

Insights into Analogy Completion from the Biomedical Domain

Denis Newman-Griffis, Albert Lai, Eric Fosler-Lussier

The Ohio State University National Institutes of Health, Clinical Center
Washington University in St. Louis

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Findings:

- ▶ Current embeddings are good at direct chemical/biological relationships, not so good at clinical semantics.
- ▶ Changes need to be made to the standard analogy methods to reflect the complexity of real data.

¹<https://github.com/OSU-slatelab/BMASS>

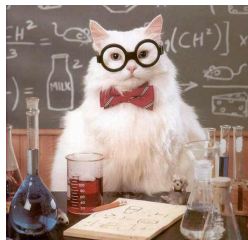


The analogy completion task

BMASS

How can we make analogies more realistic?

Findings and challenges on our dataset



The analogy completion task

London : England :: Paris : France



The analogy completion task

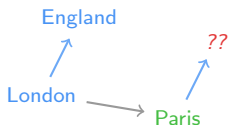
London : England :: Paris : _____



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$$d^* = \operatorname{argmax}_{d \in V} (\cos(d, Eng - Lndn + Paris))$$



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France

Switzerland

Italy

urology

swimming

purple

Latvia



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Unified Medical Language System (UMLS)



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Normalized concepts

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common cold
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Relation triples

subject { C0450297
relation { RO:has-finding-site
object { C0341532
}



BMASS - BioMedical Analogic Similarity Set

ID	Name	Amb
<i>Lab/Rx</i>		
L1	form-of	1.0
L2	has-lab-number	1.1
L3	has-tradename	1.5
L4	tradename-of	1.3
L5	associated-substance	1.6
L6	has-free-acid-or-base-form	1.0
L7	has-salt-form	1.1
L8	measured-component-of	1.3
<i>Hierarchical</i>		
H1	refers-to	1.0
H2	same-type	10.4
<i>Morphological</i>		
M1	adjectival-form-of	1.1
M2	noun-form-of	1.0

ID	Name	Amb
<i>Clinical</i>		
C1	associated-with-malfunction-of-gene-product	2.6
C2	gene-product-malfunction-associated-with-disease	1.5
C3	causative-agent-of	4.6
C4	has-causative-agent	2.0
C5	has-finding-site	1.9
C6	associated-with	1.2
<i>Anatomy</i>		
A1	anatomic-structure-is-part-of	1.6
A2	anatomic-structure-has-part	5.4
A3	is-located-in	1.4
<i>Biology</i>		
B1	regulated-by	1.0
B2	regulates	1.0
B3	gene-encodes-product	1.1
B4	gene-product-encoded-by	2.4

Cross-product of 50 samples for each relation:

2,450 analogies for each relation \Rightarrow **61,250 total analogies**



This dataset represents real biomedical relationships. . .



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But it doesn't fit the standard paradigm!



“Unassuming” the standard assumptions

3 key assumptions in evaluation methodology:

- ▶ Single Answer
- ▶ Same Relationship(s)
- ▶ Informativity

Each is violated in recent analogy datasets

- ▶ Google², BATS³, Sem-Para⁴

All are problematic in real-world data!

²Mikolov et al. 2013

³Gladkova et al. 2016

⁴Köper et al. 2015



“Unassuming” the standard assumptions

Single Answer

Same Relationship

Informativity

The given analogy has only one correct target.

- ▶ Enforced by argmax over candidates for completing the analogy.
- ▶ If multiple analogies, must get at least one wrong.

Problem cases

flu : nausea :: fever : $\left\{ \begin{array}{l} \text{sweating} \\ \text{weakness} \end{array} \right\}$



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Easy fix!

Allow for multiple correct answers; also report on all of them, for fuller picture.



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Same Relationship

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All information relating exemplars a and b also relates query c to d .

- ▶ Enforced by treating full vector difference as relation of interest.
- ▶ Many relations have partial overlap with one another.

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————— *Problem cases* —————

$\underbrace{\text{brother} : \text{sister}}$	$::$	$\underbrace{\text{husband} : \text{wife}}$
MaleCounterpart		MaleCounterpart
SiblingOf		MarriedTo



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Single Answer

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All information relating exemplars *a* and *b* also relates query *c* to *d*.

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————— *Problem cases* —————

brother : sister :: husband : wife

MaleCounterpart
SiblingOf

MaleCounterpart
MarriedTo

wrist pain : shoulder pain :: bipolar disorder : trazodone

CoOccursWith

CoOccursWith
TreatmentFor



“Unassuming” the standard assumptions

Single Answer

Same Relationship

Informativity

The relationship between exemplars *a* and *b* is specific enough to suggest the correct target *d* for query *c*.

- ▶ Issue with very broad semantic or hierarchical relationships.

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Generally related (*UMLS*)

socks : stockings :: Finns : Finnish language



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Fix during dataset generation

Review samples from each relation to ensure they're properly determined.



Modifying the evaluation methodology

$$a : b :: c : \underline{\quad} \rightarrow d^* = \operatorname{argmax}_{d \in V} (\cos(d, b - a + c))$$

Evaluating analogies under 3 settings:



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Single-Answer (SA) Single candidate target for each analogy selected as the only “correct” answer.

flu : nausea :: fever : $\left\{ \begin{array}{l} \text{sweating} \\ \text{weakness} \end{array} \right\} \rightarrow \begin{array}{l} \text{weakness} \\ \text{temperature} \\ \text{sweating} \\ \text{nodule} \end{array} \quad \times$



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Evaluating analogies under 3 settings:

Single-Answer (SA) Single candidate target for each analogy selected as the only “correct” answer.

Multi-Answer (MA) All candidate targets for each analogy are considered to be correct.

All-Info (AI) Use all possible exemplar objects and all candidate targets.

$$\text{flu} : \left\{ \begin{array}{l} \text{nausea} \\ \text{cough} \end{array} \right\} :: \text{fever} : \left\{ \begin{array}{l} \text{sweating} \\ \text{weakness} \end{array} \right\} \rightarrow \frac{1}{2} \left(\begin{array}{l} b - a = \\ + \text{nausea} - \text{flu} \\ + \text{cough} - \text{flu} \end{array} \right)$$



Reporting 3 metrics over ranked candidates:

Acc_R Relaxed accuracy; correct if any valid answer is the top choice

MAP Mean average precision

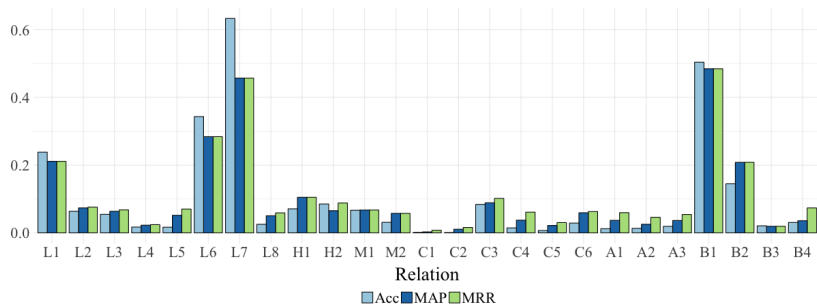
MRR Mean reciprocal rank

weakness
temperature
sweating
nodule

Acc_R 1.0
MAP $\frac{5}{6}$
MRR 1.0



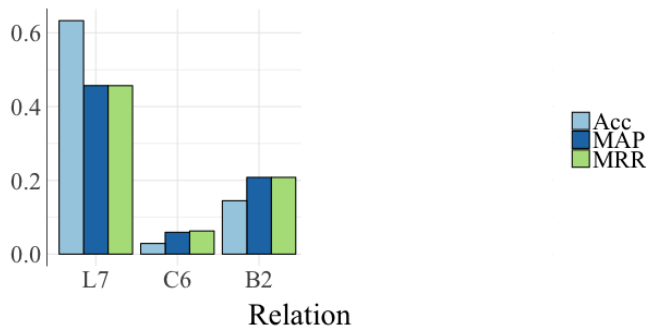
Overall results



- ▶ Results shown for Multi-Answer setting.
- ▶ Average performance is around 11% on all metrics, with all embeddings. High variability between relationships!
- ▶ Used 5 different sets of embeddings trained on PubMed.



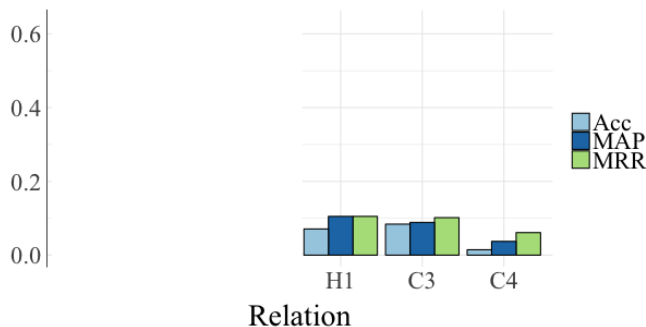
MAP/MRR give a better picture



- ▶ $MAP < Acc_R$ indicates wider distribution of correct answers on *L7* (has-salt-form)
- ▶ $MAP > Acc_R$ shows that even if top answer is wrong, correct answers aren't far down on *C6* (associated-with), *B2* (regulates)



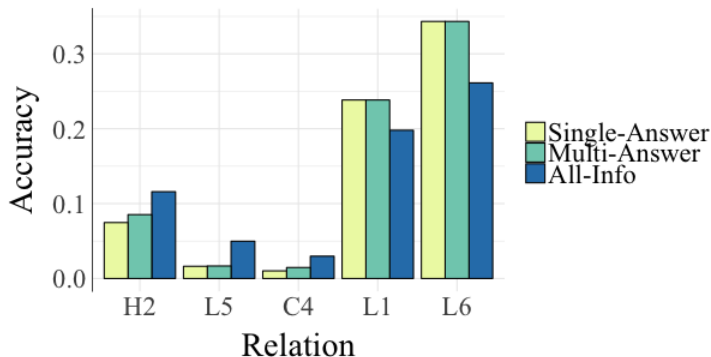
MAP/MRR give a better picture



- ▶ $MRR > Acc_R$ shows that the best correct answer stays near the top on C4 (has-causative-agent)
- ▶ $MRR \approx Acc_R$ reflects more consistent positioning of nearest correct answer on H1 (refers-to), C3 (causative-agent-of)



All-Info benefits vary



- ▶ Extra examples help on *H2* (same-type), *L5* (associated-substance), and *C4* (has-causative-agent).
- ▶ But harm *L1* (form-of) (4% absolute) and *L6* (has-free-acid-or-base-form) (8% absolute)



Moving analogies forward

Single-Answer and Informativity assumptions addressed, but not Same Relationship(s).



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- ▶ Drozd et al (2016) use a parametric logistic regression that can be used to learn affine subspaces.



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- ▶ Drozd et al (2016) use a parametric logistic regression that can be used to learn affine subspaces.

Standard linear offset method does not work for real-world data!

- ▶ Our changes help, but overall performance is still low (as with other recent datasets). Use MAP and MRR!
- ▶ **Analogies are useful!** We need to find better ways to tackle this task.



Thank you!

Dataset and source code at:

<https://www.github.com/OSU-slatelab/BMASS>

newman-griffis.1@osu.edu

