

The Role of the WordNet Relations in the Knowledge-based Word Sense Disambiguation Task

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27-30 January 2016

Global WordNet Conference 2016, Bucharest, Romania

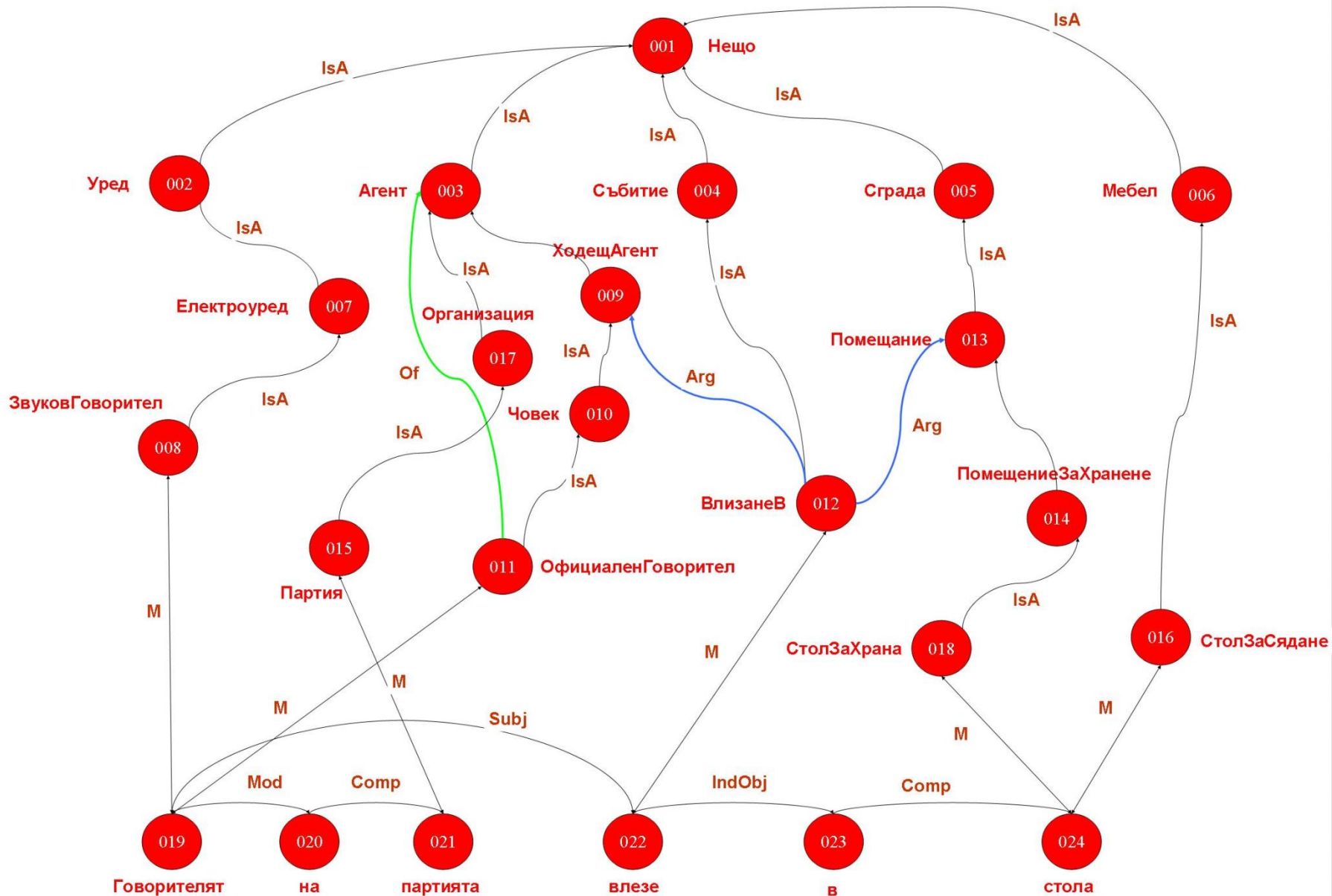


Plan of the Talk

- Brief introduction to Knowledge-based Word Sense Disambiguation (WSD)
- WSD initial experiments
- New Knowledge Graph extensions (over WordNet, Extended WordNet and SemCor)
- Contribution of the various semantic relations
- Conclusions

Knowledge-based WSD (1)

- Relies on lexical databases, such as WordNet, DBPedia, various ontologies, etc. represented as a graph (Knowledge Graph)
- Does not require large and expensive manually constructed corpora
- **But:** *often suffers from sparseness*
- Algorithms are variants of Random Walk on Graphs



UKB: Graph Based Word Sense Disambiguation and Similarity

- Knowledge-based approach to word sense classification; no supervision in the form of a manually annotated corpus needed
- Personalized PageRank algorithm
- <http://ixa2.si.ehu.es/ukb>

Initial Experiments on Bulgarian

- We use the knowledge graph developed by UKB team via mappings from Bulgarian WordNet to English WordNet

<u>Graph</u>	<u>Accuracy</u>
WN	51.72 %
WNG	53.82 %

- Not very optimistic
- A possible solution: *adding more knowledge to the graph*

Initial Knowledge Graph Enrichment

We performed several extensions of the Knowledge Graph with additional arcs

- Domain relations from WordNet
- Inferred hypernymy relations
- Syntactic relations from the gold corpus
- Extended syntactic relations

Syntactic Relations

- From *Universal Dependency Representation of BulTreeBank* dependency relations were extracted that denote **event-participant** semantic relations:

SynSet1 – DepRel – SynSet2

- 15,675 triples
- 8,772 dependency relations: 1,844 *nsubj*, 3,875 *nmod*, 1,025 *amod*, 716 *iobj* and 1,312 *dobj*

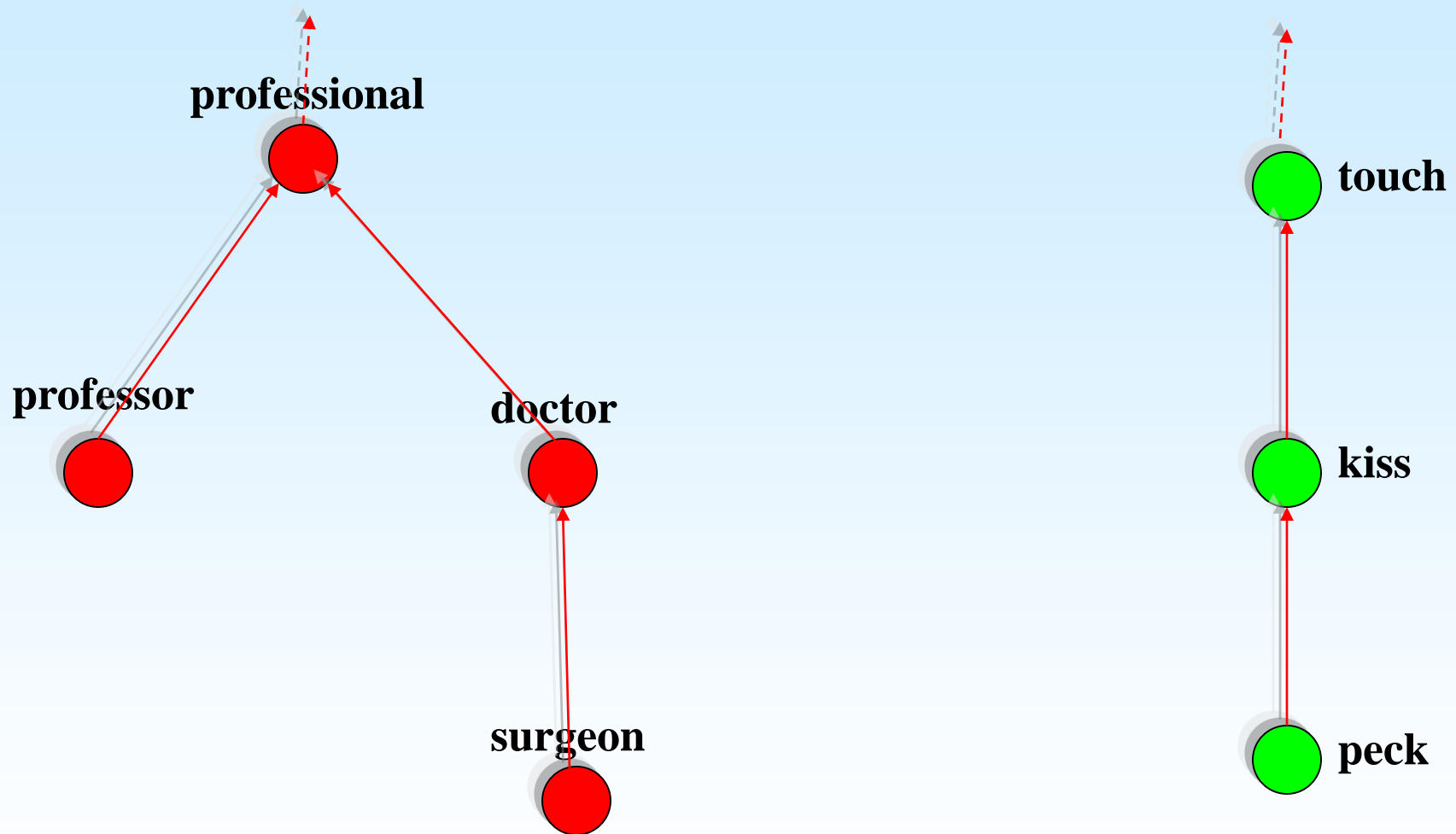
Inferred Syntactic Relations

- If in the triple **SynSet1 – DepRel – SynSet2**, SynSet11 is hyponym of SynSet1 and SynSet1 is participant in the event then we add the triple **SynSet11 – DepRel – SynSet2**
A doctor kisses a girl. → A surgeon kisses a girl.
- Resulted semantic relations: 372,247 (*nsubj*), 1,125,823 (*nmod*), 377,577 (*amod*), 114,760 (*iobj*) and 292,202 (*dobj*)

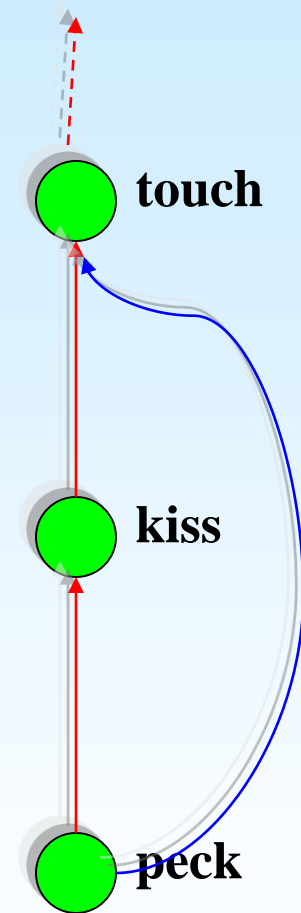
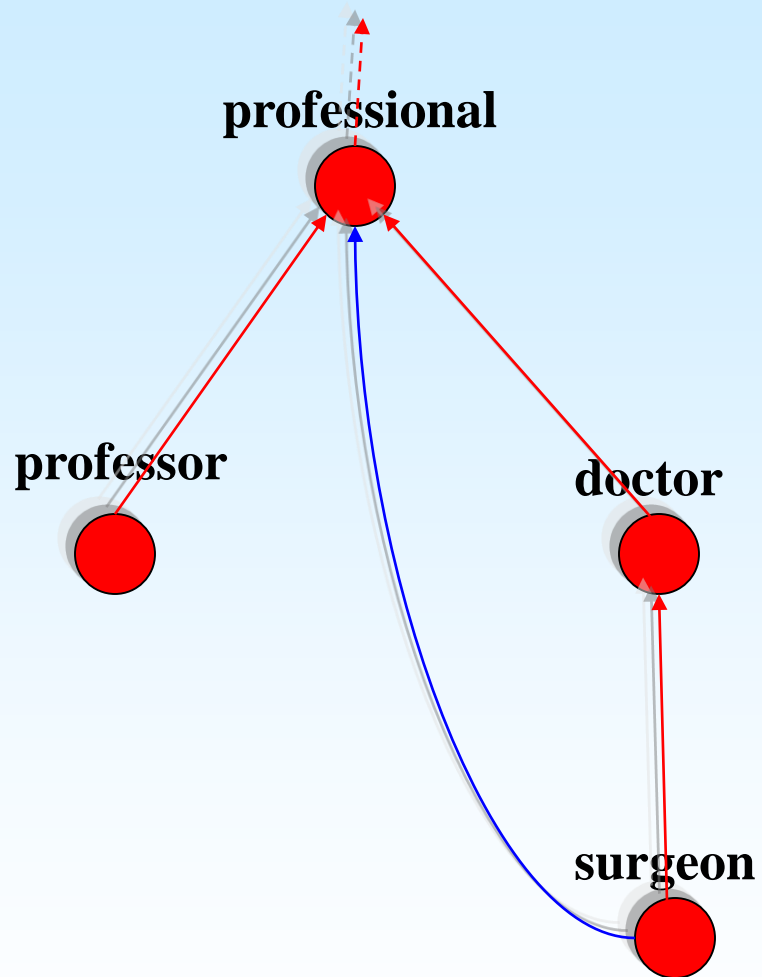
More Syntactic Relations

- The relations in the treebank are not the most general ones
- Our goal for each event to find the most general concept restricting each participant in the event. The same participants in more general event:
 - A doctor kisses a girl. → A professional kisses a woman. → A professor kisses a bar girl.*
 - A doctor kisses a girl. → A doctor touches a girl.*
- Strategy in the experiments: *move to the direct hypernym and extend with all hyponyms*

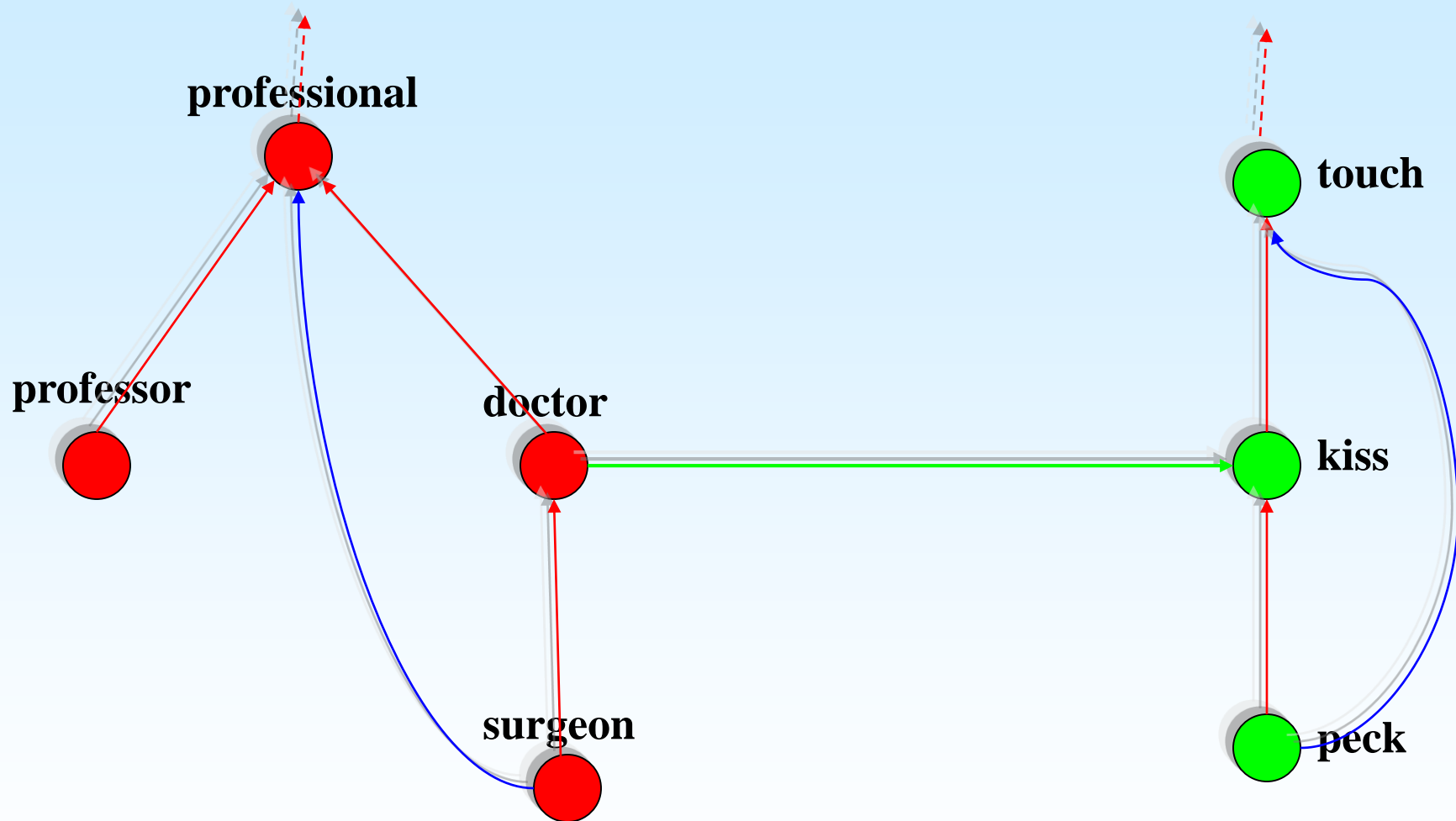
Knowledge Graph Extensions



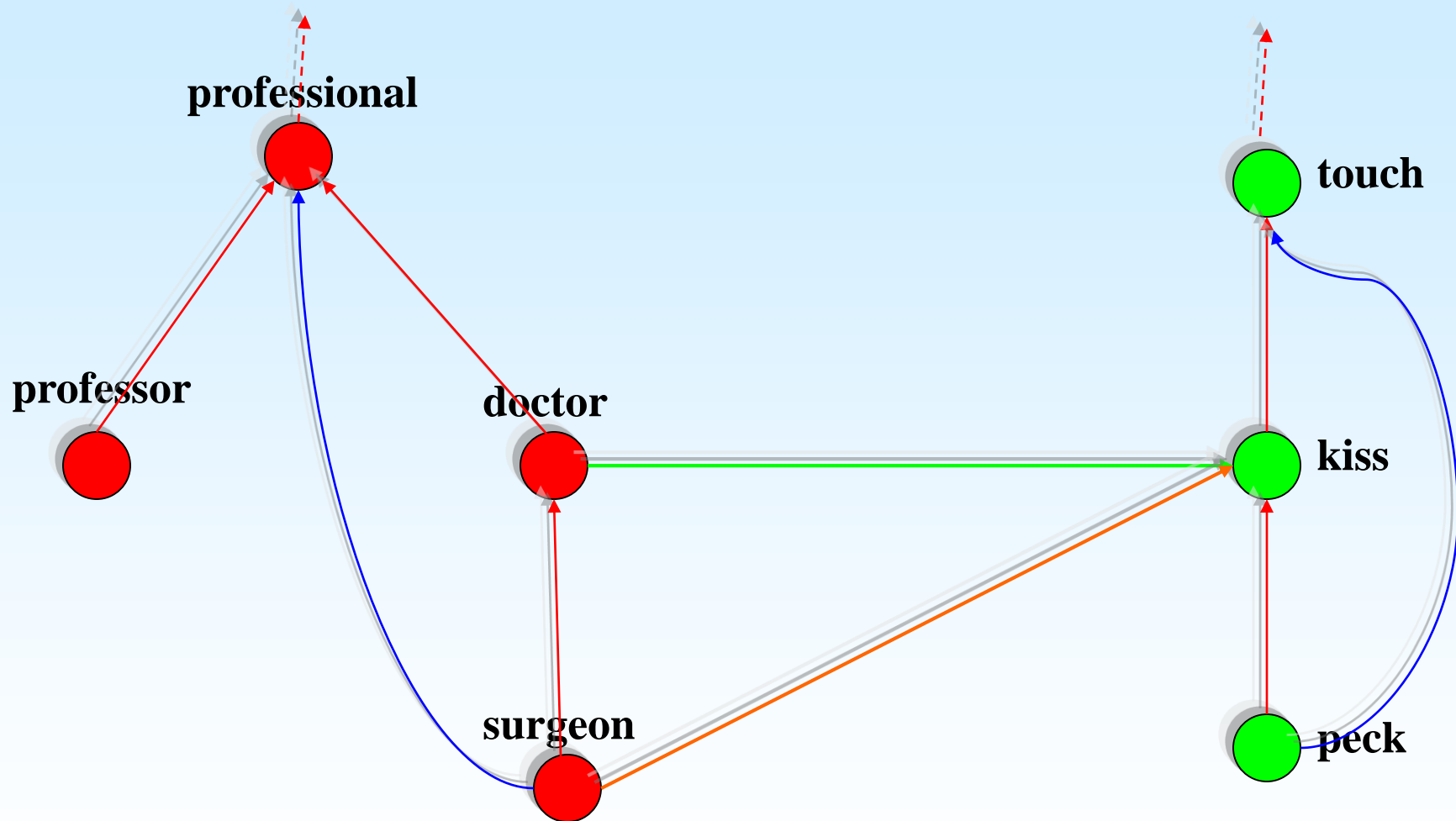
Knowledge Graph Extensions – Inheritance



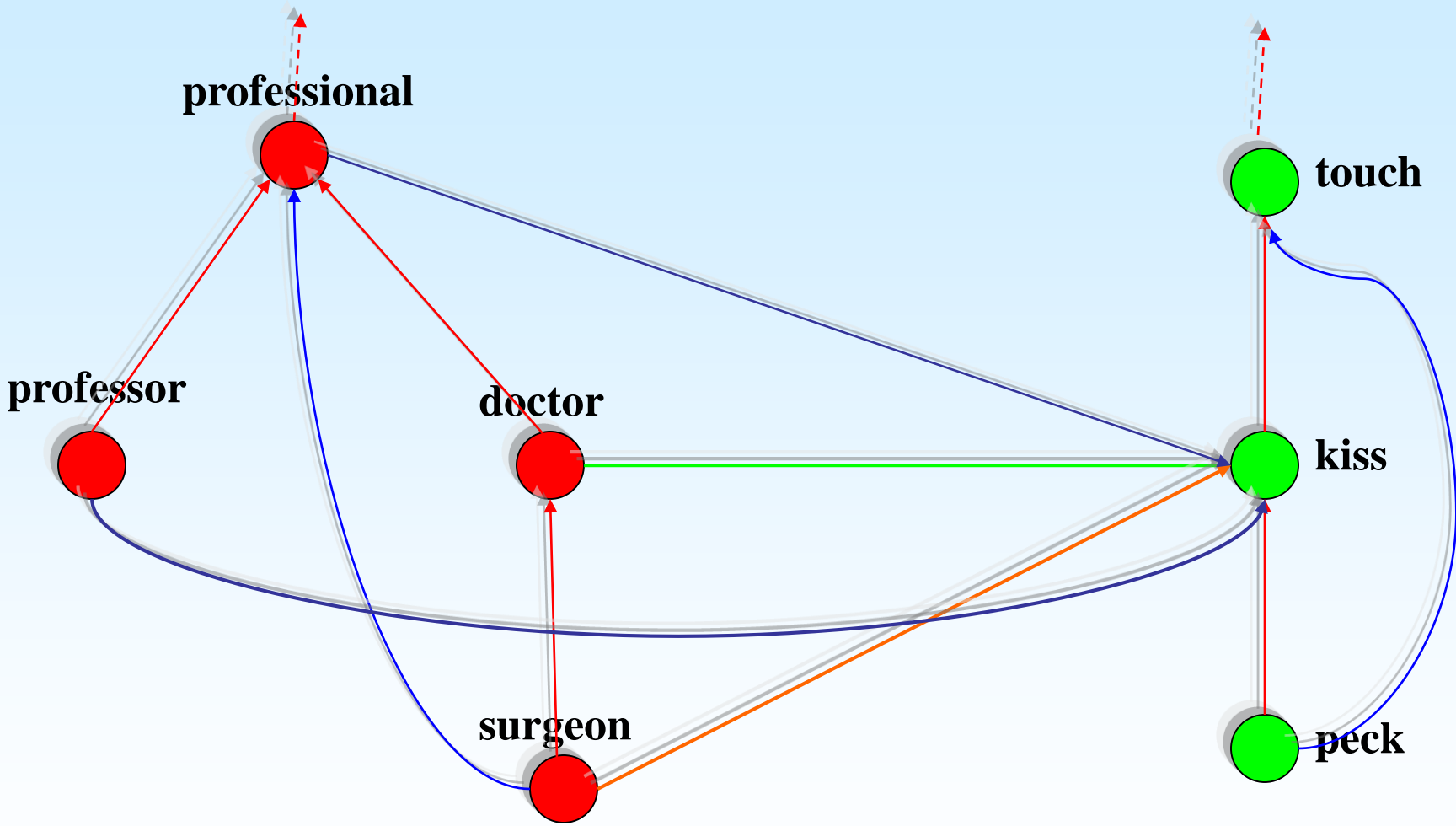
Knowledge Graph Extensions – Syntax



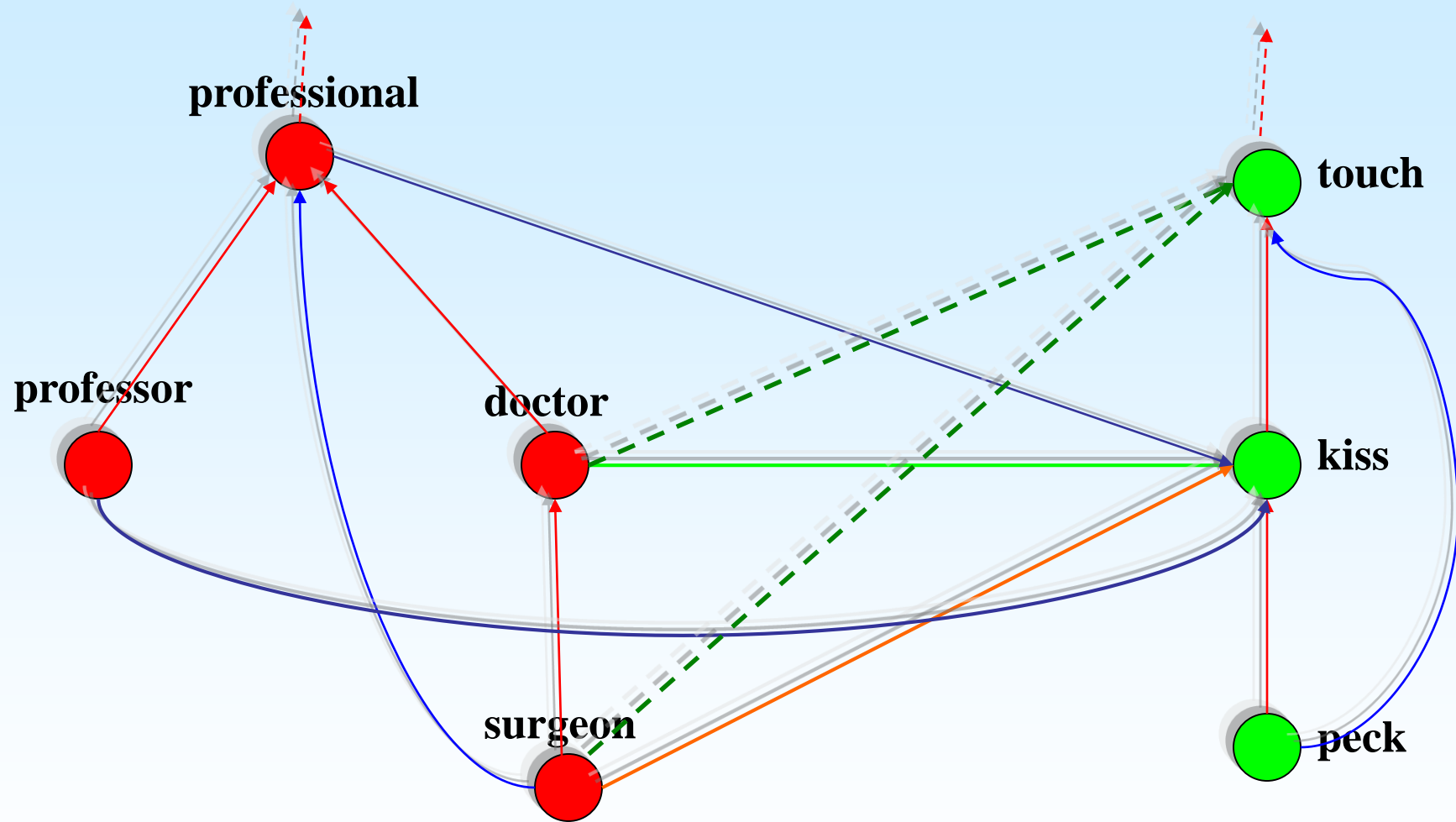
Knowledge Graph Extensions – Syntax ↓



Knowledge Graph Extensions – Syntax $\uparrow\downarrow$



Knowledge Graph Extensions – Syntax $V \uparrow$



Initial Knowledge Graphs

- **WN**: WN relations
- **WNG**: WN relations + relations from the glosses
- **WNI**: WN relations + inferred hypernymy relations
- **WNGI**: WN + glosses + hypernymy
- **WNGID1**: WN + glosses + hypernymy + synset-to-domain
- **WNGID2**: WN + glosses + hypernymy + domain synset-to-synset
- **WNGIS**: WN + glosses + hypernymy + dependency relations
- **WNGISE**: WN + glosses + hypernymy + extended dependency
- **WNGISED1**: WN + glosses + hypernymy + extended dependency + synset-to-domain
- **WNGISED2**: WN + glosses + hypernymy + extended dependency + domain synset-to-synset
- **WNGISEUD2**: WN + glosses + hypernymy + extended dependency one level up + domain synset-to-synset

Initial Results for Bulgarian

<u>KGraph</u>	<u>Accuracy</u>
WN	0.517
WNG	0.538
WNI	0.535
WNGI	0.537
WNGID1	0.538
WNGID2	0.550
WNGIS	0.565
WNGISE	0.616
WNGISED1	0.617
WNGISED2	0.624
WNGISEUD2	0.656

New Experiments

- To study the extension of knowledge graph evaluated on different language and corpus: SemCor corpus – divided in training and test part (3 : 1)
- 16 relations constituting WordNet knowledge graph
- Similarly for the relations within Extended WordNet
- Syntactic Relations

16 WordNet Relations

KGraph	SemCor	BTB
WN	49.24	51.72
GL	51.48	47.02
WNG	58.83	53.82
WN-Hyp	33.38	44.89
WN-Hyp + WN-Ant	39.79	47.55
WN-Hyp + WN-At	35.77	46.18
WN-Hyp + WN-Cls	34.12	46.11
WN-Hyp + WN-Cs	33.30	40.94
WN-Hyp + WN-Der	38.93	49.26
WN-Hyp + WN-Ent	33.09	44.29
WN-Hyp + WN-Ins	33.89	45.00
WN-Hyp + WN-Mm	33.42	44.61
WN-Hyp + WN-Mp	35.60	45.03
WN-Hyp + WN-Ms	33.32	45.00
WN-Hyp + WN-Per	39.62	47.29
WN-Hyp + WN-Ppl	33.29	40.57
WN-Hyp + WN-Sa	38.07	44.48
WN-Hyp + WN-Sim	42.71	44.49
WN-Hyp + WN-Vgp	33.96	41.11

16 WordNet Relations- Best Results

- Combination of relations with similar or better results from the whole graph – 49.24 %

**WN-Hyp + WN-Ant + WN-Der + WN-Per + WN-Sa +
WN-Sim + WN-Mp + WN-Cls : 49.10 %**

**WN-Hyp + WN-Ant + WN-Der + WN-Per + WN-Sa +
WN-Sim + WN-Mp + WN-Cls + WN-Vgp : 49.50 %**

Inference over WordNet Relations

WN-HypInfer – transitive closure

WN-AntInfer – disjoint relation for N-N and V-V: man-woman
→ bachelor-woman

WN-Cs1stVerbInfer – each hyponym of the first argument
could be a cause for the synset of the second argument

WN-Cs2ndVerbInfer – the synset of the first argument could be
a cause for each hypernym of the second argument

WN-DerVNInfer – noun derived from verb are participants: kiss
→ kisser

WN-InsInfer – an instance of a class → instance of super classes

Inference over WN Relations: Results

KGraph	Accuracy	KGraph	Accuracy
WN+WN-HypInfer	54.15	WNG+WN-HypInfer	58.93
WN+WN-AntInfer	48.49	WNG+WN-AntInfer	59.08
WN+WN-ClsInfer	48.48	WNG+WN-ClsInfer	57.66
WN+WN-Cs1stVerbInfer	49.21	WNG+WN-Cs1stVerbInfer	58.85
WN+WN-Cs2ndVerbInfer	49.25	WNG+WN-Cs2ndVerbInfer	58.80
WN+WN-DerNAInfer	48.49	WNG+WN-DerNAInfer	58.41
WN+WN-DerNNInfer	47.82	WNG+WN-DerNNInfer	58.62
WN+WN-DerNVInfer	47.79	WNG+WN-DerNVInfer	55.68
WN+WN-DerVNInfer	48.69	WNG+WN-DerVNInfer	58.89
WN+WN-Ent1stVerbInfer	49.21	WNG+WN-Ent1stVerbInfer	58.84
WN+WN-Ent2ndVerbInfer	49.21	WNG+WN-Ent2ndVerbInfer	58.79
WN+WN-InsInfer	48.89	WNG+WN-InsInfer	58.23

Extended WordNet Relations

KGraph	Accuracy
WN+WNG-A	52.80
WN+WNG-N	56.85
WN+WNG-R	51.56
WN+WNG-V	52.61

Syntactic Relations from SemCor

KGraph	Accuracy
WNG+SC-AA	59.08
WNG+SC-AN	59.13
WNG+SC-AV	59.28
WNG+SC-NN	58.69
WNG+SC-NV	59.20
WNG+SC-RA	59.35
WNG+SC-RN	58.77
WNG+SC-RR	58.92
WNG+SC-RV	59.24
WNG+SC-VN	58.92
WNG+SC-VV	59.09

Best Results

WNG + SC-AA + SC-AN + SC-AV + SC-NN + SC-NV + SC-RA + SC-RN + SC-RR + SC-RV + SC-VN + SC-VV : *60.13* %

WNG + SC-AA + SC-AN + SC-AV + SC-NV + SC-RA + SC-RN + SC-RR + SC-RV + SC-VN + SC-VV : *60.14* %

WNG + SC-AA + SC-AN + SC-AV + SC-NV + SC-RA + SC-RR + SC-RV + SC-VN + SC-VV + WN-HypInfer + WN-AntInfer : *60.42* %

Conclusions

- Factors influence the results
 - The connectivity in the knowledge graph
 - The non-monotonicity of the presented knowledge
- Knowledge transfer between languages
- Future work
 - Application of more complex inference rules
 - Modification of relations per synset and context
 - Algorithm optimization to handle large knowledge graphs
 - Integration with other approaches

