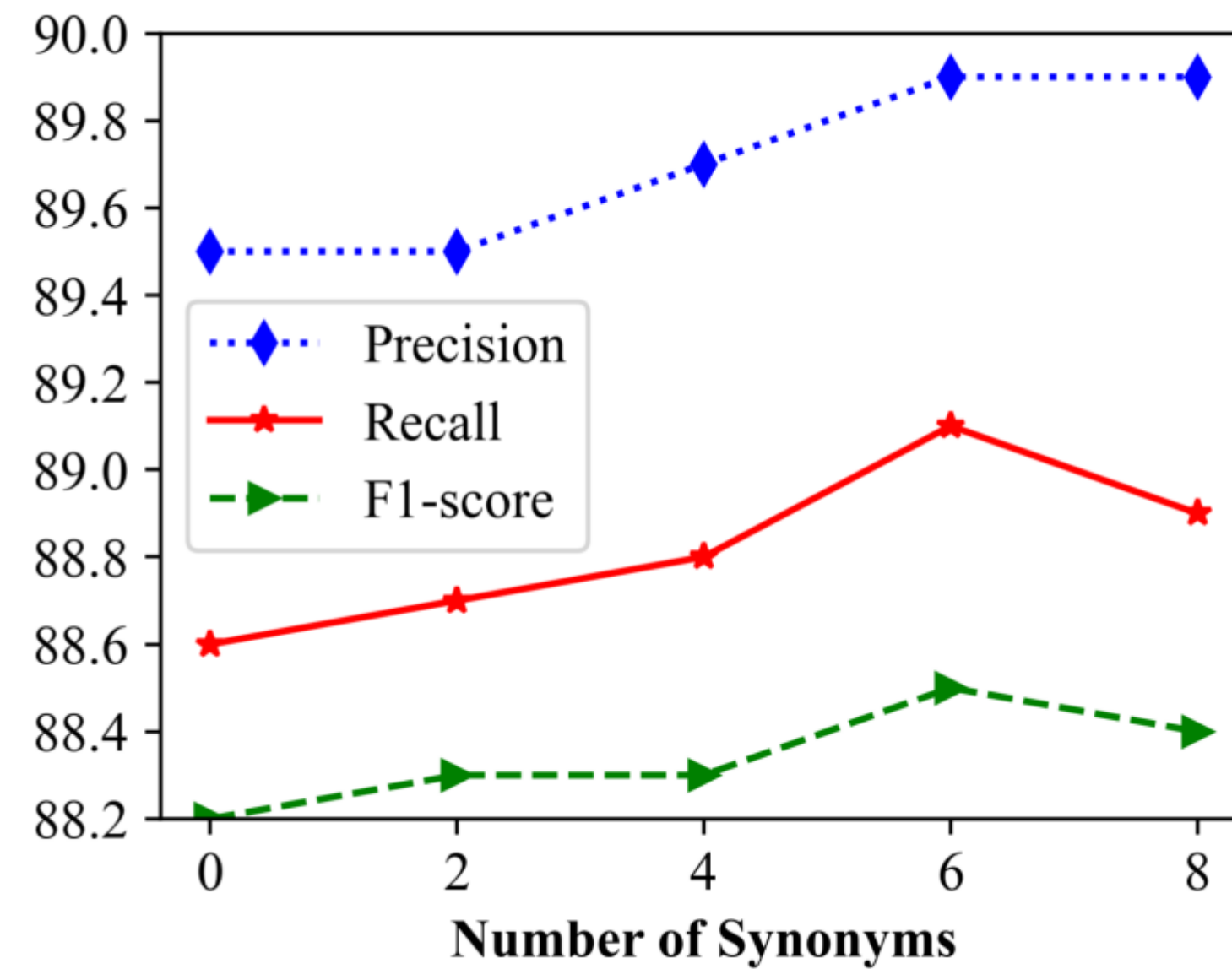
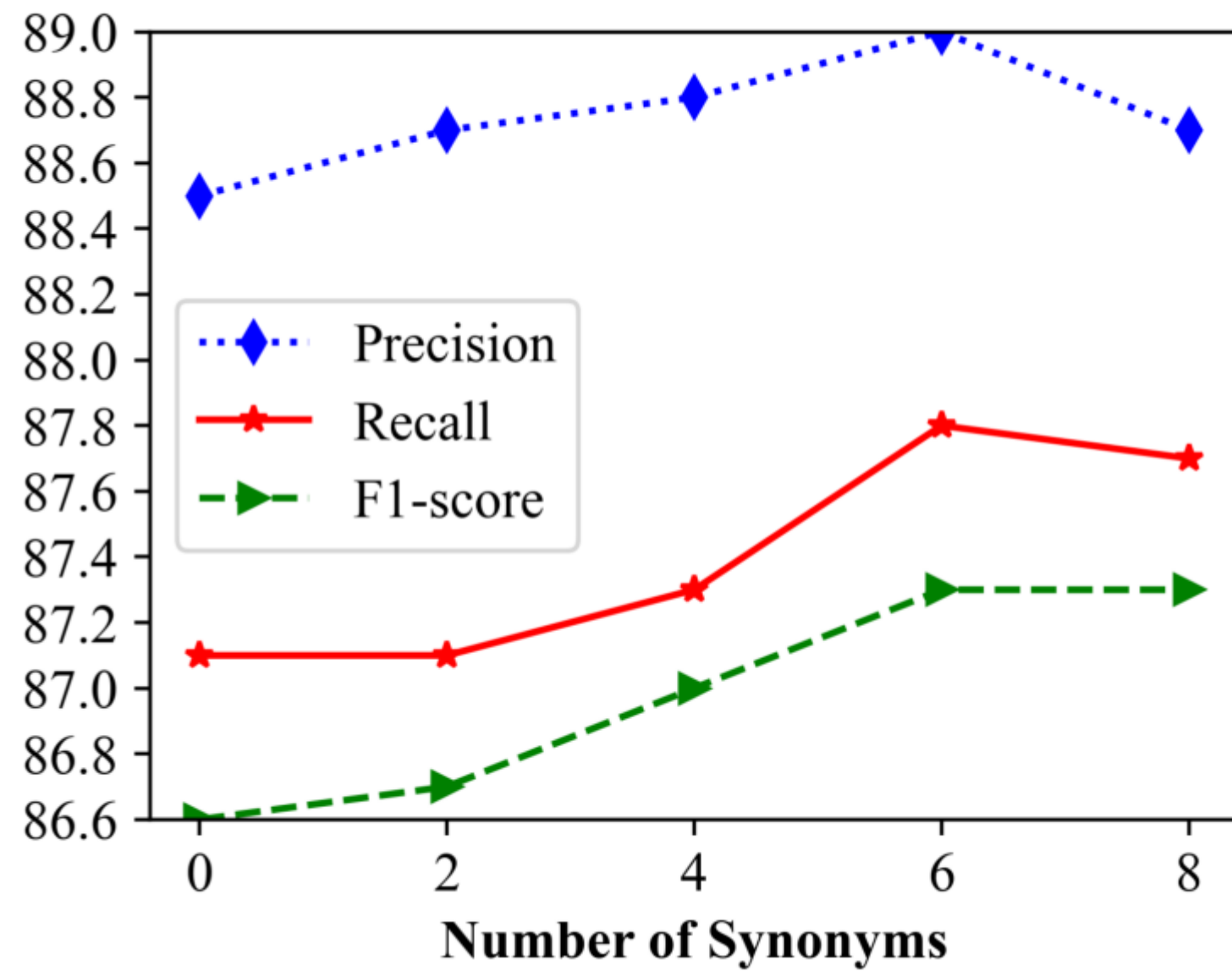
Model	MedMentions			BC5CDR		
	Precision	Recall	F1	Precision	Recall	F1
NCEL	OOM	OOM	OOM	65.7	67.3	65.2
BIOSYN	OOM	OOM	OOM	69.1	68.8	70.1
SAPBERT	53.1	56.4	52.3	70.2	72.9	72.4
Dual Encoder	62.9	67.4	65.6	84.8	82.1	83.0
Zhu	66.5	68.1	65.4	83.2	84.0	81.1
LATTE	88.2	86.5	85.6	88.2	87.0	86.3
B-LBConA	<u>88.5</u>	<u>87.1</u>	<u>86.5</u>	<u>89.1</u>	<u>88.2</u>	<u>87.3</u>
MMR-FEK (our)	<b>89.0*</b>	<b>87.8*</b>	<b>87.3*</b>	<b>89.9*</b>	<b>89.1*</b>	<b>88.5*</b>
Improvement(%)	0.5	0.7	0.8	0.8	0.9	1.2



# Ablation Study



# Influence of Number of Synonyms



# Code

The code is available from my GitHub page:

**<https://github.com/Stubborn-z/MMR-FEK>**

Thanks