

NLP4DL Workshop - EGC 2022 (Blois, France)

Fine-tuning Pre-trained Transformer Language Models for Biomedical Event Trigger Detection

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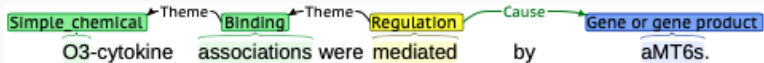
Introduction

- Biomedical event extraction is a complex **information extraction task** that helps to **identify key information** from large sets of textual data for further applications;
 - e.g. pathway curation, study of biomolecular mechanisms of infectious diseases, drug labeling and epigenetic changes.

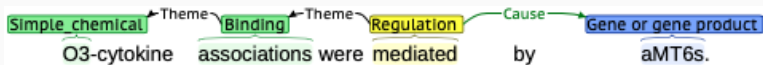
- Biomedical event extraction is a complex **information extraction task** that helps to **identify key information** from large sets of textual data for further applications;
 - e.g. pathway curation, study of biomolecular mechanisms of infectious diseases, drug labeling and epigenetic changes.
- A biomedical event contains an **event trigger** and one or more **arguments**;
 - Event triggers generally refer to nouns or verbs that express a **circumstance, process** or **eventuality**.
 - Arguments refer to **biomedical entities** or other **events**.

'[...] O3-cytokine associations were mediated by aMT6s.'

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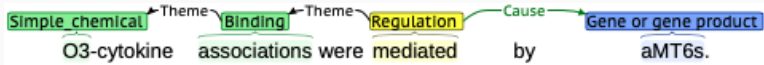
Biomedical event extraction: Definition



Event 1 - *Binding*

- **Trigger word:** 'associations'
- **Trigger category:** Binding
- **Argument word:** 'O3'
- **Argument category:** Simple_chemical
- **Role:** Theme

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- **Trigger category:** Binding
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- **Argument category:** Simple_chemical
- **Role:** Theme

Event 2 - *Regulation*

- **Trigger word:** 'mediated'
- **Trigger category:** Regulation
- **Argument word 1:** *Event 1*
- **Role 1:** Theme
- **Argument word 2:** 'aMT6s'
- **Argument category 2:** G_or_G_P
- **Role 2:** Cause

Biomedical event trigger detection: Definition

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- The extraction of biomedical events can be divided into two main sub-tasks; **event trigger detection** and **argument identification**.
- **Event trigger detection** identifies and classifies the event triggers into a set of predefined categories of events.
 - It has a critical role in building events, since the triggers are the targets that allow the **construction of an event**.
 - **More than 60 %** of biomedical event extraction **errors** occur in this sub-task [8].

Event trigger detection is challenging!

- The same event can be represented in the form of different expressions;
 - '[...] the mechanism that **activates**_{+Reg} infiltrating macrophages [...]'
 - '[...] a limited role in post-ischemic macrophage **activation**_{+Reg}.'
 - '[...] antibodies that **activated**_? inflammatory cytokine expression.'

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 - '[...] the mechanism that **activates**_{+Reg} infiltrating macrophages [...]'
 - '[...] a limited role in post-ischemic macrophage **activation**_{+Reg}.'
 - '[...] antibodies that **activated**_? inflammatory cytokine expression.'
- They can be represented as single words or multi-words;
 - '[...] the **neuroprotective efficacy**_{-Reg} of epigallocatechin-3-gallate (EGCG) [...]'
 - '[...] TLR4/NF-B pathway in LPS+A-**induced**_{+Reg} rat microglia [...]'

Event trigger detection is challenging!

- They can present in-domain language or not;
 - '[...] Noncanonical Inflammasome via TLR4/NF-B **Pathway***Pathway*.'
 - '[...] and **Neurotoxicity***Carcinogenesis* by Suppressing the Activation of Inflammasome'.
 - 'EGCG **attenuates***—Reg* microglial inflammation [...]'

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 - '[...] Noncanonical Inflammasome via TLR4/NF-B **Pathway**_{Pathway}'
 - '[...] and **Neurotoxicity**_{Carcinogenesis} by Suppressing the Activation of Inflammasome'.
 - 'EGCG **attenuates**_{Reg} microglial inflammation [...]'
- The same word can represent a different event according to the context (or the manual annotation?);
 - 'Anti-Survival and Pro-Apoptotic **Effects**_{Reg} of 6-Shogaol [...]'
 - '[...] has anticancer **effects**_{Reg} on many types of tumors'.

Biomedical event trigger detection: Techniques

- **Neural networks** have been widely adopted for event trigger detection since they do not require the **design of functions** or use **additional tools** for their training.
- Models pre-trained on **transformers** architectures are commonly used for solving NLP tasks due to their positive achievements in performance.

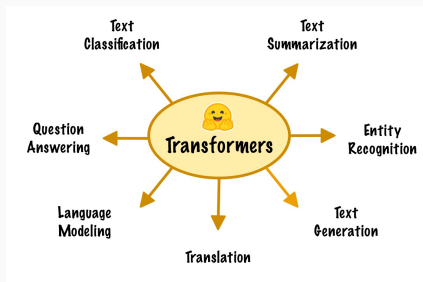


Figure obtained from: <https://towardsdatascience.com/transformers-implementing-nlp-models-in-3-lines/-of-code-475639c3611d>

Bidirectional Encoder Representations from Transformers

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step

Model:



Dataset:



Objective:

Predict the masked word
(language modeling)

2 - Supervised training on a specific task with a labeled dataset.

Supervised Learning Step

Model:
(pre-trained
in step #1)



Dataset:

Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached...	Not Spam

- BERT variants in the **biomedical** domain: BioBERT, PubMedBERT, BioMedRoBERTa, among others.

Figure obtained from <https://jalammar.github.io/illustrated-bert/>.

Work proposal and Contributions

This work compares five transformer language models (BERT, BioBERT, SciBERT, PubMedBERT and BioMedRoBERTa) for detecting biomedical event triggers using seven merged biomedical datasets to identify which model is the most appropriate for tackling this task;

This work compares five transformer language models (BERT, BioBERT, SciBERT, PubMedBERT and BioMedRoBERTa) for detecting biomedical event triggers using seven merged biomedical datasets to identify which model is the most appropriate for tackling this task;

1. Identify whether using a transformer model pre-trained on the biomedical domain language presents advantages in performance.
2. Analyze whether using different biomedical corpus together for the models' training can improve event triggers detection.

Methods

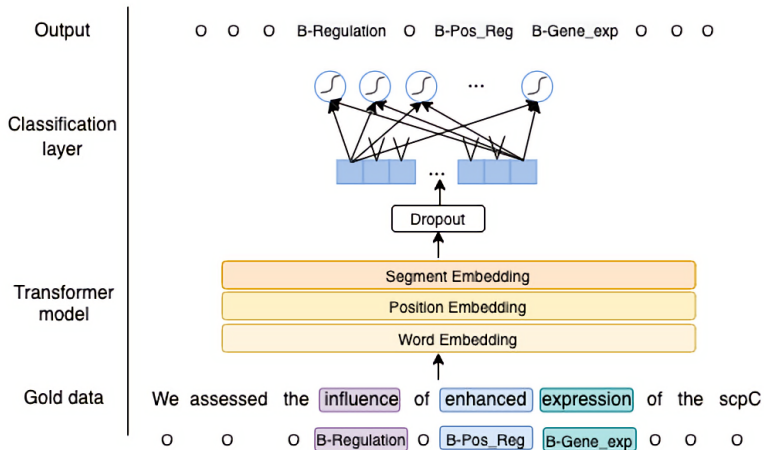
Detection of biomedical event triggers

The detection of biomedical event triggers can be considered as a **multi-class problem**;

IOB (Inside-Outside-Beginning) annotation of event triggers

'PTHrP	drives	breast	tumor	initial	progression	and	metastasis ...'
'O'	'B-Regulation'	'O'	'O'	'B-Development'	'I-Development'	'O'	'B-Metastasis'

Model proposal



Experimental settings and Evaluation

Dataset	No. Triggers	No. Events	Documents	Train/Dev/Test
CG 2013	9,790	17,248	PubMed abstracts	300/100/200
EPI 2011	2,035	2,453	PubMed abstracts	600/200/400
GENIA 2011	10,210	13,560	MEDLINE abstracts	1,000 (total)
GENIA 2013	4,676	6,016	PMC full-text	34 (total)
ID 2011	2,155	2,779	PMC full-text	15/5/10
PC 2013	6,220	8,121	PubMed abstracts	260/90/175
MLEE	5,554	6,677	PubMed abstracts	131/44/87

- Total train and test sets: 19,855 and 4,964 sentences.
- Total trigger classes: 58.

Model	Pre-training	Corpus
BERT	from scratch	WikiPedia + BookCorpus
BioBERT	from BERT	PubMed
SciBERT	from scratch	PMC* + Semantic scholar
PubMedBERT	from scratch	PMC* + PubMed
BioMedRoBERTa	from BERT	Semantic scholar

- Each model was fine-tuned for 10, 30 and 100 epochs.
- Precision, Recall and F1-score were measured for evaluation.

*PMC = PubMed Central

Evaluation of pre-trained models fine-tuned for trigger detection

Model	10 epochs			30 epochs			100 epochs		
	P	R	F1	P	R	F1	P	R	F1
BERT	0.57	0.67	0.62	0.60	0.68	0.64	0.62	0.68	0.65
BioBERT	0.51	0.61	0.55	0.57	0.59	0.58	0.72	0.75	0.73
SciBERT	0.59	0.64	0.61	0.61	0.65	0.63	0.70	0.70	0.70
PubMedBERT	0.49	0.61	0.54	0.58	0.66	0.61	0.58	0.62	0.60
BioMedRoBERTa	0.48	0.49	0.47	0.52	0.52	0.51	0.55	0.50	0.52

Category grained evaluation (BioBERT - 100 epochs)

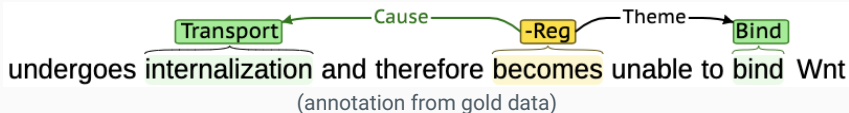
Trigger category	P	R	F1	Support	Trigger category	P	R	F1	Support
Amino_acid_catabolism	1.00	1.00	1.00	1	Entity	0.63	0.74	0.68	398
Glycolysis	1.00	0.90	0.95	10	Degradation	0.68	0.68	0.68	19
Acetylation	0.86	0.99	0.92	82	Transcription	0.65	0.70	0.67	175
Phosphorylation	0.89	0.94	0.91	207	Synthesis	1.00	0.50	0.67	2
Deglycosylation	0.83	1.00	0.91	5	Conversion	0.55	0.75	0.64	28
Process	0.84	0.96	0.90	136	Regulation	0.66	0.57	0.61	556
Deacetylation	0.81	1.00	0.90	13	Blood_vessel_development	0.52	0.72	0.60	18
Metastasis	0.84	0.92	0.88	53	Transport	0.62	0.54	0.59	42
Methylation	0.85	0.90	0.87	73	Planned_process	0.65	0.54	0.59	104
Demethylation	0.75	1.00	0.86	3	Metabolism	0.57	0.57	0.57	7
Ubiquitination	0.82	0.90	0.86	67	Cell_death	0.56	0.58	0.57	43
Gene_expression	0.82	0.88	0.85	754	Growth	0.50	0.67	0.57	3
Hydroxylation	0.82	0.85	0.84	27	DNA_demethylation	0.40	1.00	0.57	2
Glycosylation	0.81	0.84	0.82	67	DNA_domain_or_region	0.57	0.57	0.57	7
DNA_methylation	0.82	0.82	0.82	77	Development	0.49	0.54	0.51	39
Cell_differentiation	0.92	0.73	0.81	15	Dephosphorylation	0.33	1.00	0.50	1
Carcinogenesis	0.78	0.81	0.79	31	Deubiquitination	1.00	0.33	0.50	3
Activation	0.78	0.80	0.79	65	Inactivation	0.44	0.53	0.48	15
Protein_catabolism	0.70	0.87	0.78	30	Catalysis	0.38	0.56	0.45	16
Pathway	0.79	0.76	0.78	168	Breakdown	0.40	0.50	0.44	4
Cell_proliferation	0.77	0.73	0.75	37	Mutation	0.45	0.41	0.43	32
Binding	0.72	0.79	0.75	434	Protein_processing	0.25	1.00	0.40	1
Negative_regulation	0.71	0.79	0.75	586	Anaphora	0.23	0.14	0.18	49
Localization	0.71	0.77	0.74	164	Protein_domain_or_region	0.00	0.00	0.00	5
Infection	1.00	0.56	0.71	9	Cell_division	0.00	0.00	0.00	2
Cell_transformation	0.76	0.67	0.71	39	Catabolism	0.00	0.00	0.00	5
Positive_regulation	0.72	0.68	0.70	1,276	Remodeling	0.00	0.00	0.00	1
Dissociation	0.64	0.78	0.70	9	Translation	0.00	0.00	0.00	2
Death	0.69	0.69	0.69	16	Dehydroxylation	0.00	0.00	0.00	1

Examples of ambiguous event triggers in gold data

‘When the dickkopf protein (Dkk) binds to Kremen and LRP5, this last **undergoes internalization and therefore becomes unable to bind Wnt**; this leads to degradation of beta-catenin and to inhibition of bone formation’.

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- The model incorrectly classified **becomes** as 'Regulation'.

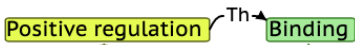
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'On the other hand, stimulation of T cells with mAb 9.3 increased the level of intracellular Ca^{2+} and triggered the activation of p56 (lck) and c-Raf-1, but **was unable to induce the binding of transcription factors to the IL-2 promoter.**'

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was unable to induce the binding of transcription factors to the IL - 2
(annotation from gold data)

- The model incorrectly classified **unable to induce** as 'Negative regulation'.

Examples of ambiguous event triggers in gold data

'Thus, Egr-2, in addition to Egr-3, regulates FasL expression in activated normal T cells, and Egr-2 is **likely to play a direct role in aberrant fasL up-regulation in lpr/lpr and gld/gld CD4(-)CD8(-)T cells.**'

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likely to play a direct **Reg** **role** in aberrant fasL **+Regulation** up - regulation in lpr / lpr
(annotation from gold data)

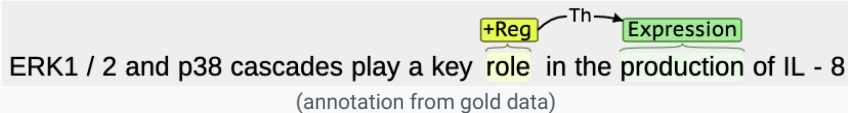
- The model correctly classified **role** as 'Regulation'.

Examples of ambiguous event triggers in gold data

'By using PD-98059 and SB203580, two potent and selective inhibitors of MEK1 and p38, respectively, we have demonstrated that both **ERK1/2 and p38 cascades** play a key role in the production of IL-8 by monocytes and PMN stimulated with bacterial fractions.'

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Conclusions and Future work

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- Using different corpus merged as input data can enrich event detection, since they provide more trigger categories and samples to train the model.

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- Biomedical data presents very specialized language that can be difficult to model for event trigger detection.
- BioBERT presents the highest performance in detecting biomedical event triggers when it is trained during 100 epochs.
 - This result suggests that a model pre-trained on biomedical data that starts its pre-training from BERT weights is the best strategy for biomedical event trigger detection.
- Using different corpus merged as input data can enrich event detection, since they provide more trigger categories and samples to train the model.
- However, the categories of triggers with high number of samples do not necessarily present high performance.
 - These results suggest that the triggers samples may present ambiguities, making it difficult for the model to achieve the generalization, even if the number of samples is relatively significant.

For the next steps:

- to enrich the information given to the model by **adding extra features**, as the Parts-Of-Speech [4] or the syntactic dependency path [8], to **reduce ambiguities**;
- to **merge** the trigger categories with the **lowest support** to other categories with similar events to **reduce the imbalance** of the data.

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