Learning In-context Learning for Named Entity Recognition

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Outline

- Introduction
- Meta-function pre-training
- Experiments
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Named entity recognition

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- **Diversity** of entity types
- **Lack** of high-quality annotations

Few-shot learning

- **Fine-tuning-based methods**
- **Metric-based methods**

Drawbacks of few-shot NER methods

- Fine-tuning-based methods
  - Re-training (expensive for large-scale models)
  - Cannot identify novel types on-the-fly
- Metric-based methods
  - Limited to the architectures
  - Sensitive to the domain shift

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➡ **In-context learning**

In-context learning

- The model is given a few demonstrations (and instruction) of the task at inference time as conditioning but no weights are updated.

Input

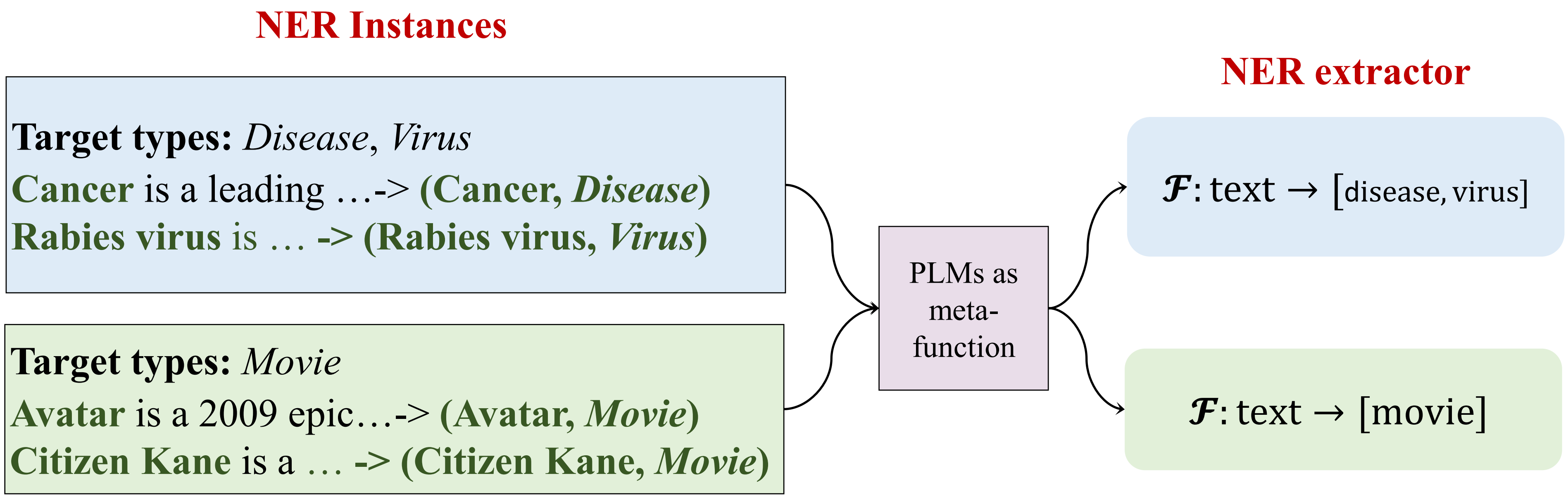
Instruction	**Target types:** *disease; virus*
Demonstrations	**Text:** *Cancer is a leading cause of death worldwide.*
	Entities: *Cancer is disease.*
	Text: *Rabies virus is estimated to cause around 55,000 deaths per year.*
	Entities: *Rabies virus is virus.*
Text	**Text:** *SARS-CoV-2 is a strain of coronavirus that causes COVID-19.*

Output

Entities: *SARS-CoV-2 is virus. COVID-19 is disease.*

Meta-function view

- We model pre-trained language models as a meta-function for NER.
  - **Meta-function**: $\lambda_{instruction,demonstraions,text}.\, M$
  - The new extractor can be implicitly constructed by instruction and demonstrations $(\lambda. M)(insturction, demonstraions) \;\; \rightarrow \;\; \{\mathcal{F}: text \rightarrow entities\}$



Meta-function pre-training

- Inject in-context NER ability into PLMs

In-context learning input

Target types: *disease, virus*
Text: **Cancer** is a leading …
Entities: **Cancer** is *disease.*
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Text: SARS-CoV-2 is a strain of coronavirus that causes COVID-19.

→ PLMs as meta-function → $\mathcal{F}$: text $\rightarrow$ [disease, virus]

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Implicitly constructed extractor

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NER Instances

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Fine-tuning

Fine-tuned surrogate golden extractor

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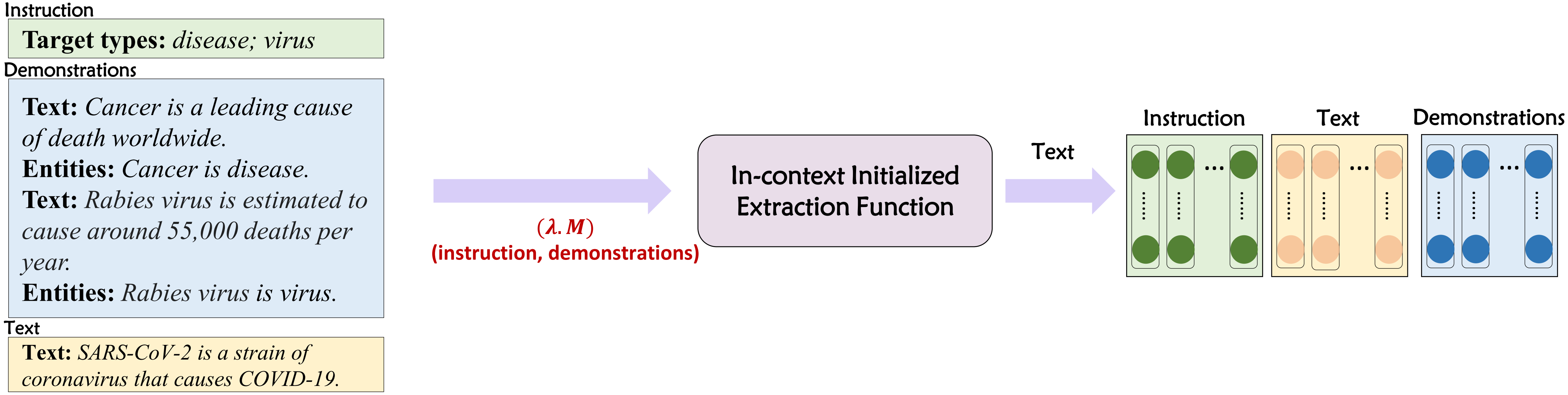

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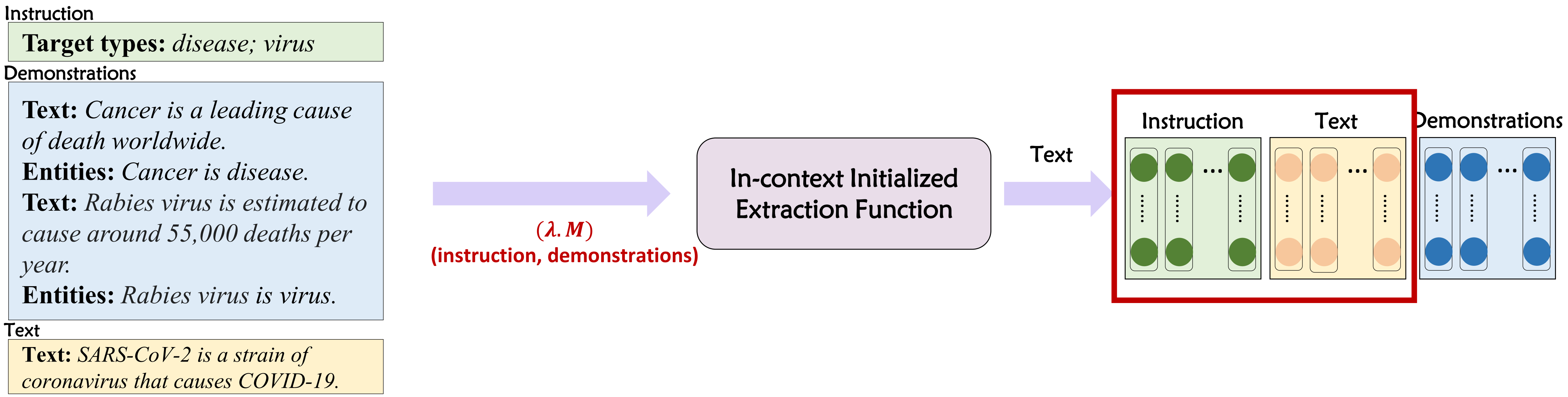

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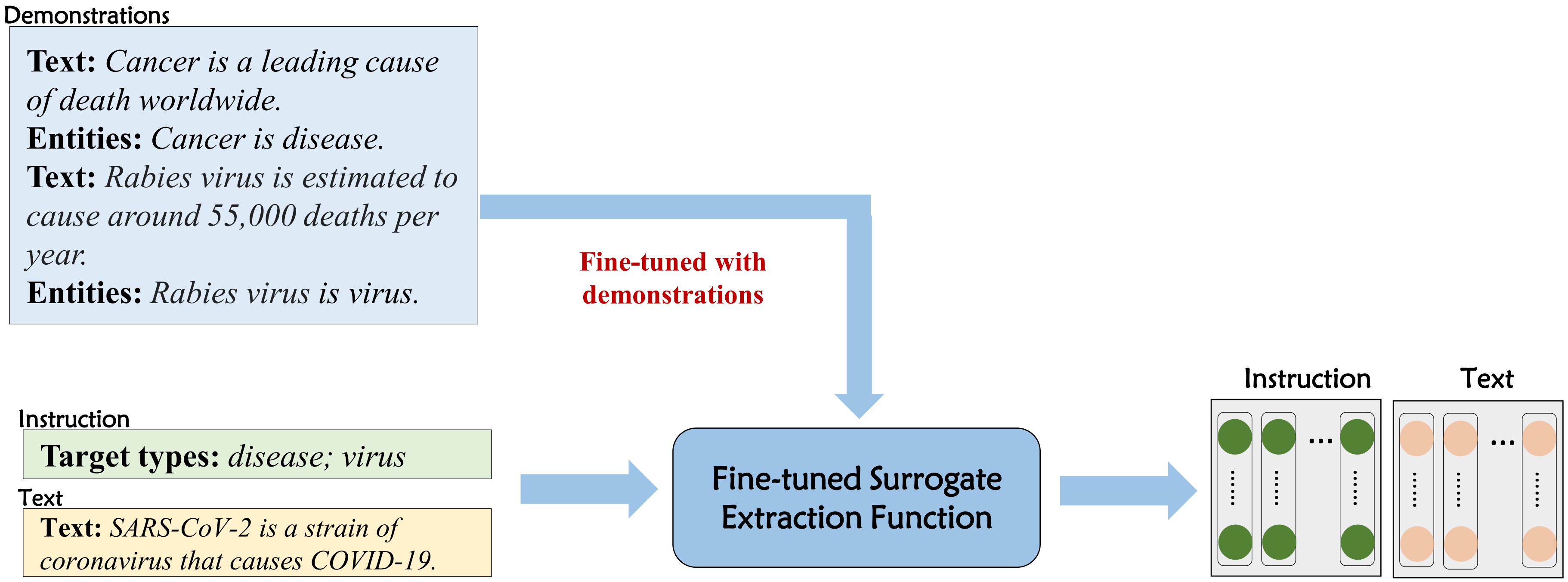

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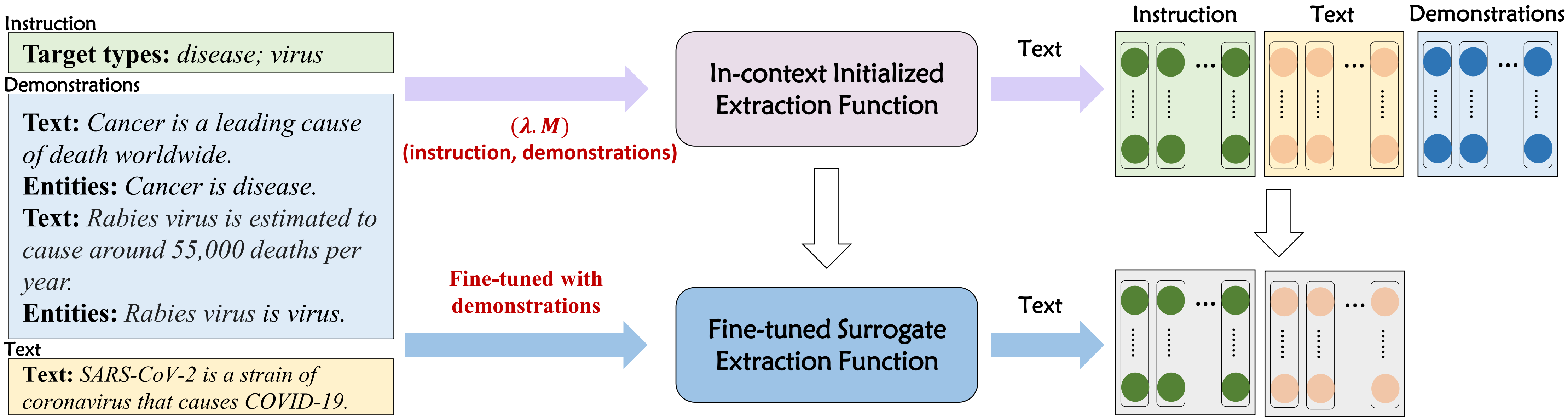

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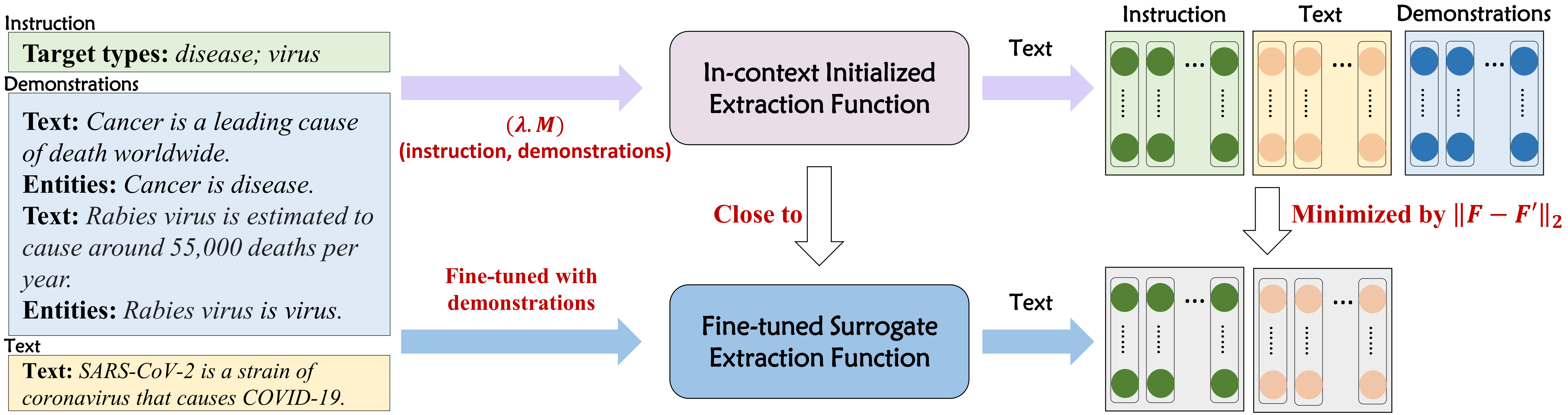

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Overall pre-training

- Optimizing PLMs via a meta-function loss
- Optimizing PLMs via an extraction loss
  - the sequence-to-sequence entity extractor directly models the generation probability token by token in an auto-regressive way

$$\boldsymbol{\mathcal{L}_{extraction}} = -\log \prod P(y_i | y_{<i}, X, \theta))$$

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$$\Downarrow$$

$$\mathcal{L} = \mathcal{L}_{extraction} + \alpha \mathcal{L}_{meta-function}$$

$$\Uparrow$$

$$\mathcal{L}_{meta-function} = Average(d(F_{in-context}, F'_{fine-tuned}))$$

Pre-trained data

- In-context task sampling: sample instance from NER dataset
  - Sample N target entity types and demonstrations
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  - randomly substituting names with a set of type indicators like <type1>, <type2>, …
- Entity extraction task
  - we also conduct traditional NER settings (without demonstrations) to improve the ability to extract entities from text when pre-training

Pseudo Extraction Language Modeling Task

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I think **this movie** is cool and I really **like** it very much

Type anonymization

<type2>: **this movie** <type14>: **like**

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I think **this movie** is cool and I **like** it very much.

<type2>: **this movie**   <type14>: **like**

Instruction and demonstrations

Target type: <type2>, <type14>
Text: I think **[MASK1]** is cool and I **[MASK2]** it[MASK3].
Entities: [MASK1] is <type2>. [MASK2] is <type14>

Pseudo Extraction Language Modeling Task

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I think **this movie** is cool and I **like** it very much.

<type2>: **this movie** <type14>: **like**

Input

Target type: <type2>, <type14>
Text: I think **[MASK1]** is cool and I **[MASK2]** it[MASK3].
Entities: [MASK1] is <type2>. [MASK2] is <type14>
Text: I do not like it.

Output

Entities: like is <type14>.

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Baselines

- The baselines include models with different scales and architectures.

- We conduct in-context learning and metric-based few-shot methods.

Models	#Param
T5v1.1-large	770M
GPT2-xl	1.5B
T5-xl	3B
GPT-J-6B	6B
T5-xxl	11B
OPT-13B	13B
GPT-Neox-20B	20B
OPT-30B	30B
OPT-66B	66B
ProtoNet	345M
NNShot	345M
StructShot	345M
CONTAINER	345M

Main result

Models	#Param	CoNLL03		WNUT17		NCBI-disease		SEC-filings		AVE
		1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	
Pre-trained Language Models										
T5v1.1-large	770M	38.61	44.90	25.52	26.32	26.02	37.63	41.89	53.44	36.79
GPT2-xl	1.5B	33.69	39.55	22.63	24.86	25.54	33.25	42.83	**57.05**	34.93
T5-xl	3B	38.99	45.74	26.39	26.31	23.10	36.78	30.58	42.22	33.76
GPT-J-6B	6B	46.14	50.10	31.41	30.93	35.82	40.98	40.12	39.61	39.39
T5-xxl	11B	40.97	46.14	24.76	25.27	12.19	26.34	32.65	42.44	31.35
OPT-13B	13B	46.65	51.71	27.74	28.36	23.73	34.00	41.60	43.10	37.11
GPT-Neox-20B	20B	52.68	58.12	**36.29**	35.68	35.42	42.85	45.07	45.17	43.91
OPT-30B	30B	42.86	44.77	25.85	27.44	22.31	32.76	40.83	46.52	35.42
OPT-66B	66B	43.83	53.89	30.77	32.00	25.87	34.58	39.15	47.01	38.39
Pre-trained NER Models										
ProtoNet	345M	30.04	60.26	9.74	23.03	24.73	42.32	16.79	23.67	28.82
NNShot	345M	41.92	58.39	15.76	21.78	31.59	33.14	30.19	37.86	33.83
StructShot	345M	42.34	58.44	15.78	22.05	19.87	31.48	30.40	38.44	32.35
CONTAINER	345M	45.43	61.69	15.64	20.37	23.24	27.02	34.07	40.44	33.49
MetaNER-base	220M	53.94	62.59	25.55	30.41	35.00	37.24	46.88	51.39	42.88
MetaNER	770M	**57.40**	**63.45**	31.59	**36.52**	**40.01**	**44.92**	**52.07**	54.87	**47.60**

Meta-function pre-training can effectively inject in-context learning ability into PLMs.

Ablation studies

	CoNLL03			NCBI-disease		
	P	R	F1	P	R	F1
MetaNER	73.59	57.19	**64.34**	**54.96**	**36.85**	**43.79**
w/o MF	68.97	57.62	62.77	38.27	35.26	36.28
w/o LM	70.86	**57.99**	63.77	37.54	34.82	35.67
w/o anonymization	**74.75**	52.86	61.93	47.47	35.30	40.48

MF: meta-function pre-training
LM: pseudo extraction LM task

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Meta-function pre-training is critical for in-context learning ability

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The pseudo extraction LM task significantly benefits in-context NER

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Type name anonymization prevents in-context NER model from type name overfitting, and therefore enhances the in-context learning ability

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- We model PLMs as a meta-function for in-context NER.
- We propose the meta-function pre-training to inject in-context NER ability into PLMs.
- Experimental results show that our method is effective for in-context NER.

Thanks!

Source Code: https://github.com/chen700564/metaner-icl