Limits of Lexical Semantic Relatedness with Ontology-based Conceptual Vectors

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Introduction

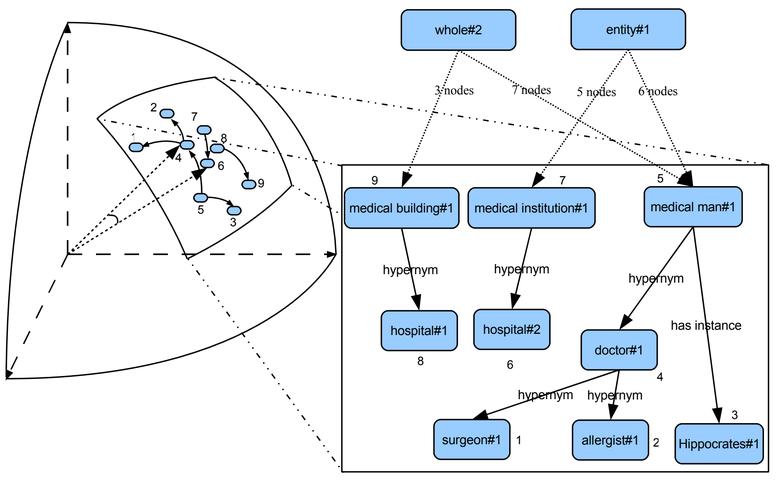
Miller-Charles dataset (1991)

- Human judgements of similarity between pairs of English words
- Machine-computed scores can be compared against dataset

We aim to

- Represent thematic aspects of text (incl. word senses) with Conceptual Vectors
- Define semantic relatedness based on conceptual vectors
- Study behavior of CVs constructed based on ontology
- . . . by comparing against Miller-Charles dataset

Complementing WordNet with Non-discrete Navigation



- WordNet: explicit semantic relations between senses
- Introduce non-discrete navigation with idea of neightbourhood
- To solve (in part) Tennis Problem of WordNet
- CVs for WordNet senses projects them onto hyperspace

Conceptual Vectors (CV)

Principle and Thematic Distance

- Inspired by componential semantics
  - Formalism projecting semantic components into vectorial space
  - CV elements correspond to concepts indirectly
  - Overlap of shared ideas between word senses X & Y:
    Thematic proximity: $Sim(X, Y) = \cos(\widehat{X, Y}) = \frac{X \cdot Y}{\|X\| \times \|Y\|}$
    Angular distance: $D_A = \arccos(Sim(A, B))$

Operations on Vectors

- Normalised Vectorial Sum ($\oplus$): averages operand vectors
- Vectorial Term-to-Term Product ($\odot$): highlights common ideas
- Weak Contextualisation: emphasizes features shared by two terms, accentuated by each other

$$\gamma(X, Y) = X \oplus (X \odot Y)$$

- Synonymy: tests thematic closeness of two meanings X and Y, each enhanced with what it has in common with a third (C)

$$Syn_R(X, Y, C) = D_A(\gamma(X, C), \gamma(Y, C))$$

- Partial Synonymy: Syn_R where the context is the sum of contextualisation of X and Y of their means

$$Syn_P(X, Y) = Syn_R(X, Y, \gamma(X, X \oplus Y) \oplus \gamma(Y, X \oplus Y))$$

Construction

- Can be computed from definitions from different sources (dictionaries, synonym lists, hand-crafted indices, . . .)
- Fabricates new CVs from existing CVs
  $\rightarrow$ requires bootstrap kernel of pre-computed CVs
- Emergence from randomised vectors (Lafourcade 2006)
  - dimension of the vector space can be chosen freely
  - more constant lexical density in vector space
  - no prior sense-to-concept mapping required
  - requires much more iterations, time and computing resources
- We try with **ontology-based CVs** first

Constructing Ontology-based CV for WordNet Senses

Vector Construction for Ontology Classes

- 1992 elements (each correspond to class in SUMO/MILO (not all were used)) in CV
- For each ontology class $\mathcal{C}$, compute $V(\mathcal{C}) = (v_1(\mathcal{C}), v_2(\mathcal{C}), v_3(\mathcal{C}), \ldots)$
  - Initialise $V^0(\mathcal{C})$ with $v_i^0(\mathcal{C}) = 1$ if v_i corresponds to $\mathcal{C}$, 0 otherwise
  - Then $V(\mathcal{C})$ with $v_i(\mathcal{C}) = v_i^0(\mathcal{C}) + \sum_{j=1}^{dim(V)} \frac{v_j^0(\mathcal{C})}{2^{dist(\mathcal{C}, \mathcal{C}_j)}}$

Constructing Ontology-based CV for WordNet Senses (cont.)

Kernel Vectors for WordNet Synsets

- For each WN sense s, initialise $V^0(s) = V(\mathcal{C})$; $\mathcal{C}$ is the SUMO/MILO class assigned to s (Niles & Pease, 2003)

Learning CVs for WN Senses

- Iteratively compute $V(s)$ as in (Schwab *et al*, 2007) but using $V^0(s)$ based on eXtended WordNet

Comparison with Miller–Charles (M&C) Set

- We define two proximity measures based on CV:

$$\text{prox}_{cv}(A, B) = 1 - \left(D_A(A, B) \div \frac{\pi}{2}\right)$$
$$\text{prox}_{syn}(A, B) = 1 - \left(Syn_P(A, B) \div \frac{\pi}{2}\right)$$

- Take highest prox_{cv} and prox_{syn} values of WN noun senses

Word Pair		M&C	prox_{cv}	prox_{syn}	Corr. with M&C	
					prox_{cv}	prox_{syn}
automobile	car	0.98	1.00	1.00	1.000	1.000
cord	smile	0.03	0.48	0.57	1.000	1.000
glass	magician	0.03	0.47	0.57	1.000	1.000
gem	jewel	0.96	1.00	1.00	1.000	1.000
rooster	voyage	0.02	0.44	0.53	0.999	0.998
magician	wizard	0.88	0.90	0.92	0.997	0.997
bird	crane	0.74	0.82	0.86	0.996	0.996
crane	implement	0.42	0.60	0.68	0.989	0.991
noon	string	0.02	0.38	0.47	0.988	0.988
bird	cock	0.76	0.78	0.83	0.983	0.985
coast	shore	0.93	0.86	0.89	0.980	0.982
journey	voyage	0.96	0.85	0.88	0.974	0.976
midday	noon	0.86	1.00	1.00	0.965	0.968
furnace	stove	0.78	0.70	0.77	0.950	0.956
implement	tool	0.74	0.67	0.74	0.936	0.944
brother	lad	0.42	0.47	0.55	0.925	0.930
food	rooster	0.22	0.34	0.43	0.920	0.921
lad	wizard	0.11	0.20	0.30	0.915	0.911
asylum	madhouse	0.90	0.70	0.76	0.901	0.897
food	fruit	0.77	0.60	0.69	0.885	0.885
boy	lad	0.94	0.62	0.70	0.856	0.860
monk	slave	0.14	0.62	0.69	0.837	0.839
car	journey	0.29	0.71	0.77	0.818	0.818
monk	oracle	0.28	0.71	0.77	0.800	0.798
coast	hill	0.22	0.71	0.77	0.777	0.774
forest	graveyard	0.21	0.81	0.85	0.735	0.731
coast	forest	0.11	0.70	0.77	0.711	0.704
brother	monk	0.71	0.34	0.43	0.644	0.634
		Corr. with M&C	**0.644**	**0.634**		

Discussion

Results are not too impressive. . .

Suitability of WN–SUMO/MILO mappings

- ‹*brother*›–‹*monk*› scored too low because mapped to very different classes (HUMAN and RELIGIOUSORGANISATION)
- ‹*coast*›–‹*hill*›, ‹*forest*›–‹*graveyard*› and ‹*coast*›–‹*forest*› considered dissimilar by humans, but all LANDAREA in mapping
- (Take these away and correlations with M&C rise to 0.800 and 0.798)

Suitability of the M&C Set

- ‹*cars*› and ‹*gasoline*› are semantically related;
  ‹*cars*› and ‹*bicycles*› are semantically similar (Resnik, 1995)
- ‹*car*›–‹*journey*›: low M&C score; high prox_{cv} and prox_{syn} scores
- M&C assesses semantic **similarity**
- CVs (via prox_{cv} and prox_{syn}) assesses semantic **relatedness**

Conclusion

- CVs can model the ideas conveyed by lexical meanings
- Can be constructed based on ontological sources
- Can be used to measure lexical semantic relatedness
- Disadvantage of ontology-based CVs:
  - non-standard density of the hierarchy
  - different philosophies in mapping lexical senses to ontology classes

Future Work

- Effects of hierarchy-free CVs i.e. construction by emergence
- Collect human ratings on lexical semantic *relatedness* as benchmark

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