



Semantic IR: Exploring Dependency and Word Embedding Features in Biomedical IR

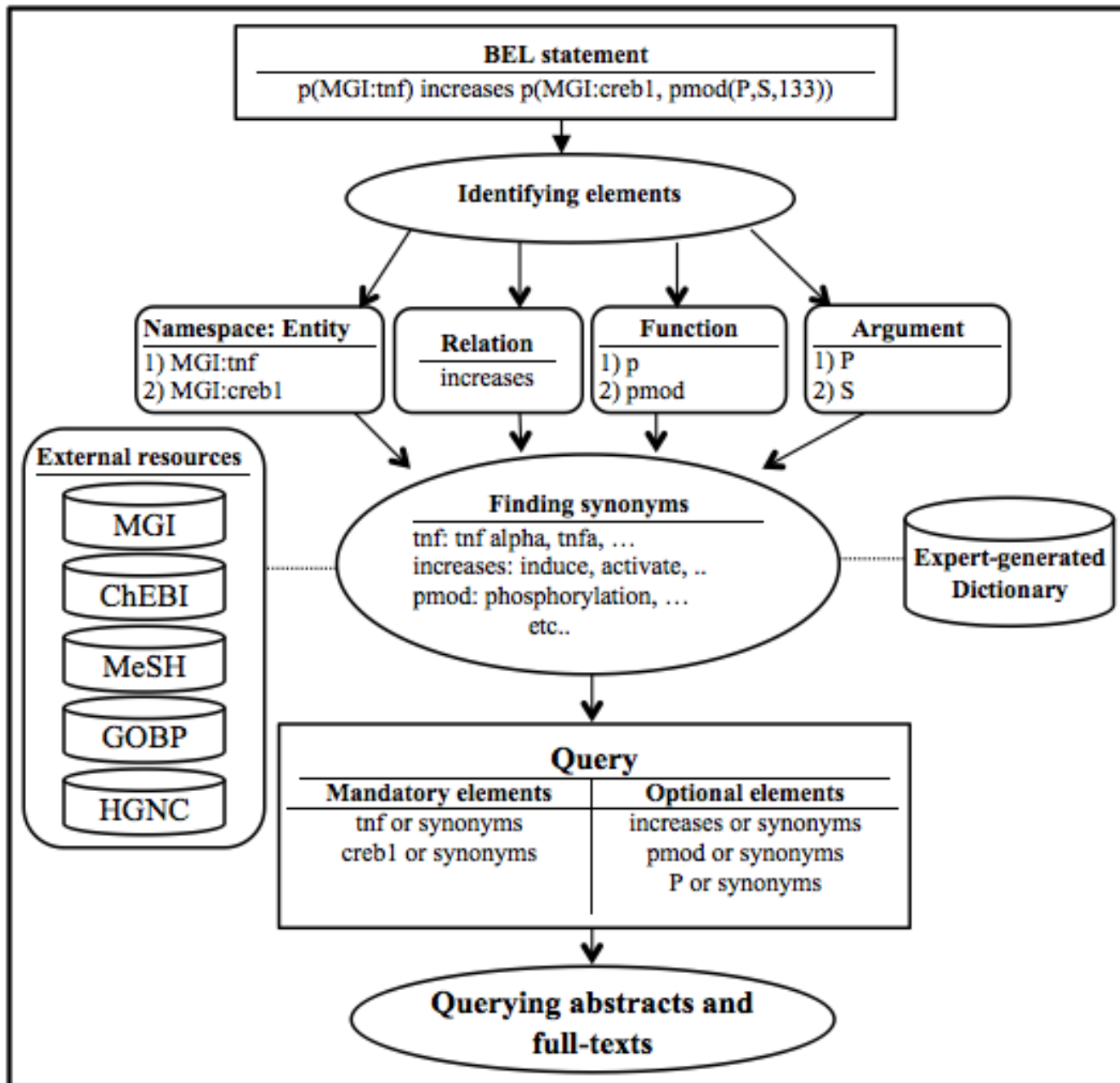
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BELTracker

- Task 2: Retrieving evidence sentence for a given BEL
 - Identifying at most 10 evidence sentences
- Two architectures
 - 2015 and 2017 competitions
 - Co-occurrence based
 - IE-based
- Main components
 - Retrieval component
 - Ranking component

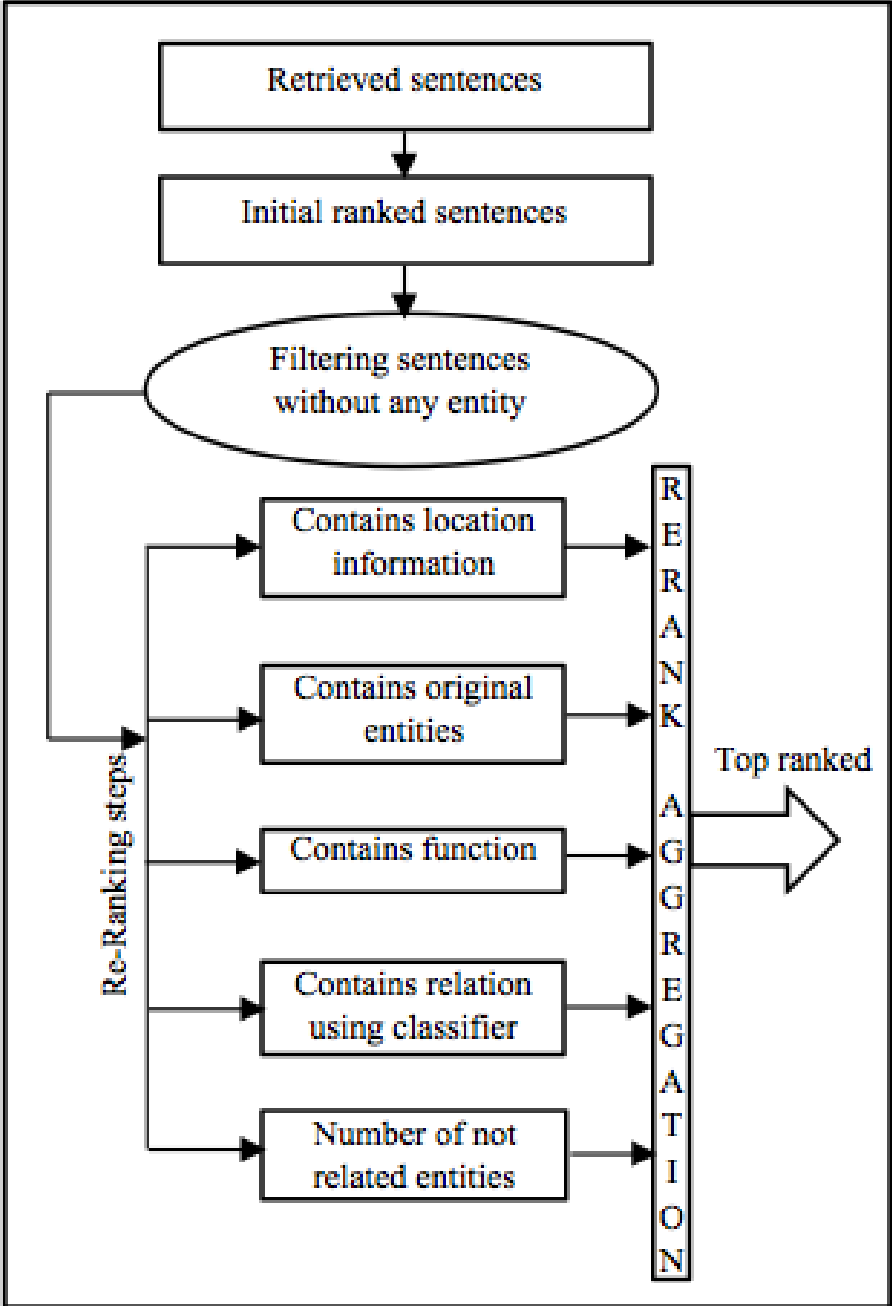
Co-occurrence based (2015)

- Indexing abstract and full-text
 - Elastic search
- Retrieval component
 - Translating the given BEL statement into a query
 - Identifying elements
 - Finding synonyms
 - Existing resources & expert-generated dictionaries
 - Retrieving relevant documents



Co-occurrence based

- Ranking component
- Top 1000 results
 - Splitting into sentences
 - Removing non-relevant sentences
- Ranking sentences based on occurrence of elements
 - Manual weight assignment for elements



IE-based (2017)

- Indexing only useful sentences
 - Using Semantic Medline
- Training classifiers for ranking
 - For each element
- Semantic
 - Word embedding
 - Dependency embedding

Semantic Medline

- SemRep
 - Extracts semantic predications from biomedical literature
 - Biomedical entities
 - ~30 predicates
 - treat, affect, interacts with, ..., **coexist with**
- Semantic Medline Database
 - A relational database
 - ~ 200 million sentences
 - ~ 90 million predications

Ranking component

- Using the same retrieval component
- Training classifier for ranking
 - Pair classification (BEL, sentence)
 - Positives from the training set
 - **How to define negative instances ???**
 - Randomly selecting a sentence for a BEL
 - Masking entity names
 - Not the same relation (inc. or dec.)
 - Not the same function
- Train three classifiers
 - Distant supervision

First classifier

- Existence of relationship
 - cat(HGNC:*SPN*) increases gtp(HGNC:*RAP1A*)
 - *RasGRP2 also catalyzes nucleotide exchange on Rap1a and SPN, but this RapGEF activity is less potent than that associated with CalDAG-GEFI.*
- Instances (Pair of BEL statement and sentence)
 - Negative instances from Semantic medline
 - Entities: the same as randomly selected BEL
 - Predicate: **coexist with**
- Features
 - Unigram, Bi-grams, Word-embedding

Second classifier

- Function

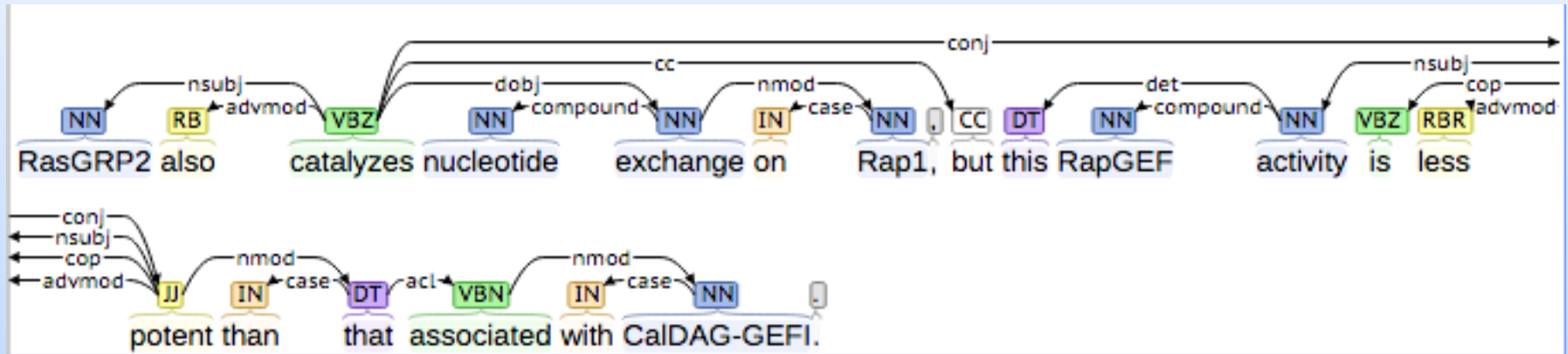
Subject	Predicate	Object
<code>cat(HGNC:RASGRP2)</code>	increases	<code>gtp(HGNC:RAP1A)</code>

- `RasGRP2` also `catalyzes` nucleotide exchange on Rap1, but this RapGEF activity is less potent than that associated with CalDAG-GEFI.
- One classifier for each function
- Instances: BEL term+ sentence
 - Positive instances from the training data
 - Negative instances others functions

Second classifier

- Features
 - Surrounding terms (window of 3-5)
 - Dependency embedding

RasGRP2 also catalyzes nucleotide exchange on Rap1, but this RapGEF activity is less potent than that associated with CalDAG-GEFI.



	RasGRP2	Catalyzes
Dependency contexts	nsubj_inv_catalyzes	nsubj_RasGPR2, advmod_also, ...

Third classifier & final score

- Relation
 - `cat(HGNC:SPN)` **increases** `r(HGNC:CD40LG)`
 - Two classes: increase and decrease
 - Instances: BEL and sentence
 - No challenge in identifying instances for each class
 - Fea. : Unigrams, bigrams, expert-generated dictionary, ..

- Final score for each retrieved sentence

$$0.40 * P_{c1} + 0.50 * P_{c2} + 0.10 * P_{c3}$$

Data

- Training set
 - Pair of BEL and corresponding sentence
 - 11066 BEL statements extracted from 6354 sentences
 - No entity or relation annotation
- Test set
 - 100 BEL statement for each competition
 - Manually evaluated by expert

Evaluation

- Precision
 - $TP / (FP + TP)$
- Criteria
 - **Full**: The sentence contains the complete BEL statement.
 - **Relaxed**: Has necessary context and/or biological background to enable extraction of BEL statement.
 - **Context**: Even though the complete or partial BEL statement cannot be extracted from the sentence, it provides the necessary context for the BEL statement.

Evaluation

- Mean Average Precision (MAP)
 - For each query
 - Precisions for relevant docs considering their rank
 - Ave. the precisions : AP
 - Mean of all APs for all Qs

- Three ranking scenarios
 - Worst: All the TPs are ranked after all FPs
 - Random: Randomly reordered the results 2000 times
 - Best: All TPs are ranked before all FPs

Results (2015 test data)

- Precision (co-occurrence based)

Criteria	True positive	False positive	Precision
Full	316	490	39.20
Relaxed	429	377	53.22
Context	496	310	61.53

- MAP

Criteria	Worst	Random	Co-occ.	IE-based	Best
Full	31.7	46.5	49.0	56.96	74.2
Relaxed	45.9	58.4	62.1	65.05	80.4
Context	55.2	65.7	68.9	73.15	83.5

Results (2017 test data)

- Two runs (top 5 evidence sentences)

Run	Criteria	True positive	False positive	Precision	MAP
ElasticSearch	Full	117	265	30.6	59.6 (+9.4)
Our system	Full	121	261	31.7 (+1.1)	50.2
ElasticSearch	Partial	175	207	45.8	77.5 (+0.8)
Our system	Partial	192	190	50.3 (+4.5)	76.7

Discussion

- Solved issues
 - Response time
 - Extensively relied upon the lexical feature
 - Without any consideration of semantics
- Dictionaries
 - 16% of BEL entities not in the corresponding sentences
 - No results for 7 BELs
 - Focusing on Full retrieval not Partial sentences

Discussion

- Only sentences in abstracts
- Ranking
 - Negative instances for the first classifier
 - No annotation for the mentions
- Evaluation
 - Need for an expert

MAYO
CLINIC



Thank you

Classifiers result

Classifier	Feature sets	Model	F-measure
Entity	Unigram, bi-gram, Embedding of terms between entities	SVM	0.946
Function	Window of 3-5, unigram, bigrams, Wo. Emb, Dep. Emb	SVM	0.821
Relation	Unigram, bi-grams, ...	SVM	0.835