Intelligent Agents

GMNNs, Latent Subjective Content Descriptions, Logical Abduction

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Recap

- Use embedding approaches to complete KGs
- Use MLNs to complete KGs
- Learn MLNs from KGs to capture "symmetries"
  - Benefit also from labeled training data
  - Can be seen as "symbolic dimension reduction"
  - Use pseudolikelihood
  - Variational EM as a learning algorithm
  - Exploit ELBO
    - Use GNNs to compute lower bound distribution

Besag, J. Statistical analysis of non-lattice data. *The statistician*, pp. 179–195, **1975**.

Neal, R. M. and Hinton, G. E. A view of the em algorithm that justifies incremental, sparse, and other variants. In *Learning in graphical models*, pp. 355–368. Springer, **1998**.

GMNN: Graph Markov Neural Networks

- Model the joint distribution of object labels $\mathbf{y}_V$ conditioned on object attributes $\mathbf{x}_V$, i.e., $\mathrm{p}_\phi(\mathbf{y}_V|\mathbf{x}_V)$
- Learning the model parameters ϕ by maximizing the lower-bound of log-likelihood of the observed (labelled) data, $\log \mathrm{p}_\phi(\mathbf{y}_L|\mathbf{x}_V)$

$$\log p_\phi(\mathbf{y}_L|\mathbf{x}_V) \geq$$
$$\mathbb{E}_{q_\theta(\mathbf{y}_U|\mathbf{x}_V)}[\log p_\phi(\mathbf{y}_L, \mathbf{y}_U|\mathbf{x}_V) - \log q_\theta(\mathbf{y}_U|\mathbf{x}_V)]$$

GMNNs: Graph Markov Neural Networks

- Towards combining statistical relational learning and graph networks
  - Approximation, but polynomial runtime

$$q_\theta(\mathbf{y}_n|\mathbf{x}_V) = \mathrm{Cat}(\mathbf{y}_n|\mathrm{softmax}(W_\theta \mathbf{h}_{\theta,n}))$$

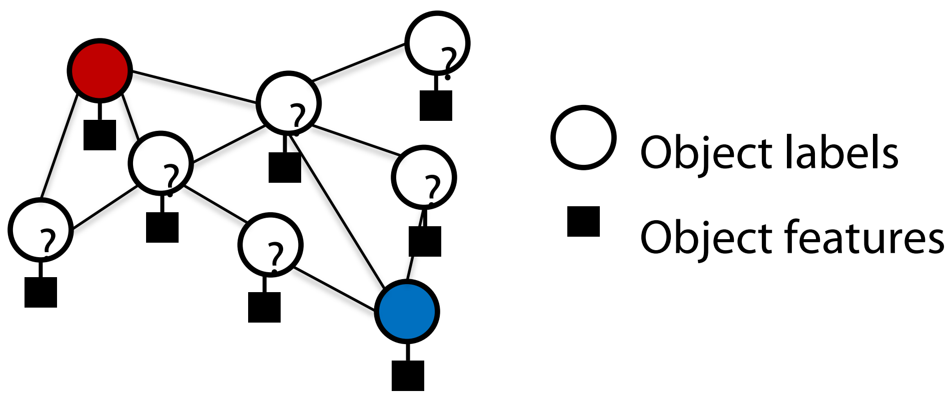
- Learning effective node representations for predicting the node labels
  - Modeling the label dependencies of nodes with Markov blanket (neighbors in the undirected setting)

$$p_\phi(\mathbf{y}_n|\mathbf{y}_{\mathrm{NB}(n)}, \mathbf{x}_V) = \mathrm{Cat}(\mathbf{y}_n|\mathrm{softmax}(W_\phi \mathbf{h}_{\phi,n}))$$

Meng Qu, Yoshua Bengio, Jian Tang:
GMNN: Graph Markov Neural Networks. In Proc. ICML 2019.

GMNN: Overall Optimization Procedure

- Two Graph networks collaborate with each other
  - p_ϕ: learning network, modeling the label dependency
  - q_θ: inference network, learning the object representations
- q_θ infer the labels of unlabeled objects trained with supervision from p_ϕ and labeled objects
- p_w is trained with a fully labeled graph, where the unlabeled objects are labeled by q_θ
- Learning w/o hidden nodes is much easier



Applications: Object/Node Classification

- Train, validation, and test are standard split
- State-of-the-art performance

Category	Algorithm	Cora	Citeseer	Pubmed
SSL	LP	74.2	56.3	71.6
SRL	PRM	77.0	63.4	68.3
	RMN	71.3	68.0	70.7
	MLN	74.6	68.0	75.3
GNN	GCN *	81.5	70.3	79.0
	GAT *	83.0	72.5	79.0
GMNN	W/o Attr. in p_ϕ	83.4	**73.1**	81.4
	With Attr. in p_ϕ	**83.7**	72.9	**81.8**

* = Taken from respective papers

SSL: Semi-Supervised Learning: Zhou, D., Bousquet, O., Lal, T. N., Weston, J., and Schölkopf, B. Learning with local and global consis- tency. In NIPS, **2004**.

GAT: Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò and Yoshua Bengio. Graph Attention Networks (GATs), In: Proc. ICLR **2018**.

Applications: Link Classification

- Construct a dual graph $\tilde{G}$ from the original graph G
  - Each edge in G -> a node in $\tilde{G}$
  - Two nodes in $\tilde{G}$ are connected if the corresponding edges in G share a node
  - Use node classification in $\tilde{G}$ for link classification in G

Category	Algorithm	Bitcoin Alpha	Bitcoin OTC
SSL	LP	59.68	65.58
SRL	PRM	58.59	64.37
	RMN	59.56	65.59
	MLN	60.87	65.62
GNN	DeepWalk	62.71	63.20
	GCN	64.00	65.69
GMNN	W/o Attr. in p_ϕ	65.59	66.62
	With Attr. in p_ϕ	**65.86**	**66.83**

SSL: Semi-Supervised Learning: Zhou, D., Bousquet, O., Lal, T. N., Weston, J., and Schölkopf, B. Learning with local and global consis- tency. In NIPS, **2004**.

Summary so far

- A fundamental problem on graphs:
  Semi-supervised node classification
- GMNN: towards combining statistical relational learning and graph networks
  - Model the label dependency with one graph neural network
  - Learn effective node representations with another graph neural network
- State-of-the-art results on semi-supervised node classification, unsupervised node representation, and link classification
  - But: Are the improvements statistically significant?
- Code available at:
  https://github.com/DeepGraphLearning/GMNN

Hm… Do we get useful MLNs?

- Very many simplifications…
  - Rough estimations of respective distributions …
- Do GMNNs really capture the semantics of MLNs?
  - No notion of algorithmic correctness applied
  - What is actually computed with all those simplifications?
- Three dimensions for evaluation
  - Scalability
  - Scalability
  - Scalability
- Seriously: Evaluation w.r.t. other systems' performances (or even human performance)

Probably okay for IR !
But, can we use the
models also for other
applications?

Text Semantics

- In natural language processing (NLP), semantics is concerned with the meanings of texts.
- There are two main approaches to represent meaning
  - Vector representation:
    - Texts are embedded into a high-dimensional space.
  - Propositional or formal semantics:
    - A block of text is to converted into a formula (to be annotated with a formula) in a logical language, e.g. predicate calculus.

Combination of Approaches

Propositional:

- “dog bites man” ➔ bites(dog-1, man-1) or (dog-1, bites, man-1)
- bites(*,*) is a binary relation. man, dog are objects
- Logical form / KG
- Probabilities can be attached

Islam Beltagy, Cuong Chau, Gemma Boleda, Dan Garrette, Katrin Erk, Raymond Mooney. **Montague Meets Markov: Deep Semantics with Probabilistic Logical Form**. In: Proc. Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 1: Proceedings of the Main Conference and the Shared Task: Semantic Textual Similarity. 11–21. **2013**.

Vector representation:

- vec(“dog bites man”) = (0.2, -0.3, 1.5,…) $\in \Re^n$
- Sentences similar in meaning should be close to this embedding (e.g., use human judgments)

I. Beltagy, Stephen Roller, Pengxiang Cheng, Katrin Erk, and Raymond J. Mooney. 2016. **Representing meaning with a combination of logical and distributional models**. Comput. Linguist. 42, 4. 763–808. **2016**.

Descriptions for Text Semantics

- Propositions can be seen as a database (CWA)
  - RDF Tiples (s, p, o)
  - Query answering w.r.t. ontologies (OBDA)
- Propositions can be seen as a knowledge graph (OWA)
  - Ground formulas R(i1, i2)
  - Do propositions really represent (common) knowledge?
    - Possibly sometimes with named entities
    - Usually not
- Need task-specific on-the-fly representations
  - Can be subjective
  - No need for common knowledge or consensus
  - Can even represent propositions that are considered as false
  - Probability values do not model whether a proposition is true but model whether a proposition is suitable (for a task)
  - Find most-probabily suited SCDs (MPSSCDs)

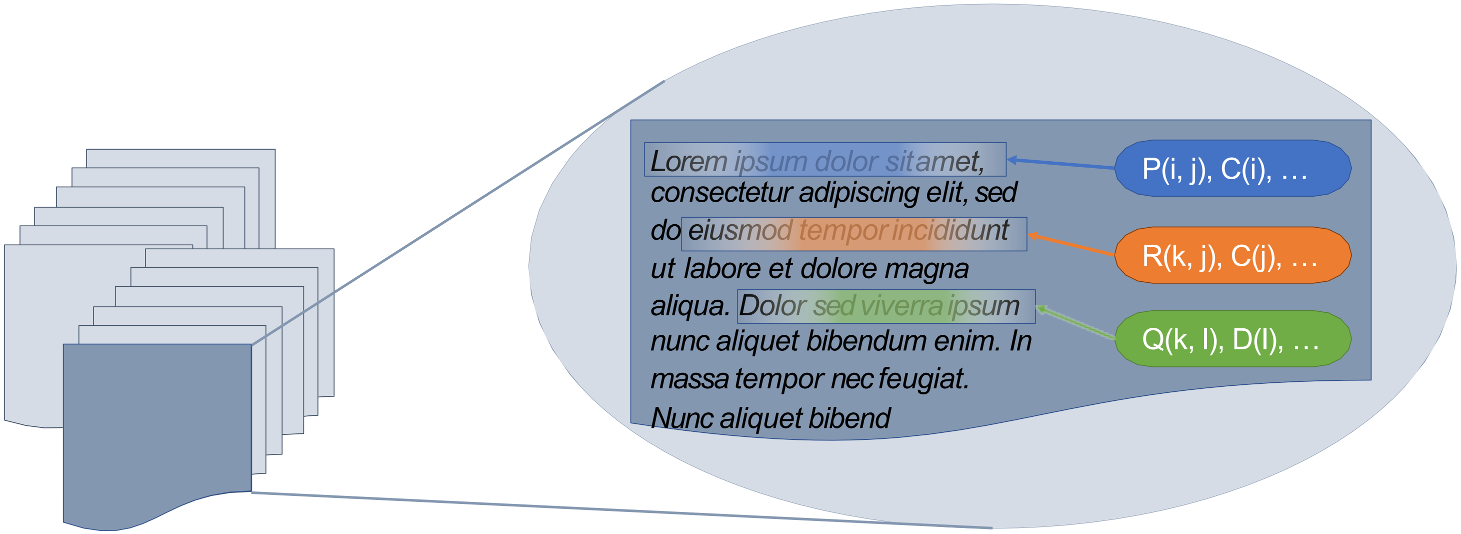
Ontology =
set of predicate logic
formulas =
knowledge base

For OBDA (Ontology-
Based Data Access)
see the course
Information Systems
(CS4130-KP06)

Felix Kuhr, Magnus Bender, Tanya Braun, Ralf Möller: Augmenting and Automating Corpus Enrichment. In: Int. J. Semantic Computing. Vol.14, (2), p.173-197. 2020.

Latent Subjective Content Descriptions

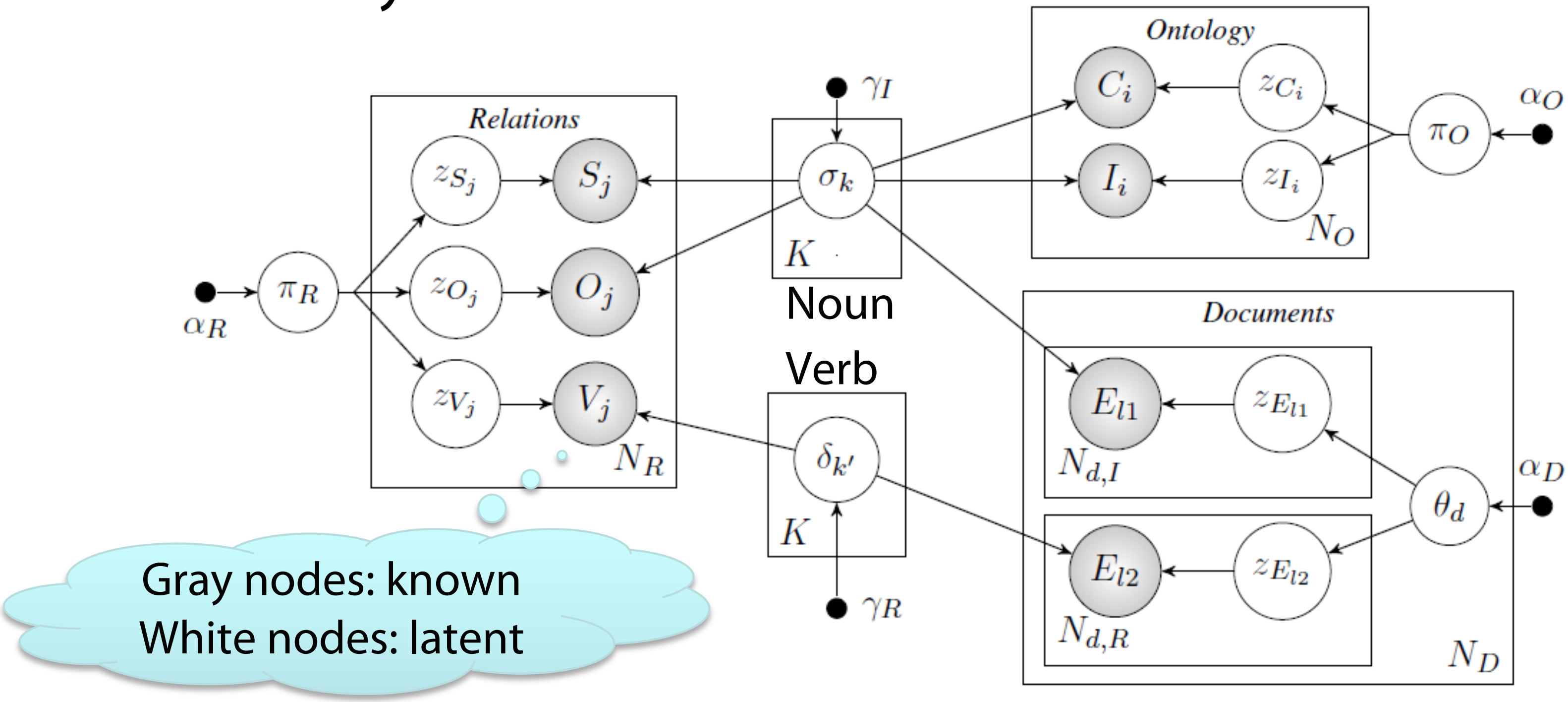
- Subjective Content Decriptions (SCDs) describe content for a specific purpose
- An SCD may cover a (part of a) sentence, a paragraph, or a whole document
- SCDs add a value for different tasks, e.g., document retrieval
- Granularity of SCDs depends on the application
- Document contains SCDs from possibly multiple ontologies
- Must derive SCDs automatically



Felix Kuhr, Magnus Bender, Tanya Braun, Ralf Möller: Context-specific Adaptation of Subjective Content Descriptions. In: Proceedings of the 15th IEEE International Conference on Semantic Computing (ICSC-21), **2021**

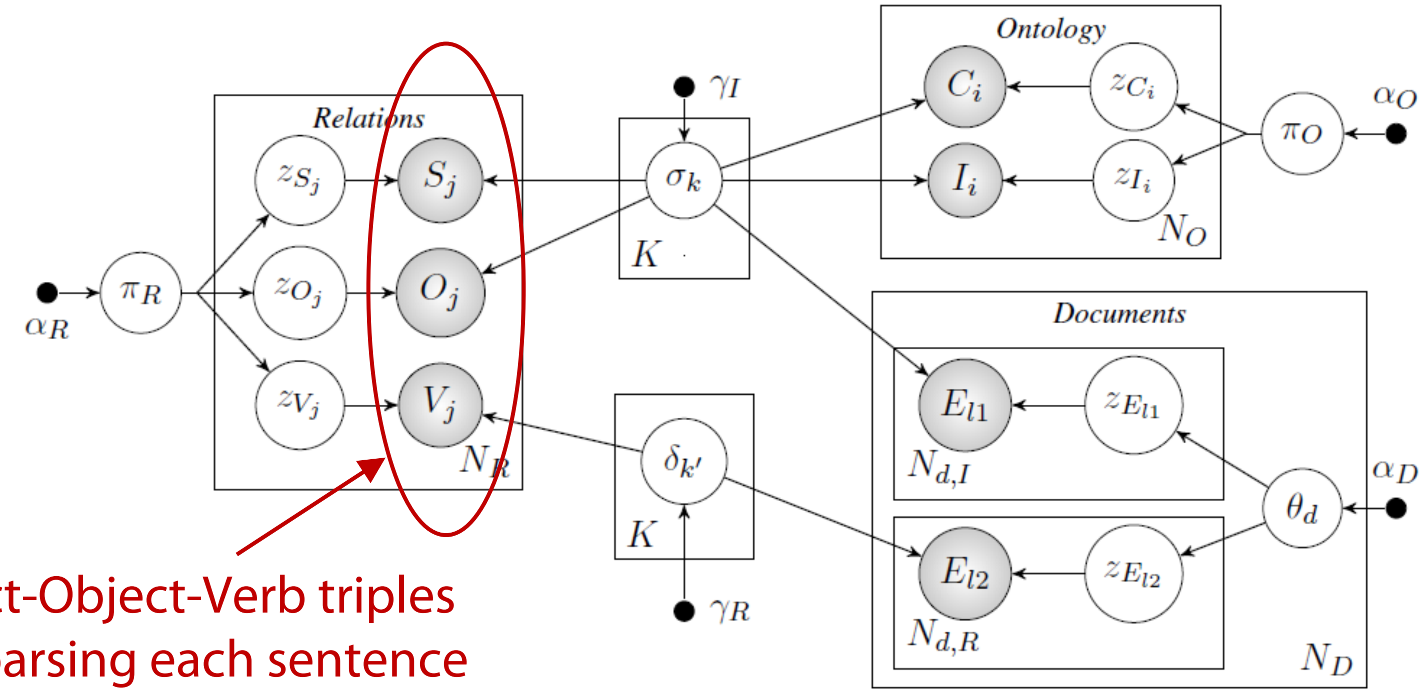
KB-LDA and SCDs

- Ontologies vs. topics
- Contemporary approaches use latent variable models to group entities (objects) and the relations between them in a data-driven way



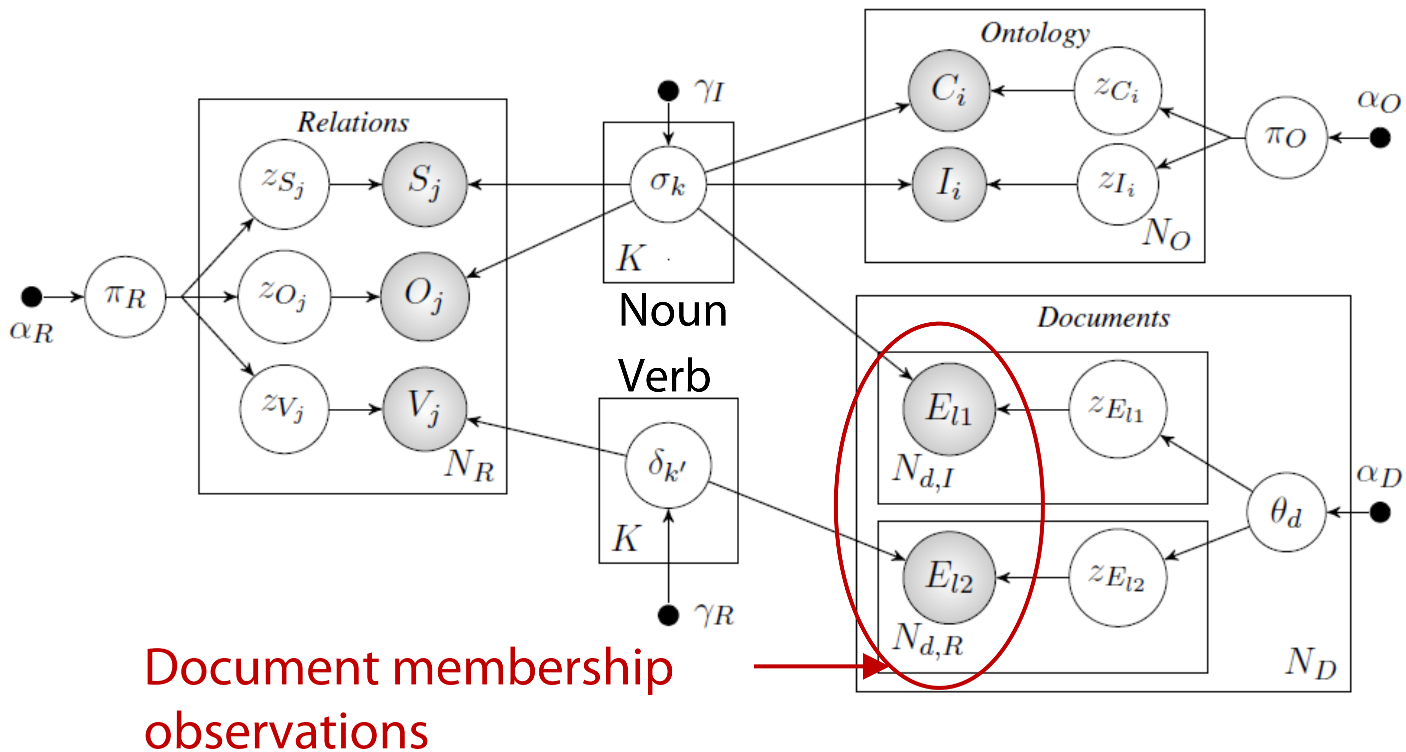
“KB-LDA: Jointly Learning a Knowledge Base of Hierarchy, Relations, and Facts,” Dana Movshovitz-Attias. William W. Cohen, ACL **2015**

KB-LDA and SCDs



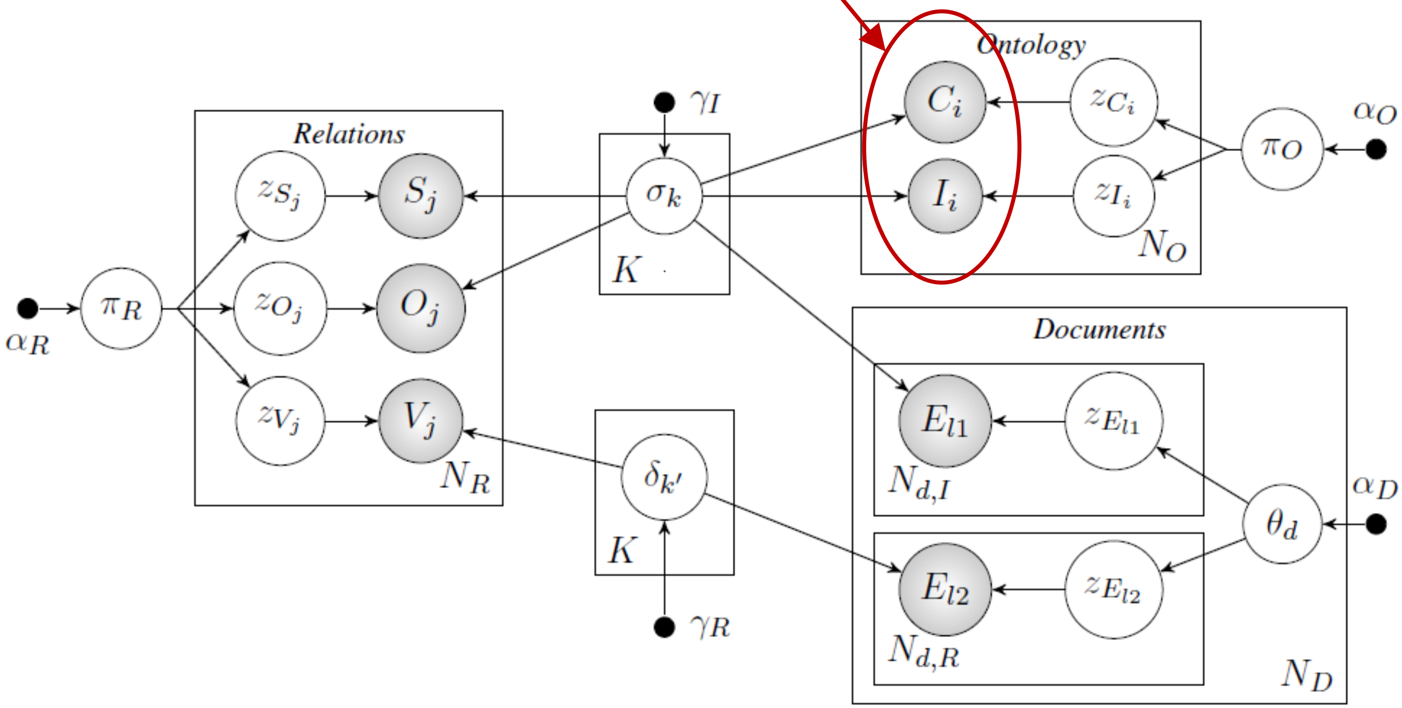
Subject-Object-Verb triples
from parsing each sentence

KB-LDA and SCDs



KB-LDA and SCDs

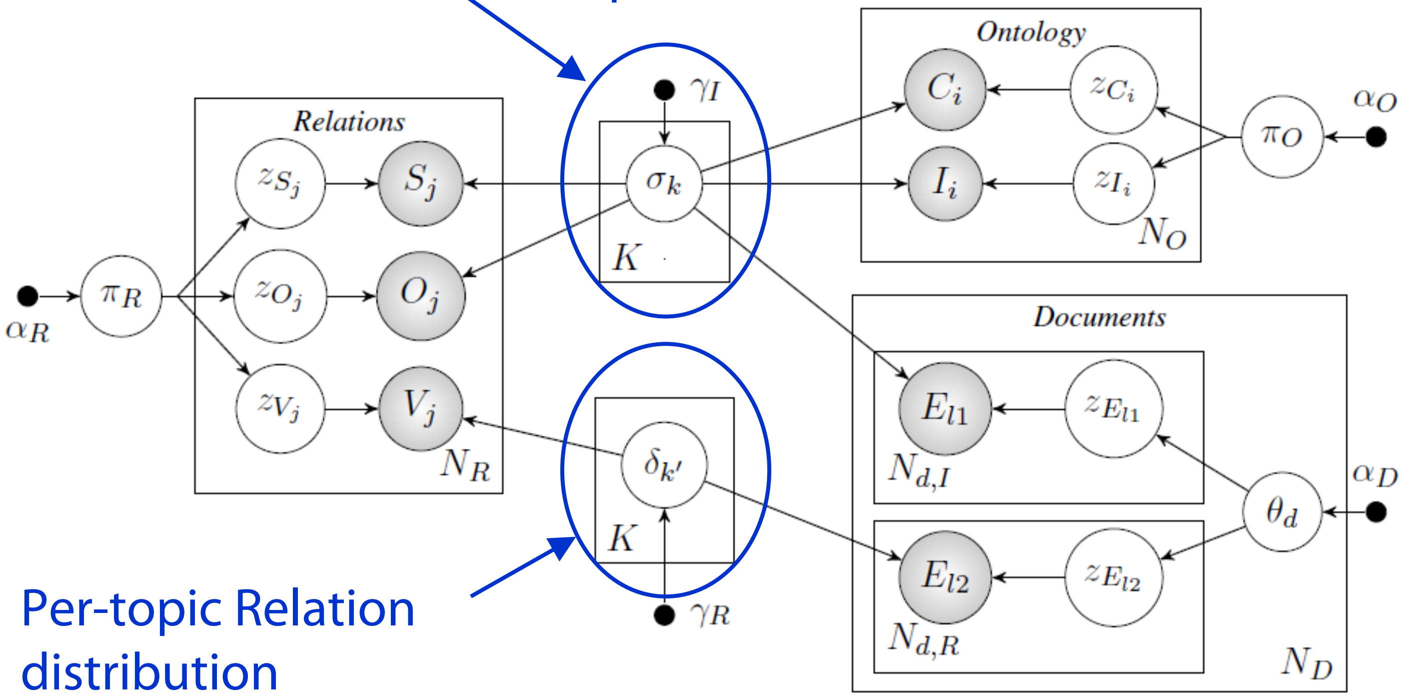
Class-instance relations found from
linguistic patterns (Hearst Patterns)
"Netscape, an early web browser…"



KB-LDA and SCDs

Per-topic instance distribution

Think of it as a matrix mapping topic to instance distribution



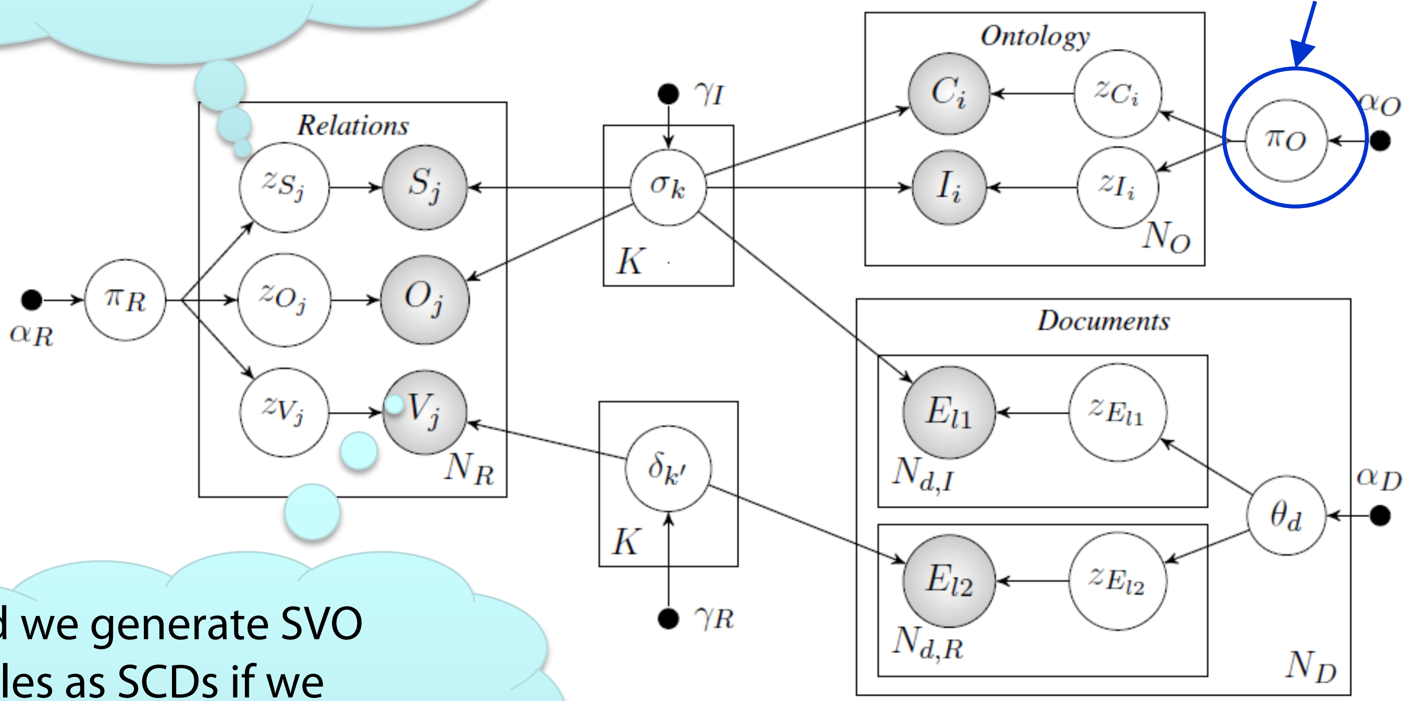
Per-topic Relation distribution

A matrix mapping topic to relation distribution

KB-LDA and SCDs

We could fix the topic nodes due to the task for which SCDs are generated

topic distribution for ontologies

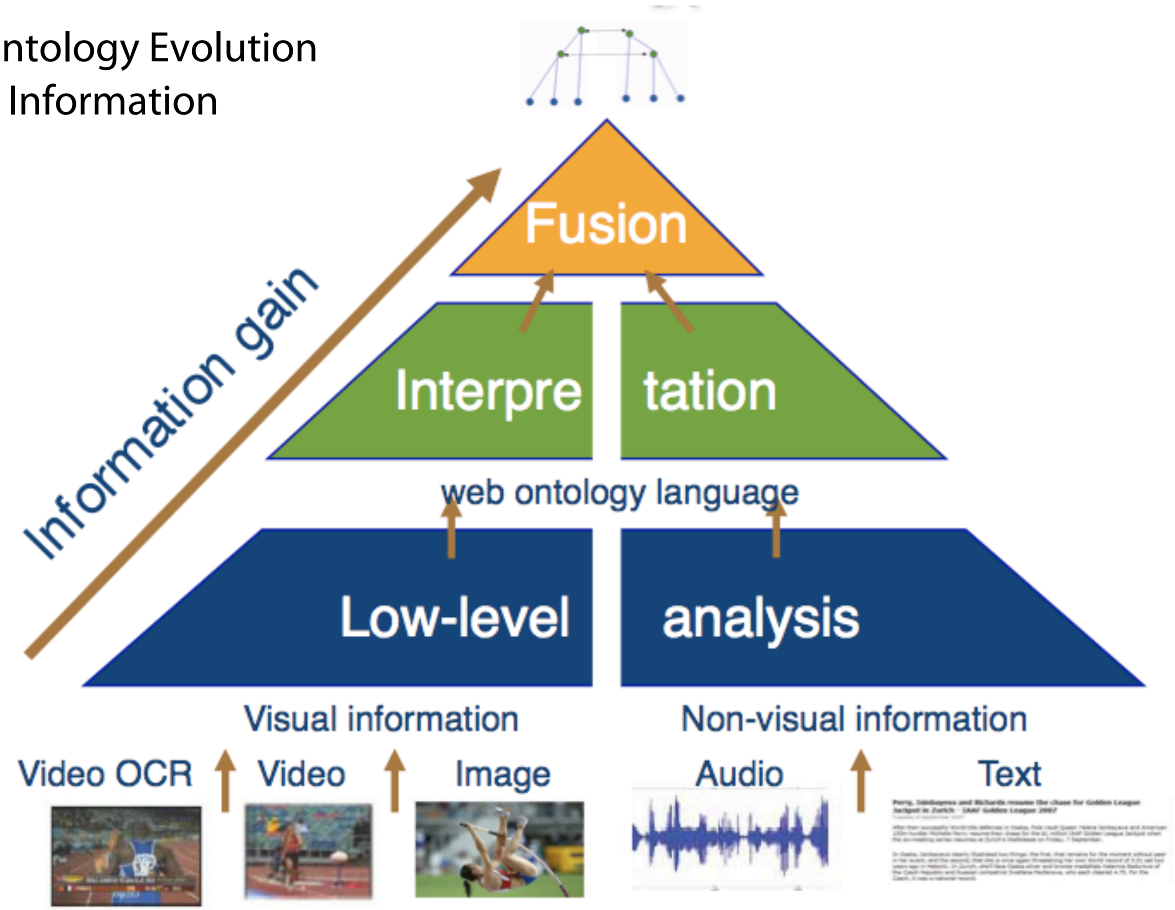


Could we generate SVO triples as SCDs if we assumed that the SVO nodes were latent?

"KB-LDA: Jointly Learning a Knowledge Base of Hierarchy, Relations, and Facts," Dana Movshovitz-Attias. William W. Cohen, ACL **2015**

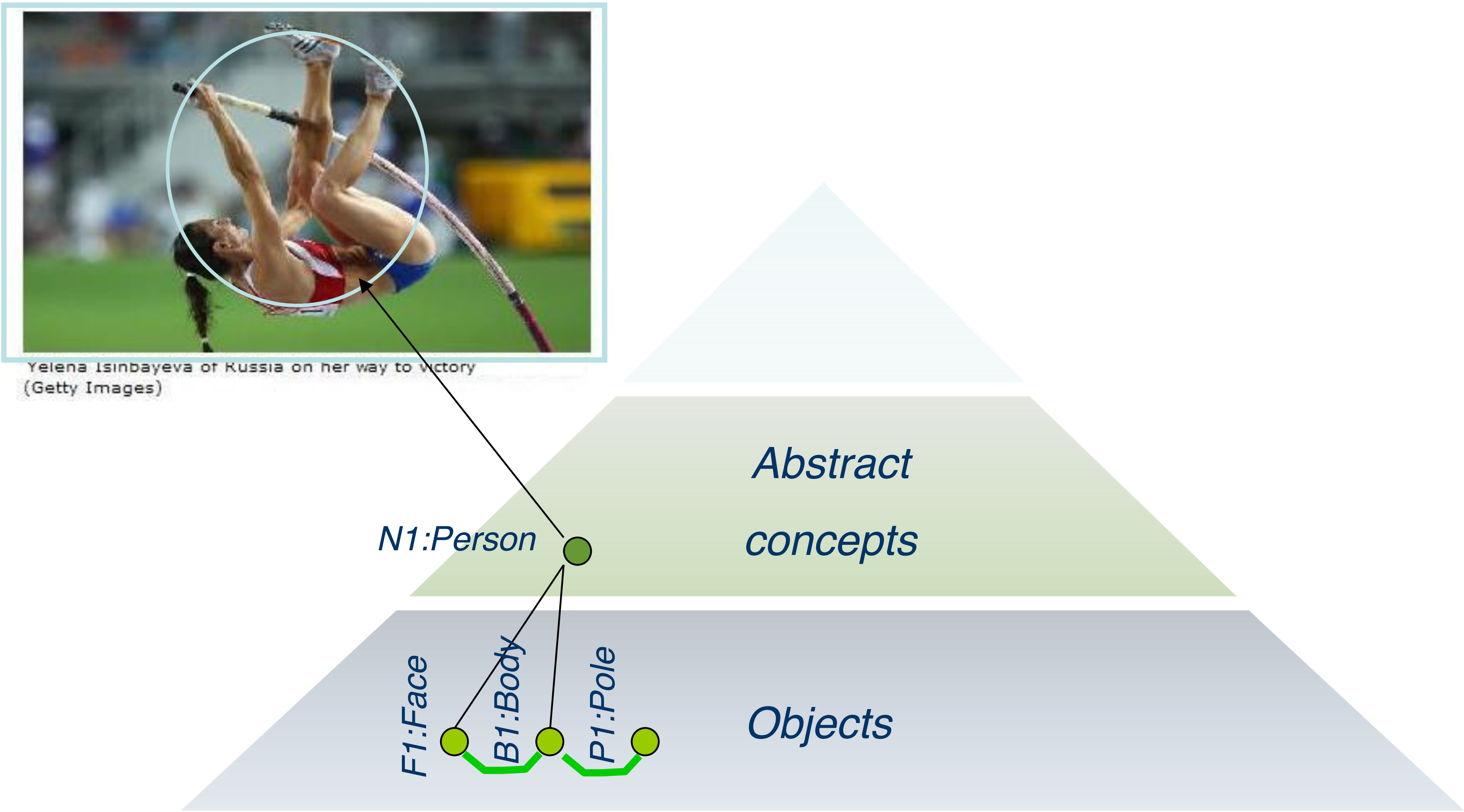
SCD Derivation: Multimedia Information Extraction

Bootstrapping Ontology Evolution with Multimedia Information Extraction
[BOEMIE 2006]



S. Castano, S. Espinosa, A. Ferrara, V. Karkaletsis, A. Kaya, R. Möller, S. Montanelli, G. Petasis, and M. Wessel. **Multimedia Interpretation for Dynamic Ontology Evolution**. In *Journal of Logic and Computation*, volume 19, pages 859–897. Oxford University Press, **2008**.

Interpretation = Explanation



Logical Abduction

Given:

- Background knowledge, *B*, in the form of a set of (Horn) clauses in first-order logic
- Observations, *O*, in the form of atomic facts in first-order logic

Find:

- A hypothesis, *H*, a set of assumptions (logical formulae) that logically entail the observations given the theory

$$B \cup H \models O$$

- Typically, best explanation is the one with the fewest assumptions, e.g., minimizes |H|

Sample First-order Abduction Problem

- Background Knowledge:

  $\forall x\, \forall y\, (\text{Mosquito}(x) \wedge \text{Infected}(x, \text{Malaria}) \wedge \text{Bite}(x, y) \rightarrow$
  $\text{Infected}(y, \text{Malaria}))$

  $\forall x\, \forall y\, (\text{Infected}(x, \text{Malaria}) \wedge \text{Transfuse}(\text{Blood}, x, y) \rightarrow$
  $\text{Infected}(y, \text{Malaria}))$

- Observations:

  Infected(John, Malaria)

  Transfuse(Blood, Mary, John)

- Explanation:

  Infected(Mary, Malaria)

Previous Work in Logical Abduction

- Several first-order logic-based approaches
[Kautz & Allen 86; Poole et al. 87; Stickel 88; Ng & Mooney 91; Kakas et al. 93]
- Perform first-order "backward" logical reasoning to determine the set of assumptions being sufficient
to deduce observations

- Size of H is not necessarily the right score
- Why not finding the set H that maximizes
P(Infected(John, Malaria) ^ Transfuse(Blood, Mary, John))?
  - Find those explanations that maximize the probability of the observations

Abduction using MLNs and Transformation

- Given:

  Infected(Mary,Malaria) ∧ Transfuse(Blood,Mary,John) → Infected(John,Malaria))

  Transfuse(Blood, Mary, John)

  Infected(John, Malaria)

- The clause is satisfied whether Infected(Mary, Malaria) is true or false
- Given the observations, a world has the same probability in MLN whether the explanation is true or false, explanations cannot be inferred
- The MLN inference mechanism is inherently *deductive and not abductive*

Kate, R. J., and Mooney, R. J. Probabilistic abduction using Markov logic networks. In IJCAI-09 Workshop on Plan, Activity, and Intent Recognition. **2009**

Adapting MLNs for Abduction

- Explicitly include the reverse implications

  $\forall x\, \forall y\, (\text{Infected}(x,\text{Malaria}) \wedge \text{Transfuse}(\text{Blood},x,y) \rightarrow \text{Infected}(y,\text{Malaria}))$

  $\forall y\, (\text{Infected}(y,\text{Malaria}) \rightarrow \exists x\, (\text{Transfuse}(\text{Blood},x,y) \wedge \text{Infected}(x,\text{Malaria})))$

- Existentially quantify the universally quantified variables which appear on the LHS but not on the RHS in the original clause
- Now, given Transfuse(Blood, Mary, John) and Infected(John, Malaria), the probability of the world(s) in which Infected(Mary, Malaria) is true will be higher

Adapting MLNs for Abduction

- However, there could be multiple explanations for the same observations:

$\forall x\, \forall y\, (\mathrm{Infected}(x, \mathrm{Malaria}) \wedge \mathrm{Transfuse}(\mathrm{Blood}, x, y) \rightarrow \mathrm{Infected}(y, \mathrm{Malaria}))$

$\forall y\, (\mathrm{Infected}(y, \mathrm{Malaria}) \rightarrow$
$\quad \exists x\, (\mathrm{Transfuse}(\mathrm{Blood}, x, y) \wedge \mathrm{Infected}(x, \mathrm{Malaria})))$

$\forall x\, \forall y\, (\mathrm{Mosquito}(x) \wedge \mathrm{Infected}(x, \mathrm{Malaria}) \wedge \mathrm{Bite}(x,y) \rightarrow \mathrm{Infected}(y, \mathrm{Malaria}))$

$\forall y\, (\mathrm{Infected}(y,\mathrm{Malaria}) \rightarrow$
$\quad \exists x\, (\mathrm{Mosquito}(x) \wedge \mathrm{Infected}(x, \mathrm{Malaria}) \wedge \mathrm{Bite}(x, y)))$

- An observation should be explained by one explanation and not multiple explanations

Adapting MLNs for Abduction

- Add the disjunction clause and the mutual exclusivity clause for the same RHS term

$\forall x\ \forall y\ (\text{Mosquito}(x) \wedge \text{Infected}(x,\text{Malaria}) \wedge \text{Bite}(x,y) \rightarrow \text{Infected}(y,\text{Malaria}))$

$\forall x\ \forall y\ (\text{Infected}(x,\text{Malaria}) \wedge \text{Transfuse}(\text{Blood},x,\text{y}) \rightarrow \text{Infected}(\text{y},\text{Malaria}))$

$\forall y\ (\text{Infected}(\text{y},\text{Malaria}) \rightarrow$
$\quad \exists \text{x}\ (\text{Transfuse}(\text{Blood},x,\text{y}) \wedge \text{Infected}(x,\text{Malaria}))\ \text{v}$
$\quad \exists x\ (\text{Mosquito}(x) \wedge \text{Infected}(x,\text{Malaria}) \wedge \text{Bite}(x,\text{y})))$

$\forall y\ (\text{Infected}(\text{y},\text{Malaria}) \rightarrow$
$\quad \neg(\exists \text{x}\ (\text{Transfuse}(\text{Blood},x,\text{y}) \wedge \text{Infected}(x,\text{Malaria})))\ \text{v}$
$\quad \neg(\exists x\ (\text{Mosquito}(x) \wedge \text{Infected}(x,\text{Malaria}) \wedge \text{Bite}(x,\text{y}))))$

- Since MLN clauses are “soft constraints” both explanations can still be true (probability ranking principle can be applied)

Adapting MLNs for Abduction

- In general, for the Horn clauses $P_1 \rightarrow Q$, $P_2 \rightarrow Q$, …, $P_n \rightarrow Q$ in the background knowledge base, add:
  - A reverse implication disjunction clause

    $Q \rightarrow P_1 \vee P_2 \vee \ldots \vee P_n$
  - A mutual exclusivity clause for every pair of explanations

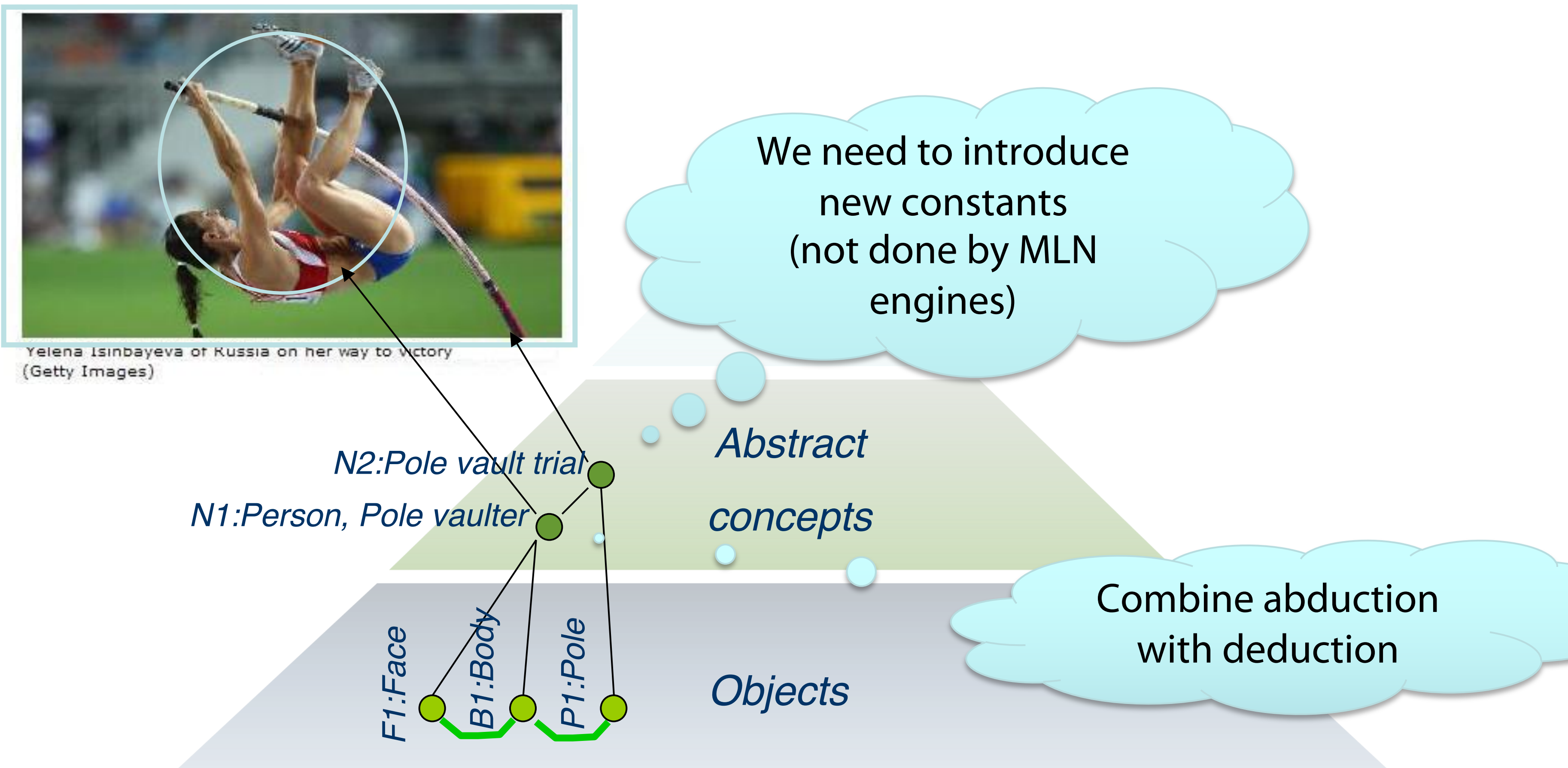
    $Q \rightarrow \neg P_1 \vee \neg P_2$

    $Q \rightarrow \neg P_1 \vee \neg P_n$

    …

    $Q \rightarrow \neg P_2 \vee \neg P_n$
- Weights can be learned from training examples or can be set heuristically

Interpretation = Explanation



SCD Generation by Deduction with MLNs

- Transformation is a general method for existing off-the-shelf deductive inference systems for MLNs
  - Handles uncertainties using MLN weights
  - Model can be trained

Kate, R. J., and Mooney, R. J. Probabilistic abduction using Markov logic networks. In IJCAI-09 Workshop on Plan, Activity, and Intent Recognition. **2009**

James Blythe, Jerry R. Hobbs, Pedro Domingos, Rohit J. Kate, and Raymond J. Mooney. 2011. Implementing weighted abduction in Markov logic. In Proceedings of the Ninth International Conference on Computational Semantics (IWCS '11). **2011**.

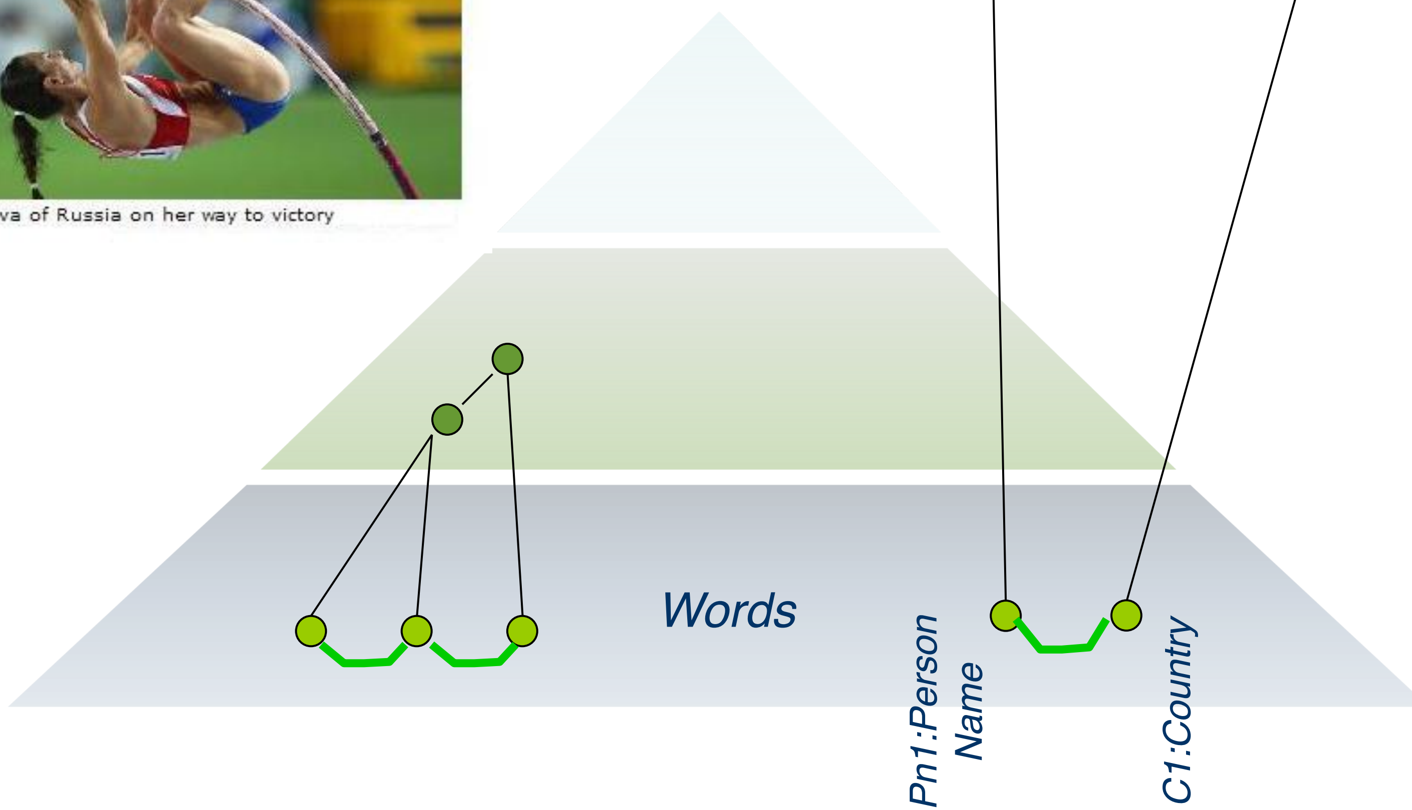
- Not clear how to control the generation of new objects (in particular in the context of recursive rules)
  - When to reuse old constants, when to create new ones?

Text modality

- Low-level analysis of text

Yelena Isinbayeva of Russia on her way to victory (Getty Images)

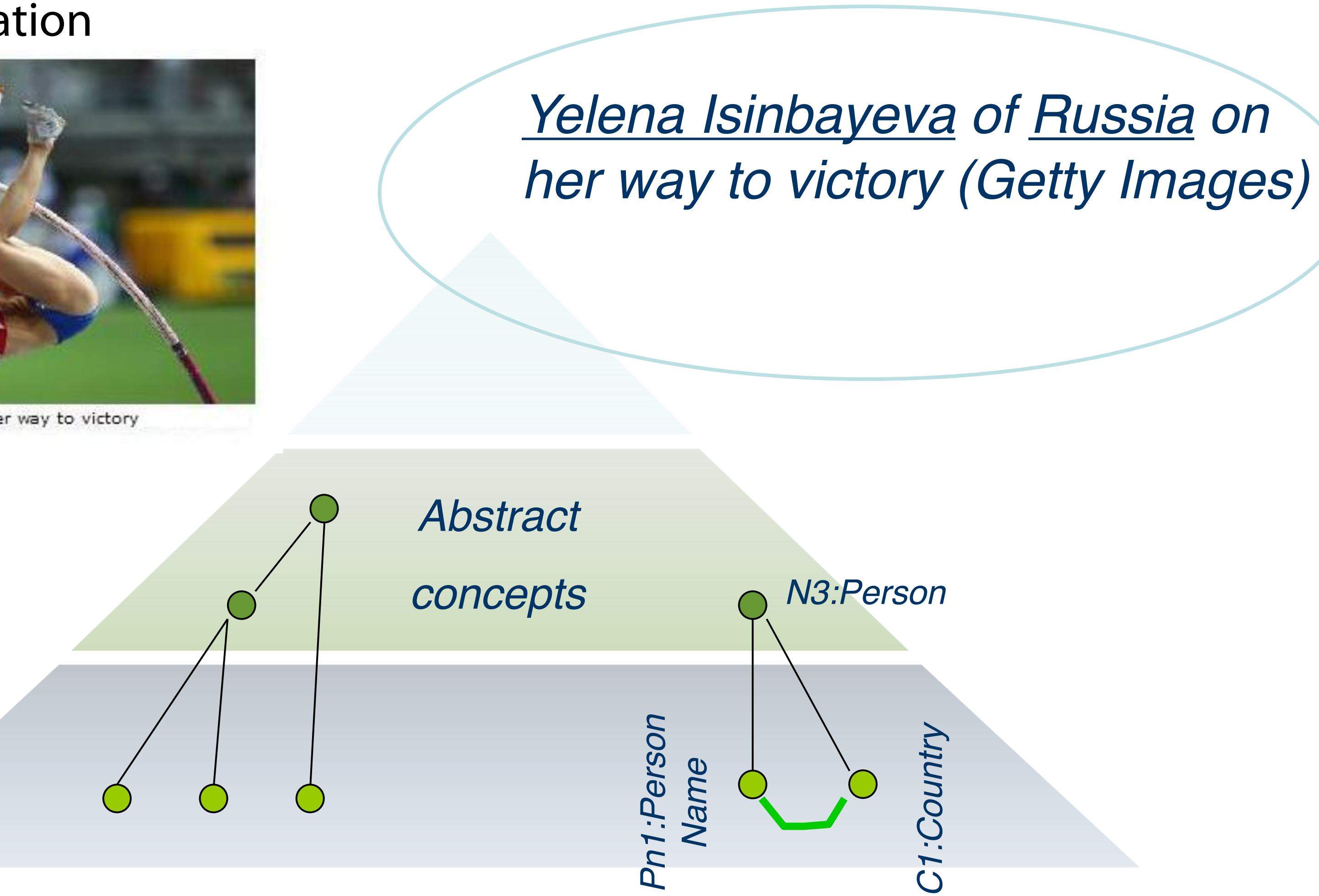
Yelena Isinbayeva of Russia on her way to victory (Getty Images)



Text modality (2)

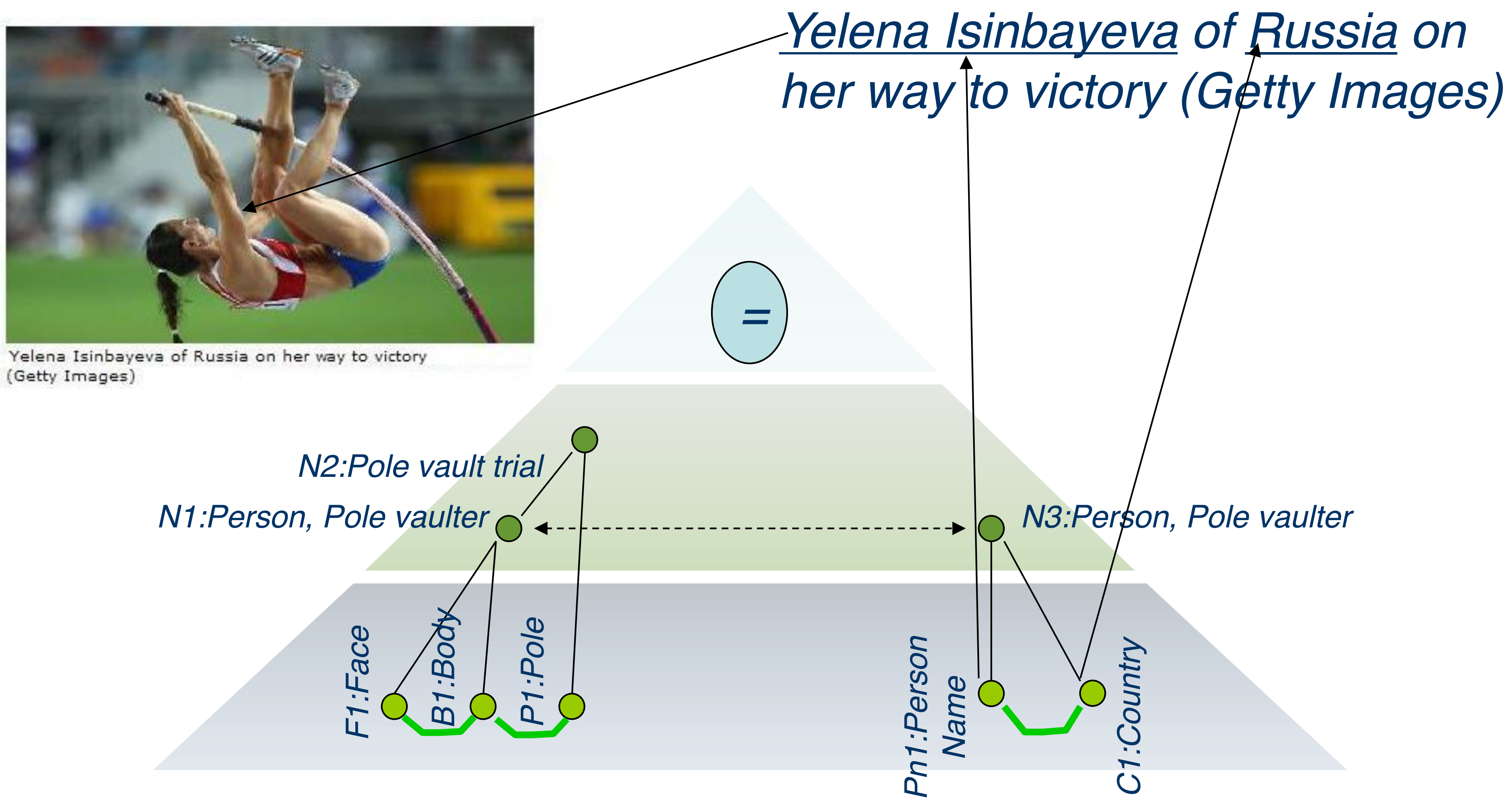
- Text interpretation

Yelena Isinbayeva of Russia on her way to victory (Getty Images)



Irma Sofia Espinosa Peraldi, Atila Kaya, Sylvia Melzer, and Ralf Möller. 2008. On ontology based abduction for text interpretation. In Proceedings CICLing'08, 194–205. **2008**.

Fusion

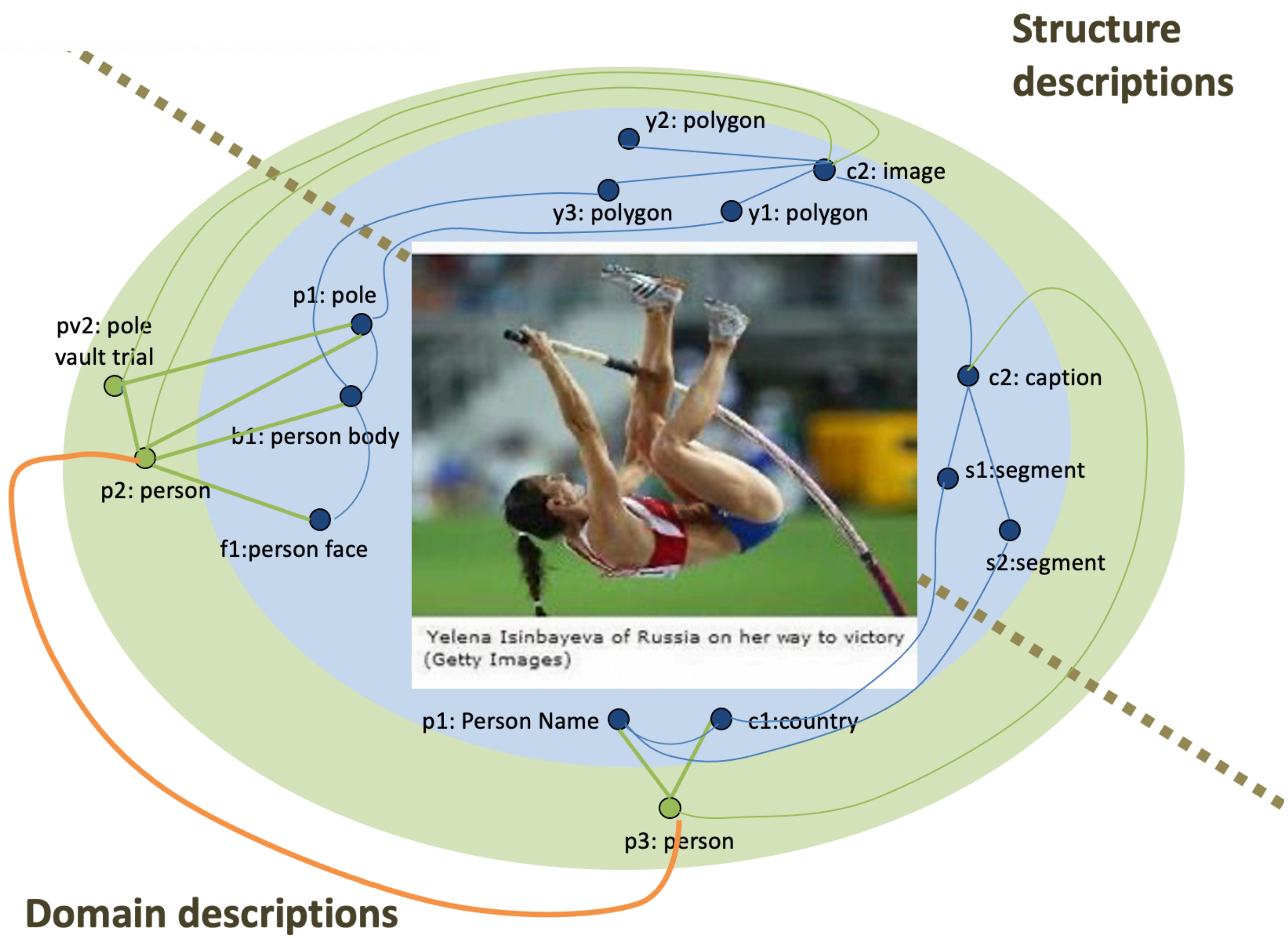


Atila Kaya: A Logic-Based Approach to Multimedia Interpretation, Dissertation, Hamburg University of Technology, **2010**.

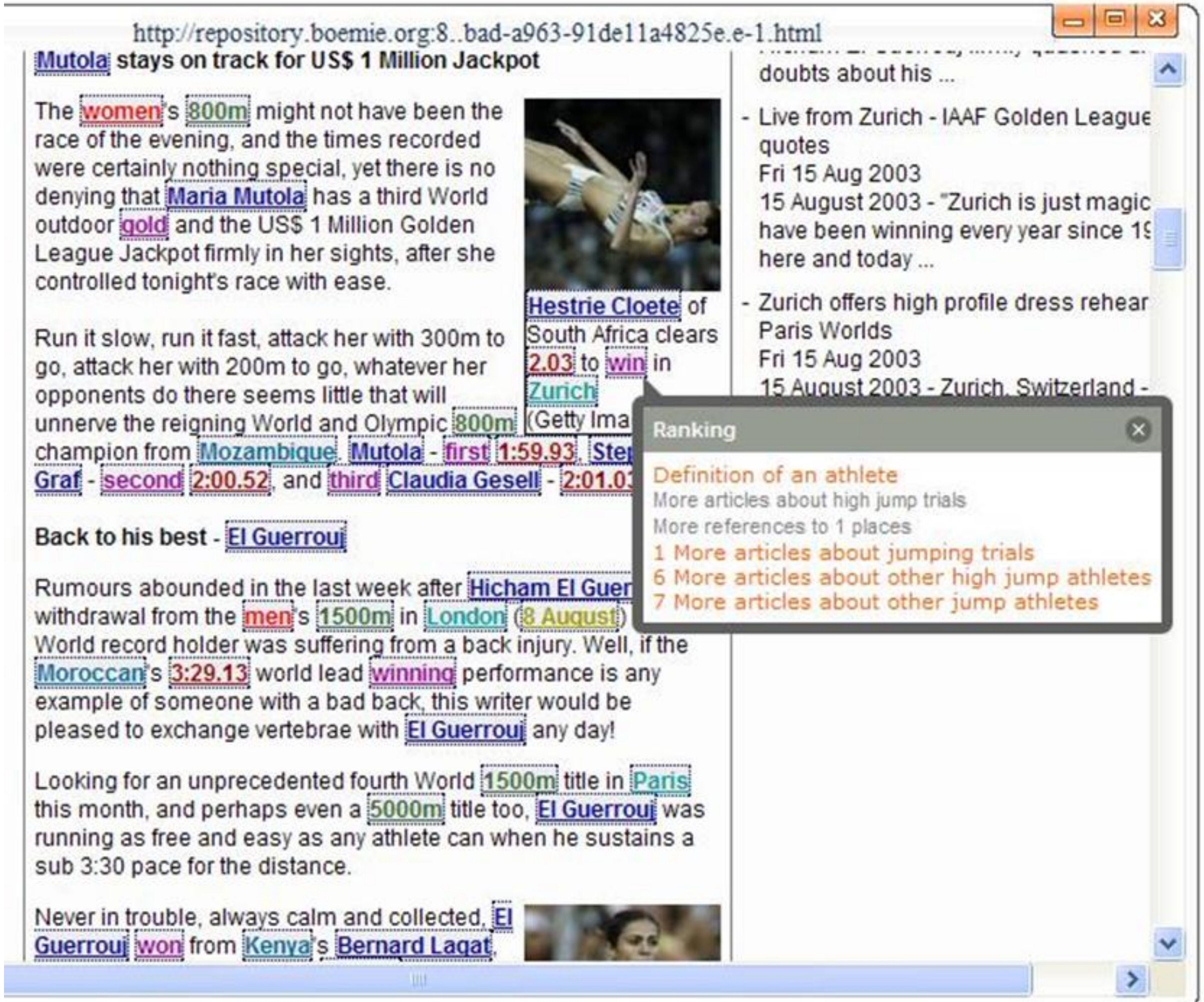
Relations between text parts

- Combine logic with embedding approaches
- Use, e.g., embeddings to represent relations between text constituents (point in an embedding space)
- Relation tuples are vectors in a embedding space
- No need to have an infinite number of predicate names for relations
- Avoid brittleness of MLNs
- Can use logic for abstraction of embedded SCDs
  - Can compute abstractions on the fly
  - Useful feature for "standard" applications that benefit from SCDs

Subjective Content Descriptions



Applications of SCDs



Sofia Espinosa, Content Management and Knowledge Management: Two Faces of Ontology-Based Text Interpretation, Dissertation, Hamburg University of Technology, **2011**.

Our Approach: Abductive query answering

- Simple example
  - Query: $ans() \leftarrow C(x), D(y), R(x,y)$
  - KG : $\{R(i,j), C(i)\}$
  - **Preferred** solution (optimal, according to score defined below)

    $x \leftarrow i, y \rightarrow j :$

    $\Delta = \{D(i)\}$
  - **Other** solution (plus 7 more, $3^2 = 9$), e.g.

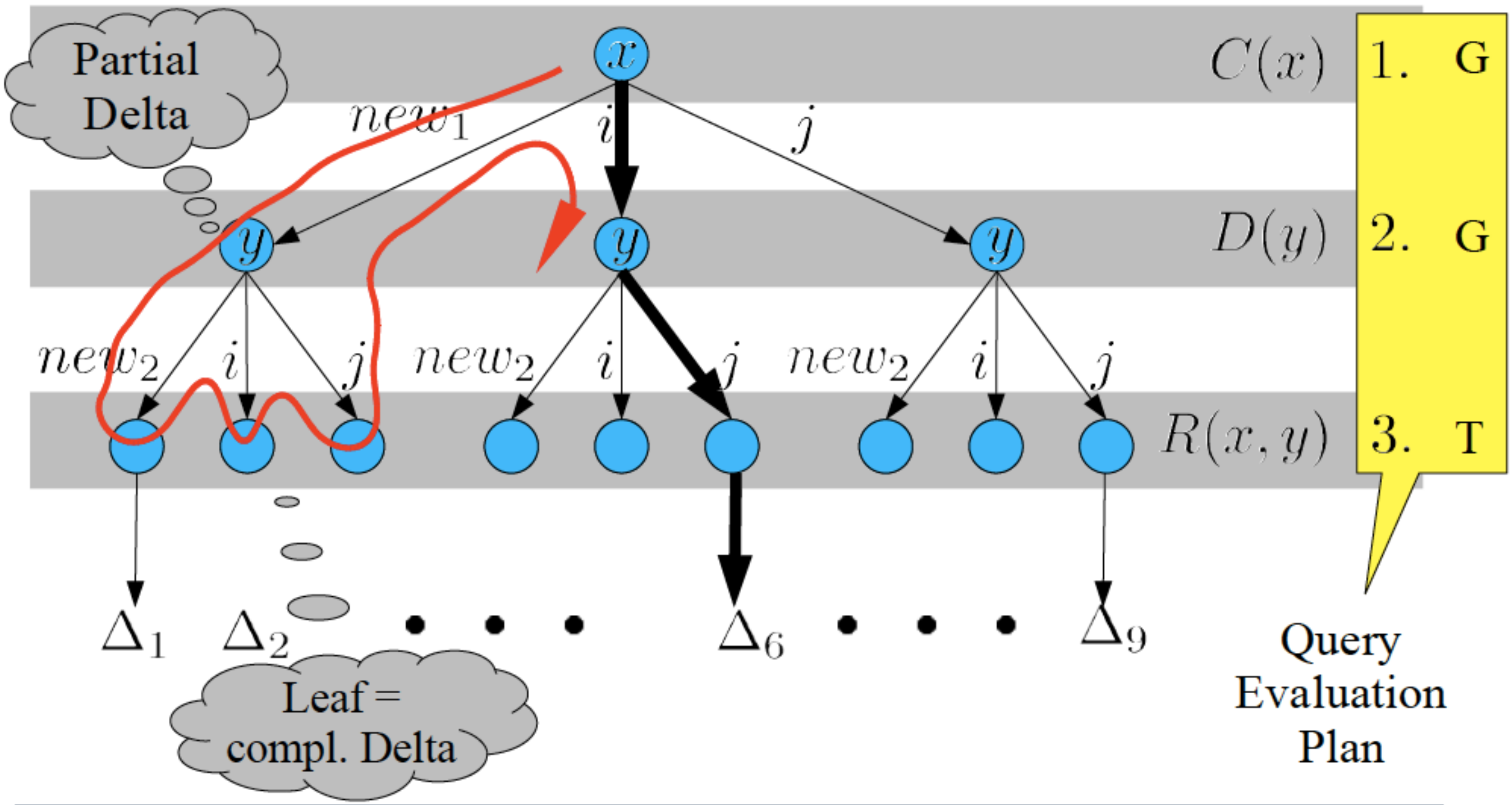
    $x \leftarrow new1, y \leftarrow new_2 :$

    $\Delta = \{C(new_1), D(new_2), R(new_1, new_2)\}$
- Exponential number of solutions has to be computed to find „the best“
  - **optimization idea:** early dynamic cutoff of search space based on score evaluation on partially computed explanations (deltas)

QA w.r.t. KB, e.g.,
KB = { $\forall x\ C(x) \rightarrow D(x)\}$
$\Delta = \{\}$

Depth-first abductive query evaluation

KG : $\{R(i,j), C(i)\}$



G = Generator, T = Tester

Score for comparing solutions

Very simple:

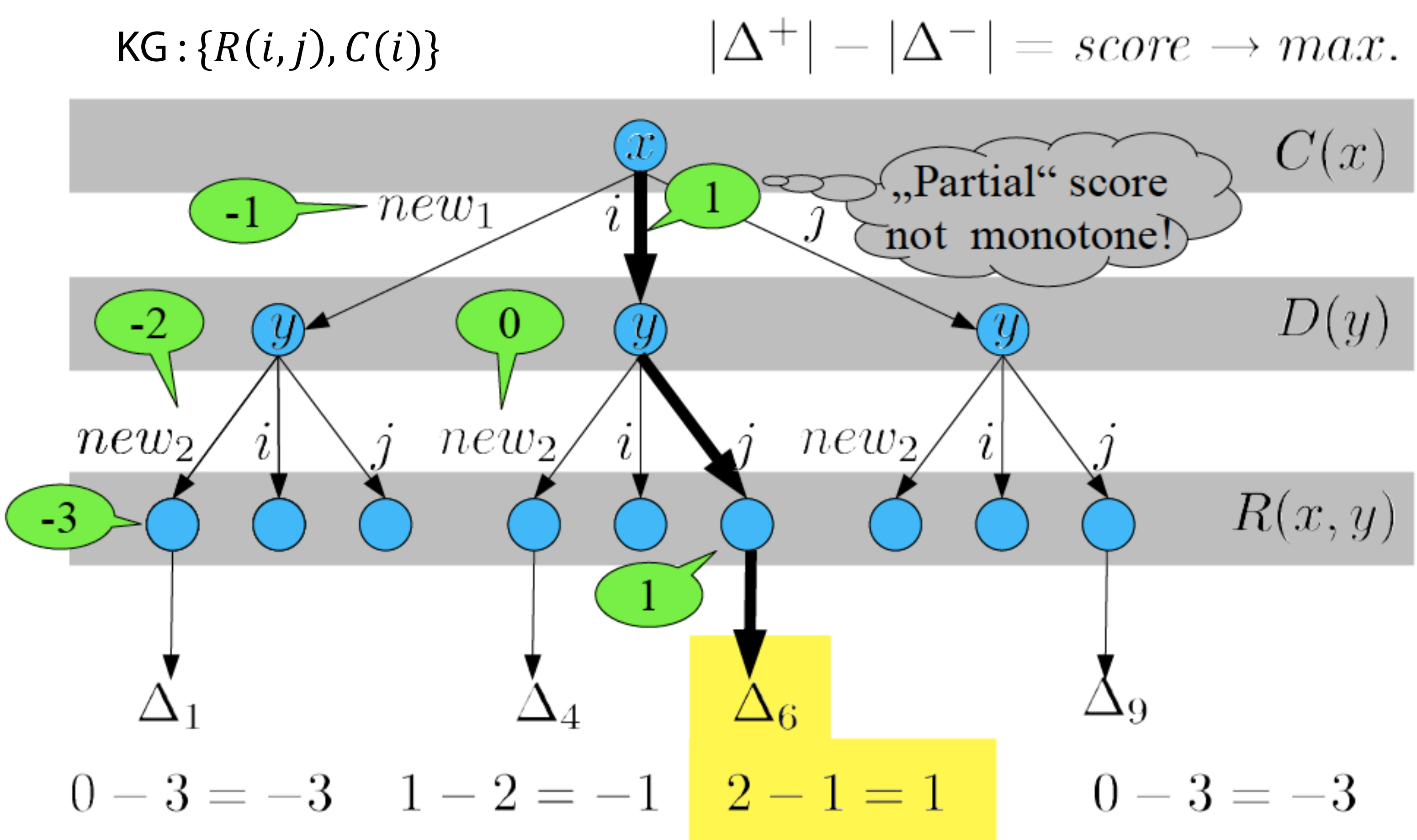
entailed Assertions minus hypothesized Assertions

$$\text{score}(\Delta) =_{def} |\Delta^+| - |\Delta^-| \rightarrow \text{ maximize}$$

$$\Delta = \Delta^+ \cup \Delta^- \text{ (entailed, hypothesized)}$$

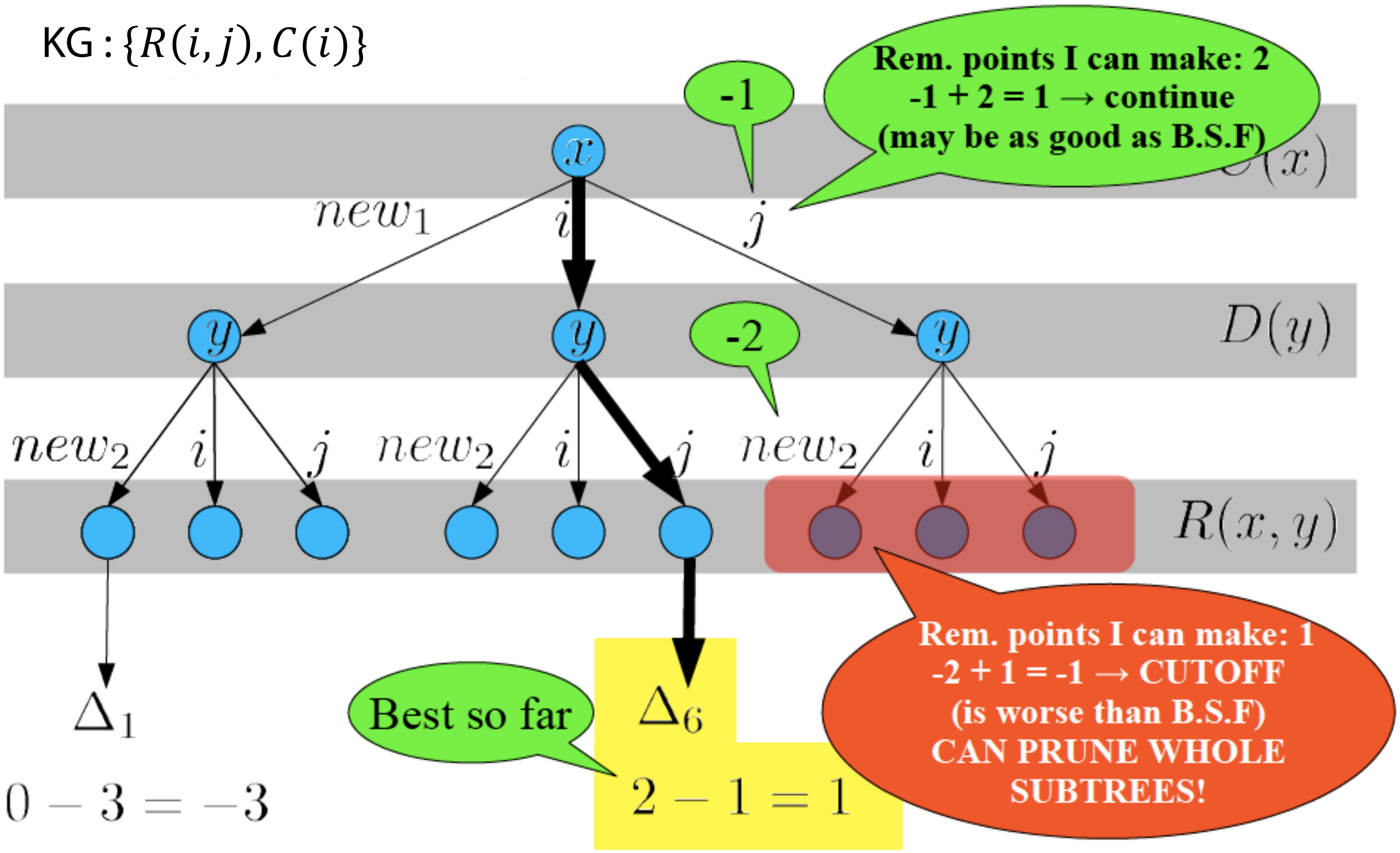
Illustration of partial scores

KG : $\{R(i,j), C(i)\}$



Score-based cutoff

KG : $\{R(i,j), C(i)\}$



More formally

$$n = |\Delta^+| + |\Delta^-| \; (n \text{ const. for each rule body})$$

$$\mathsf{score}(\Delta) =_{def} |\Delta^+| - |\Delta^-| \rightarrow \text{ maximize (not monotone)}$$

$$n + \mathsf{score}(\Delta) = 2|\Delta^+|$$

$$\mathsf{score}(\Delta) = 2|\Delta^+| - n \rightarrow \text{ maximize (and monotone!)}$$

- Let $\Delta_p \subseteq \Delta, m_p = n - |\Delta_p|$ (remaining conjuncts)
  - If $\mathsf{score}(\Delta_p) + (n - |\Delta_p|) < \mathsf{score}(\Delta_{best\_so\_far})$
    $\mathsf{score}(\Delta_{best\_so\_far}) - \mathsf{score}(\Delta_p) > (n - |\Delta_p|)$
    reject Δ_p

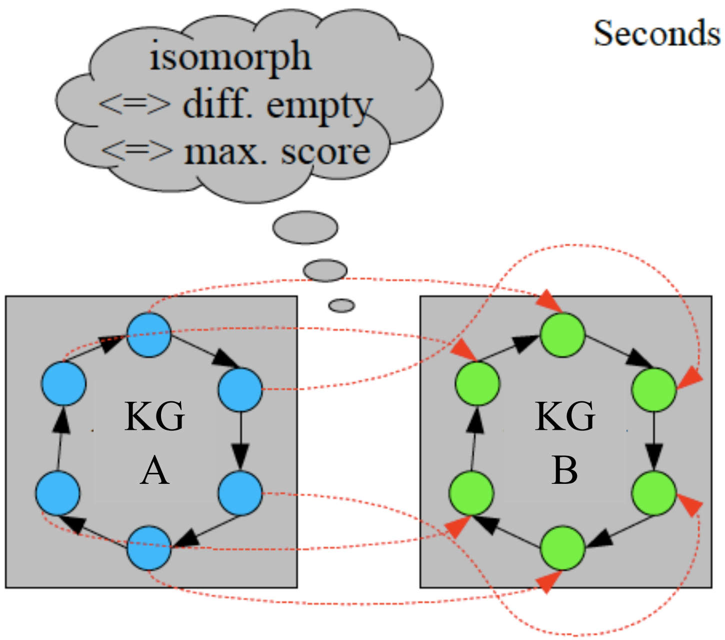
Ralf Möller, Özgür L. Özcep, Volker Haarslev, Anahita Nafissi, Michael Wessel: Abductive Conjunctive Query Answering w.r.t. Ontologies in: KI - Künstliche Intelligenz, Vol.30, (2), p.177-182, **2016**.

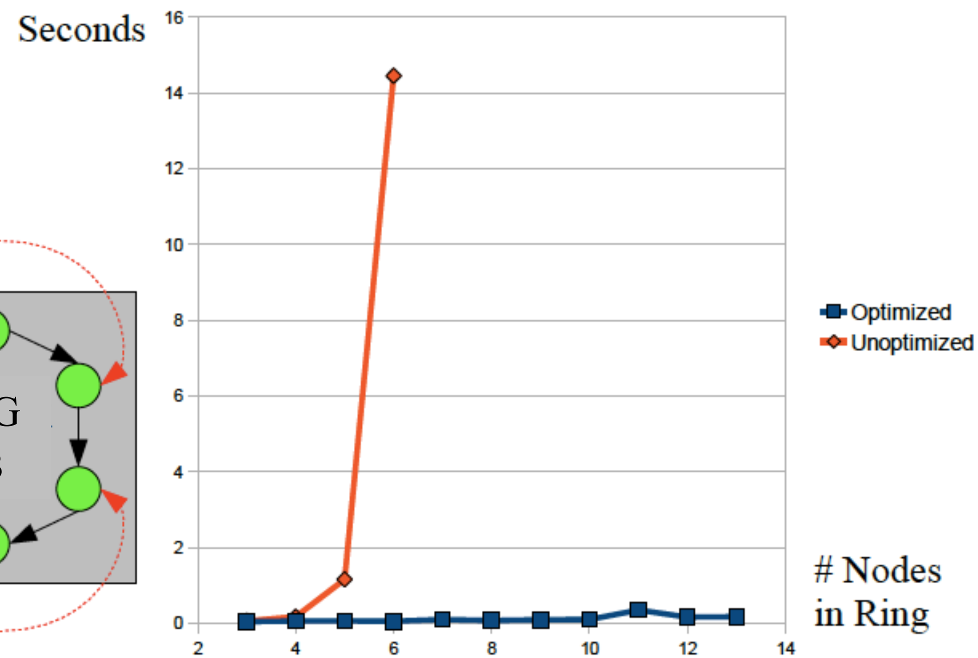
Volker Haarslev, Kay Hidde, Ralf Möller, and Michael Wessel. The RacerPro knowledge representation and reasoning system. *Semantic Web Journal*, 3(3):267–277, **2012**.

How effective is this?

- Synthetic benchmark: finding graph isomorphisms (n nodes)
- Problem reductions:

  Graph Isomorphism → Abductive query answering





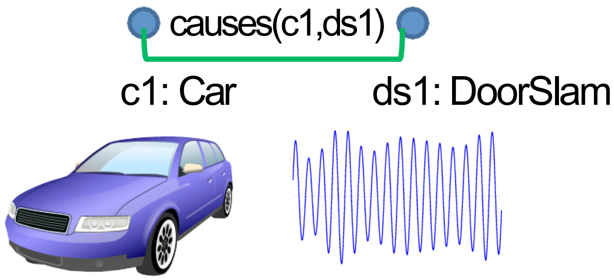
KG Difference w.r.t. KB

- “What needs to be minimally added to KG_1 such that KG_2 is entailed w.r.t. KB”
  - $\Delta^{KB}_{KG_1,KG_2} = \text{ argmin}_{\Delta} \text{ score}(\Delta) \; s.t. \; KG_1 \cup \Delta \vDash_{KB} KG_2$
- But: KG_1 and KG_2 can use different names
- Thus, a name substitution needs to be computed
  - $\Delta^{KB}_{KG_1,KG_2} = \text{ argmin}_{\Delta,\sigma} \text{ score}(\Delta) \; s.t. \; KG_1 \cup \Delta \vDash_{KB} \sigma_{KG_1}(KG_2)$

- Implemented by abductive query anwering
  - Treat KG_1 as query to be answered w.r.t. KG_2 and possibly a given first-order knowledge base KB)

Interpretation Example

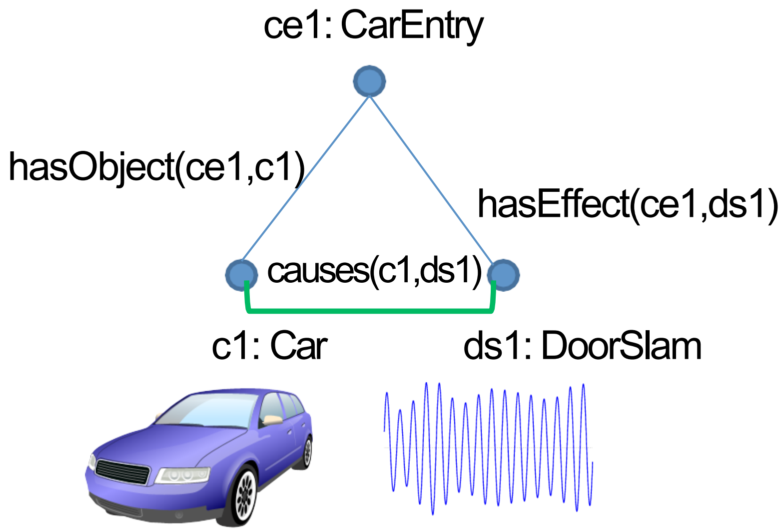
$$\forall x, y\ causes(x, y) \ \leftarrow\ \exists z\ CarEntry(z), hasObject(z, x), hasEffect(z, y), Car(x), DoorSlam(y)$$

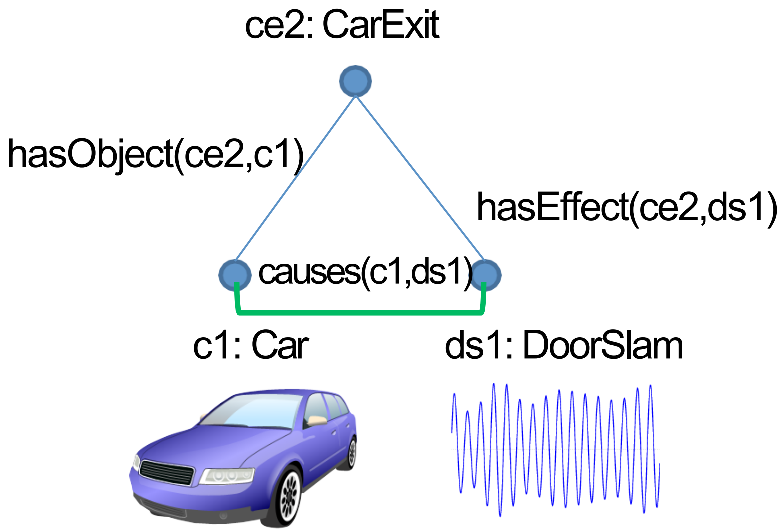


Interpretation Example Continued

$$\forall x, y\ causes(x,y) \leftarrow \exists z\ CarEntry(z), hasObject(z,x), hasEffect(z,y), Car(x), DoorSlam(y)$$

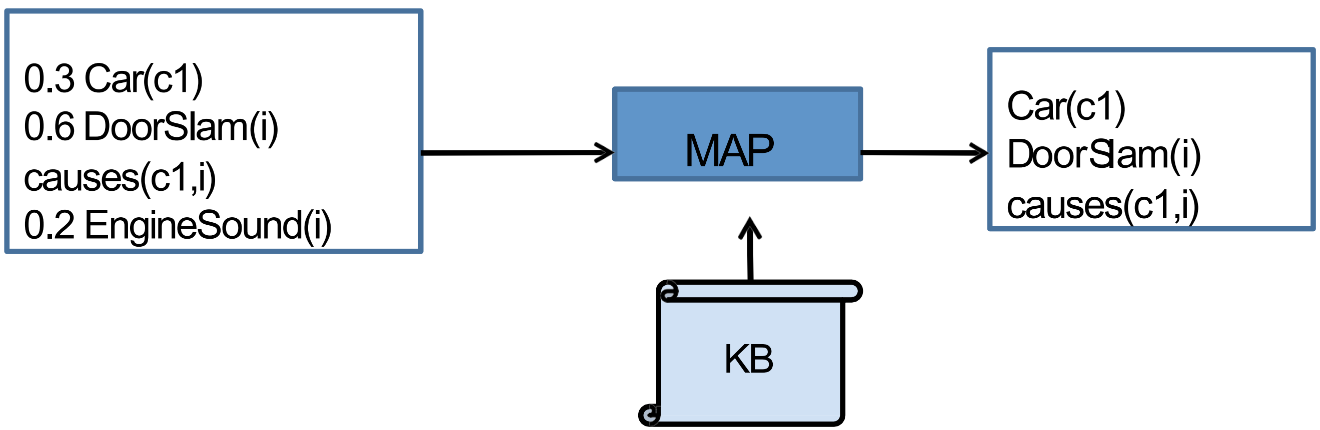
$$\forall x, y\ causes(x,y) \leftarrow \exists z\ CarExit(z), hasObject(z,x), hasEffect(z,y), Car(x), DoorSlam(y)$$



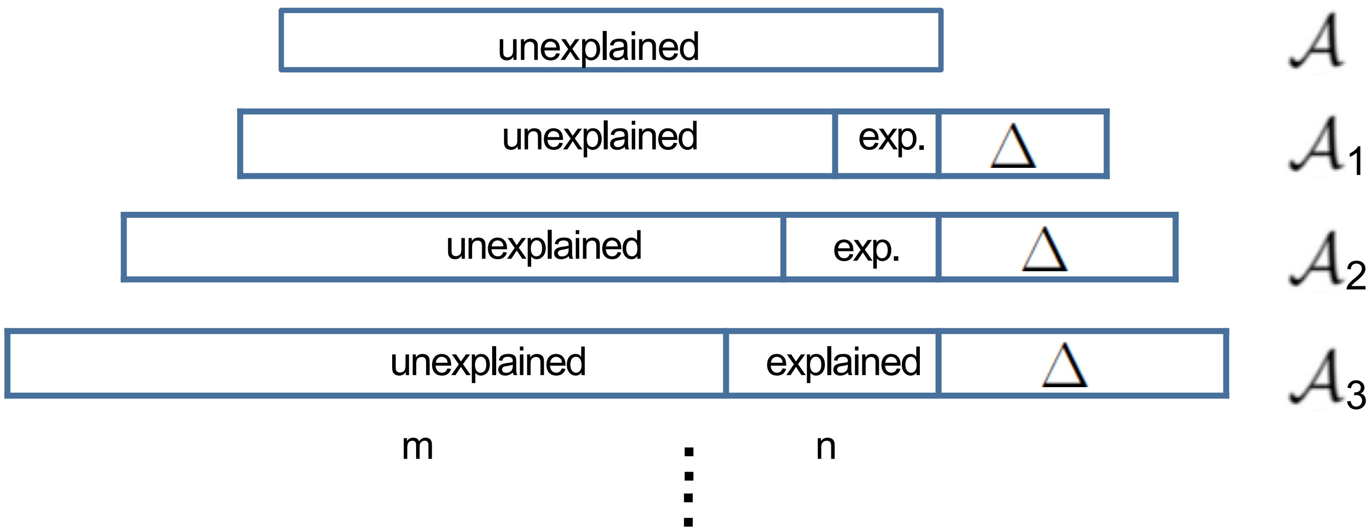


Branching

Maximum Aposterior Inference Problem



Controlling the Interpretation Process: Max_P



P-Score

$$P(\mathcal{A}, \mathcal{WR}) = \frac{1}{n+m}\left(m \times 0.5 + \sum_{i=1}^{n} P_{MLN(\mathcal{A},\mathcal{WR})}(Q_i(\mathcal{A}) \mid \vec{e}(\mathcal{A}))\right)$$

m = Number of unexplained observa(ons
n = Number of explained observa(ons

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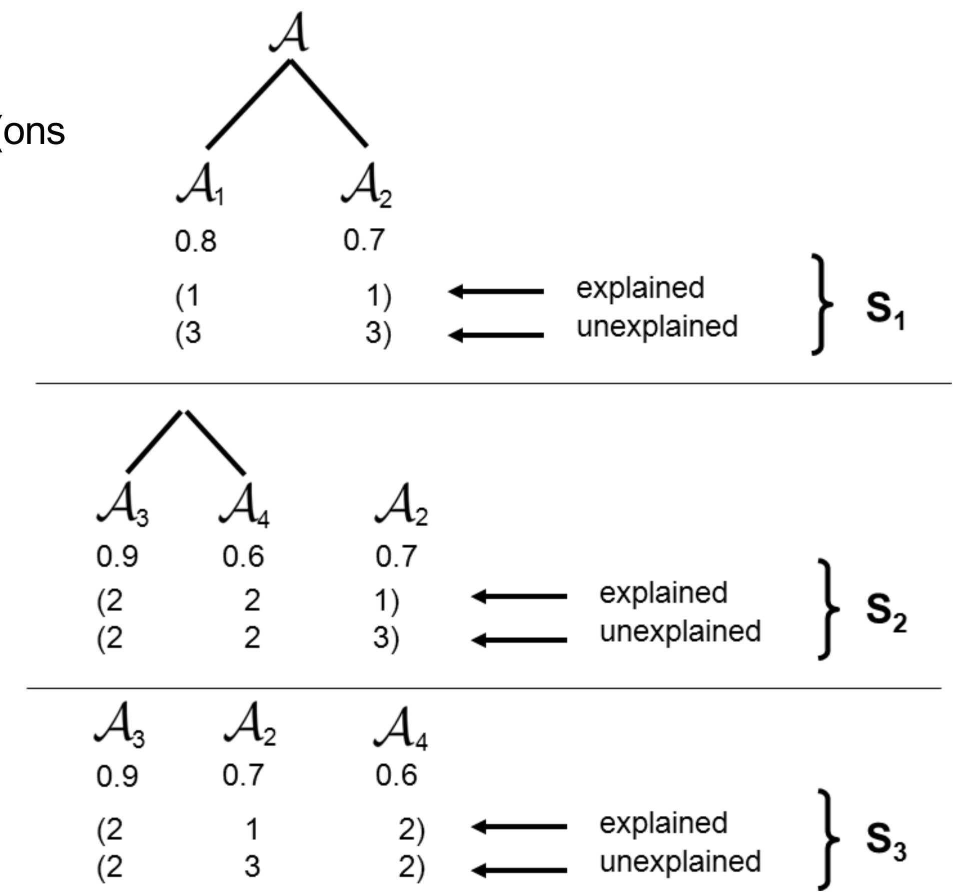
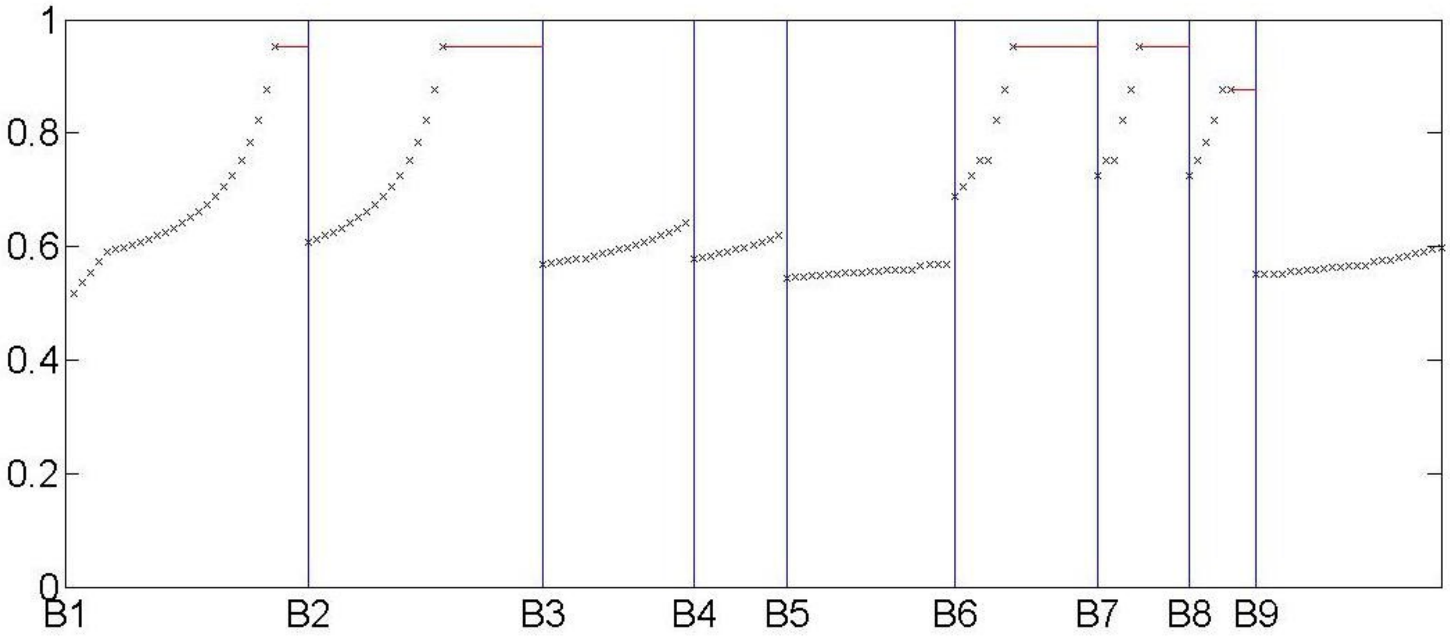
Interpretation Controlling Example: Beam Search

Assume 4 observa(ons
Depth = 2

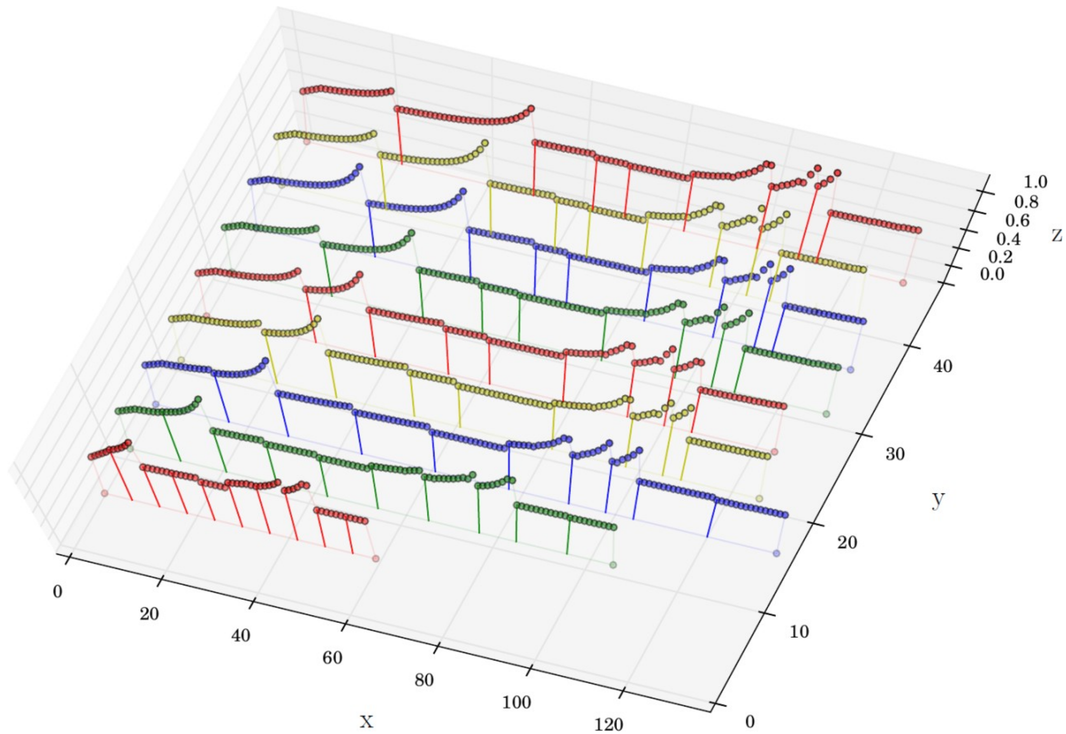


Development of the P-Score



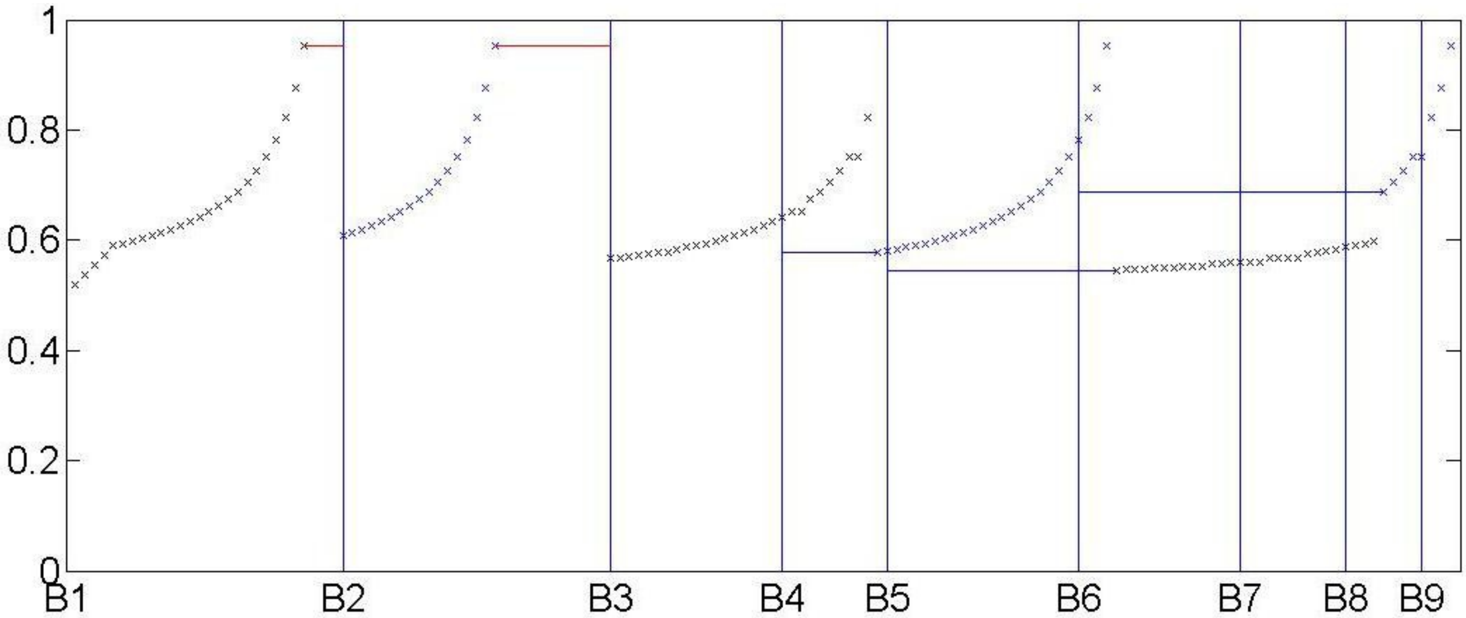
x = time axis indicated with arrival time of bunches
y = scoring value of the interpretation Abox
(Strategy : Stop--Processing)

Increasing the Score by Explaining Observations



x = time spent for explaining observations
y = number of observations to be explained in a bunch
z = scoring value

Increasing the Score by Explaining Observations



x = time axis indicated with arrival time of bunches
y = scoring value of the interpretation Abox
(Strategy : Do-Not-Stop-Processing)

Summary: Logical Abduction

- Incrementally collect process input data
  - Stream-based approach
- Control the abduction process in terms of branching (beam search), depth, and reactivity
- Deal with uncertain and inconsistent observations
- Rank interpretation alternatives probabilistically using MLNs

Anahita Nafissi, Applying Markov Logics for Controlling ABox Abduction, Dissertation, Hamburg University of Technology. **2013**.

- Increase the rank of interpretation alternatives monotonically by successively explaining observations
  - Exploit formulas if available
  - Formulas not always available, however
    - Need also other ways to construct SCDs