Thesis Oral

Grounded Knowledge Bases for Scientific Domains

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August 26, 2015

Thesis Committee:
William Cohen, Chair
Tom Mitchell
Roni Rosenfeld
Alon Halevy, Google Research



Q Who is Barack Obama's wife?



Who is Barack Obama's wife?

Michelle Obama (m. 1992)

Barack Obama, Spouse



Michelle LaVaughn Robinson Obama is an American lawyer and writer. She is married to the 44th and current President of the United States, Barack Obama, and is the first African-American First Lady of the United States. Wikipedia



More about Michelle Obama

Family of Barack Obama - Wikipedia, the free encyclopedia

en.wikipedia.org/wiki/Family of Barack Obama - Wikipedia -Michelle Obama, née Robinson, the wife of Barack Obama, was born on January 17, 1964, in Chicago, Illinois. She is a lawyer and was a University of Chicago ... Sidwell Friends School - Marian Shields Robinson - Bo - Charles T. Pavne

Michelle Obama - Wikipedia, the free encyclopedia

en.wikipedia.org/wiki/Michelle Obama - Wikipedia Michelle LaVaughn Robinson Obama (born January 17, 1964) is an American lawyer and writer. She is the wife of the 44th and current President of the United ... Craig Robinson (basketball) - Hyde Park, Chicago - Sidley Austin - Valerie Jarrett

Michelle Obama - Biography - U.S. First Lady, Lawyer ...

www.biography.com/people/michelle-obama-307592 FYI > Explore the life of Michelle Obama, the 44th first lady and wife of President Barack Obama. Learn more at Biography.com.

First Lady Michelle Obama | whitehouse.gov

https://www.whitehouse.gov/.../first-lady-michelle-obama ▼ White House ▼ First Lady Michelle LaVaughn Robinson Obama is a lawyer, writer, and the wife of the 44th and current President, Barack Obama. She is the first ...

Barack Obama was asked about 'his first wife' by a woman ...

Jan 22, 2015 - Barack Obama was asked about his 'first wife' by a woman who took a ... when she gave Obama a gift of green lipstick for Michelle Obama, who ...

Michelle Obama - Biography - U.S. First Lady, Lawyer ...



www.biography.com/people/michelle-obama-307592 -Explore the life of Michelle Obama, the 44th first lady and wife of President Barack Obama. Learn more at ...

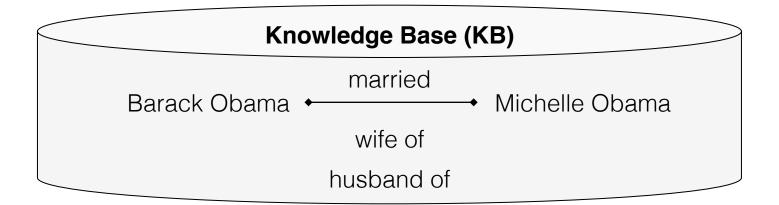
Michelle Obama - First Lady and wife of President Barack ...

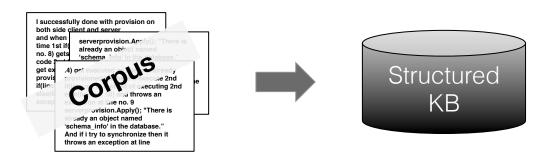


www.telegraph.co.uk > News > World News > Jul 1, 2015

Michelle LaVaughn Obama, First Lady and wife of US President Barack Obama: All the latest news and ...

Who is **Barack Obama**'s wife?









Knowledge Vault





Software

"What is the **run time** of **quick**

sort?"

Quicksort - Wikipedia, the free encyclopedia

https://en.wikipedia.org/wiki/Quicksort • Wikipedia • Animated visualization of the guicksort algorithm. The hori

Animated visualization of the **quicksort** algorithm. The horizontal lines are pivot values. **Quicksort** (sometimes called partition-exchange **sort**) is an efficient **sorting** algorithm, serving as a systematic method for placing the elements of an array in order.

Tony Hoare - Dutch national flag problem - Robert Sedgewick - Flashsort

Running Time of Quicksort - HackerRank

https://www.hackerrank.com/challenges/quicksort4 ▼

Mar 4, 2013 - The **running time of Quicksort** will depend on how balanced the partitions are. If you are unlucky and select the greatest or the smallest element ...

Quicksort Running Time - Math StackExchange

math.stackexchange.com/.../quicksort-running-time ▼ Stack Exchange ▼ Feb 18, 2011 - ... the recurrence will be: The above recurrence has the solution (I will prove this later): Hence the running time of QUICKSORT in this case is ...

Quick Sort - Personal.kent.edu

www.personal.kent.edu/~rmuhamma/Algorithms/.../Sorting/quickSort.ht... ▼
The running time of quick sort depends on whether partition is balanced or unbalanced, which in turn depends on which elements of an array to be sorted are used for partitioning. A very good partition splits an array up into two equal sized arrays.

[PDF] Quick Sort

https://www.cse.ust.hk... ▼ Hong Kong University of Science and Technology ▼ P, followed by the results of quicksort(S. 2.)) ... void quicksort(int A[], int left, int right).

...the average case running time is θ (n logn)...

[PDF] Quicksort

www.bowdoin.edu/~Itoma/...quicksort/quicksort.pdf \checkmark Bowdoin College \checkmark Quicksort(A, q + 1,r). FI. Sort using Quicksort(A,1,n). If q = n/2 and we divide in Θ (n) time, we again get the recurrence $T(n)=2T(n/2)+\Theta(n)$ for the running time ...

Biomedical

"What is the **molecular mass** of **BamA**?"

[PDF] Quiz 2 answers - with worked solutions - Bama.ua.edu www.bama.ua.edu/.../quiz2_key_with_solutions.p... ▼ University of Alabama ▼ Quiz 2 answers - with worked solutions. 1. What is average mass, in grams, of one atoms of iron? use mol wt of iron (= molar mass = mass for one mol of Fe ...

[PPT] Polymers: Introduction - Bama.ua.edu

bama.ua.edu/~kshaughn/ch338/.../poly-lecture.ppt ▼ University of Alabama ▼ Monomer: Low molecular weight compound that can be connected together to give a poymer; Oligomer: Short polymer chain; Copolymer: polymer made up of 2 ...

[PDF] Hydrogen/Deuterium exchange mass spectrometry - Bam... bama.ua.edu/.../Busenlehner_ABBreview_2005.p... ▼ University of Alabama ▼ by LS Busenlehnera - 2005 - Cited by 143 - Related articles

Oct 5, 2004 - exchange mass spectrometry (H/D exchange MS) is emerging as an efficient ... proteins having **molecular masses** in excess of 50 kDa.

TP0326, a Treponema pallidum β-Barrel Assembly ...

www.ncbi.nlm.nih.gov/... ▼ National Center for Biotechnology Information ▼ by DC Desrosiers - 2011 - Cited by 32 - Related articles

Apr 27, 2011 - In E. coli, **BamA** is the central component of a multi-protein complex consisting Native TP0326 forms part of a high **molecular mass** complex.

The crystal structure of BamB suggests interactions with ...

www.ncbi.nlm.nih.gov/... ▼ National Center for Biotechnology Information ▼ by N Noinaj - 2011 - Cited by 47 - Related articles

Jan 26, 2011 - It interacts with the periplasmic domain of **BamA**, an integral outer We determined the **molecular mass** of BamB in solution using size

...BamA at its expected molecular weight (~90 kDa)...

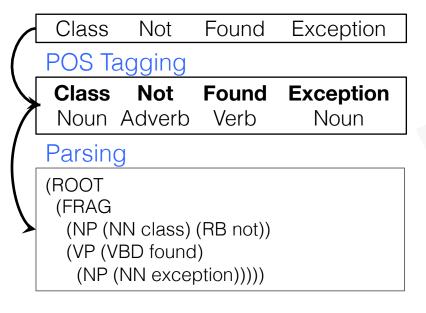
BAMA Course Survey: ... Use masses lister above to calculate the molecular mass. ...

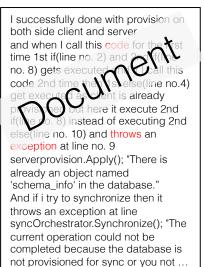
This keeps the shape of the molecule "strain or "linear" allowing these ...

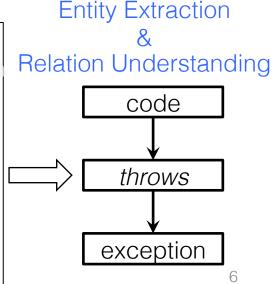
Challenges in Mining Scientific Text

- Specialized terminology
- Domain-specific language constructs

Affected NLP Techniques



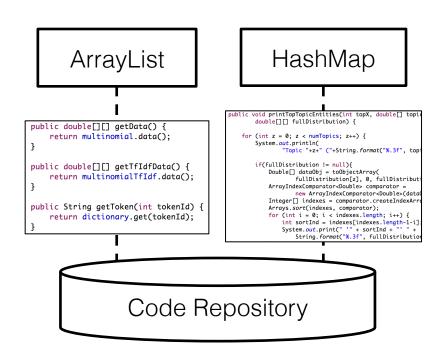


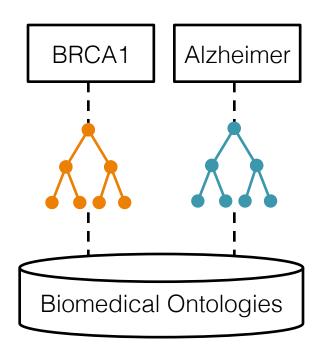


Grounding Scientific Entities

Scientific data is not found only in text

Opportunity:
Domain-specific resources

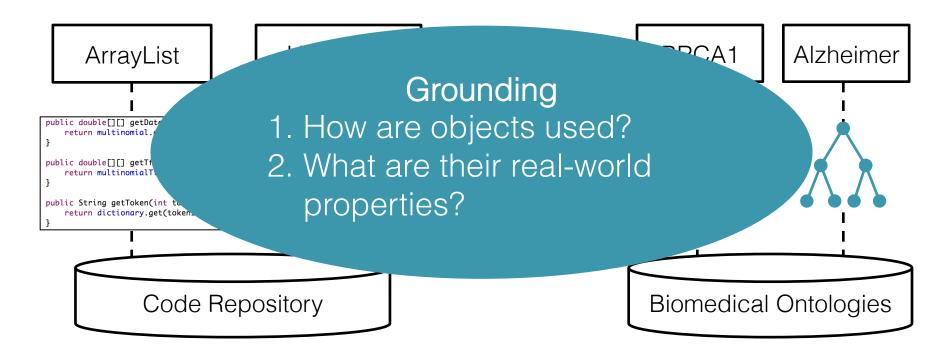




Grounding Scientific Entities

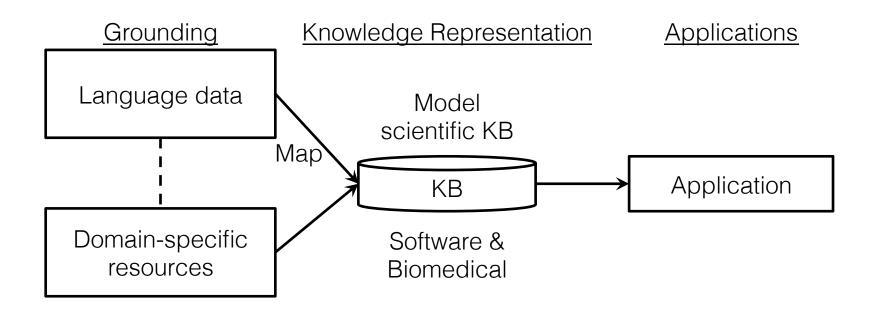
Scientific data is not ____ found only in text

Opportunity:
Domain-specific resources



Thesis Statement

"Grounding entities to specialized data from a scientific domain facilitates improved unsupervised and semisupervised algorithms for Knowledge Base construction for that domain"



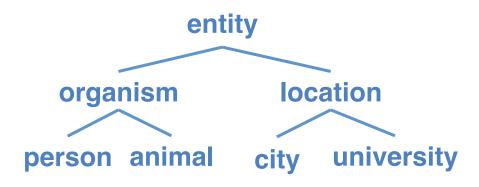
Knowledge Base Construction

Open IE

(Beijing, is the capital of, China)
(Penticton, has very, warm
summers)
(Goods, can be defined in, a
variety of ways)

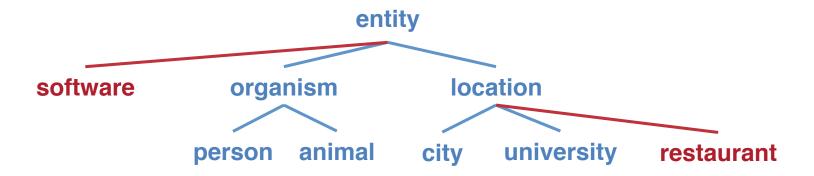
- ReVerb [Fader et al., 2011]
- TextRunner [Yates et al., 2007]

Ontology-Guided Construction



- NELL [Carlson et al., 2010]
- FreeBase [Google, 2011]
- Yago [Suchanek et al., 2007, 2008]
- Knowledge Vault [Dong et al., 2014]

Reasoning with Ontologies



- Ontologies give information context
- Easy to extract domainspecific information
- Ontologies are
 - expensive
 - require prior knowledge
- Manual ontology does not reflect language statistics

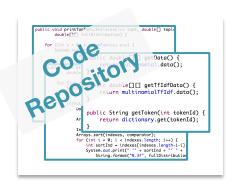
Roadmap

Statistical Language Model for Software Domain Application

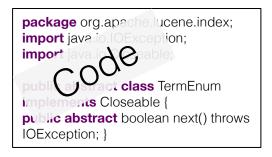
```
/* comment prediction */
```

Predicting Code Comments

Model code with statistical language models



Predict class comment



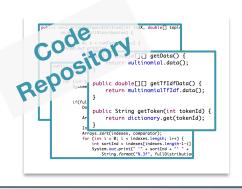


Evaluate how much typing can we save?

Up to 47%!

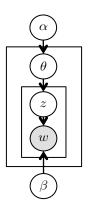
Tr<u>ain</u> a namedentity extractor

Code Modeling



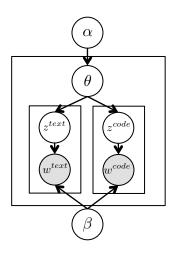
Language and domain understanding

- Shallow statistical model
 N-gram
- 2. BOW topic model **LDA**



3. Basic domain encoding (code vs. text entities)

Link-LDA



Lessons

Predicting Code Comments

- Comments are highly predictable
 - 47% of characters predicted
- Un-intuitively: Shallow statistical method performed best

3-gram: Train a named-entity extractor

link-LDA: Train a named-entity extractor

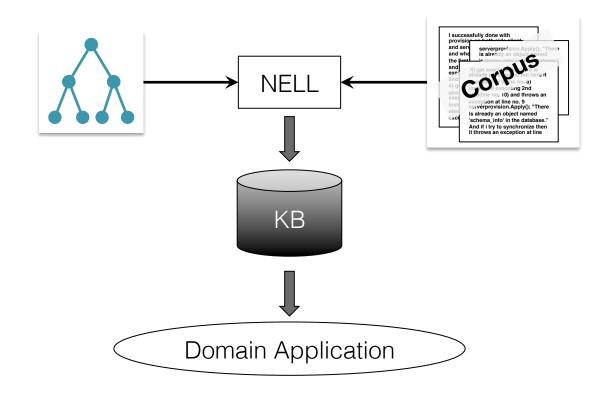
Intuitively: Domain encoding improves performance
 Link-LDA > LDA

We Need Deeper Understanding of Domain Entities

```
This method reads the next double from stdin */
                                   float
                                   long
                                    int
                        Data Type
                    Numerical Data Type
                                 Signed Integer Type
    Signed Floating-Point Type
        double
                 float
                                            int
                                   long
```

Semantics and **categorical understanding** contribute to language modeling task

We Need Deeper Understanding of Domain Entities

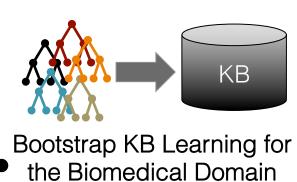


Semantics and **categorical understanding** contribute to language modeling task

Roadmap

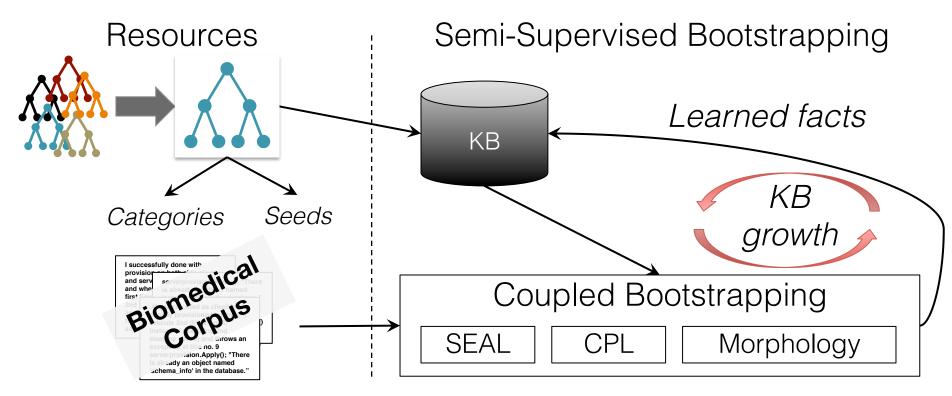
Statistical Language Model for Software Domain Application

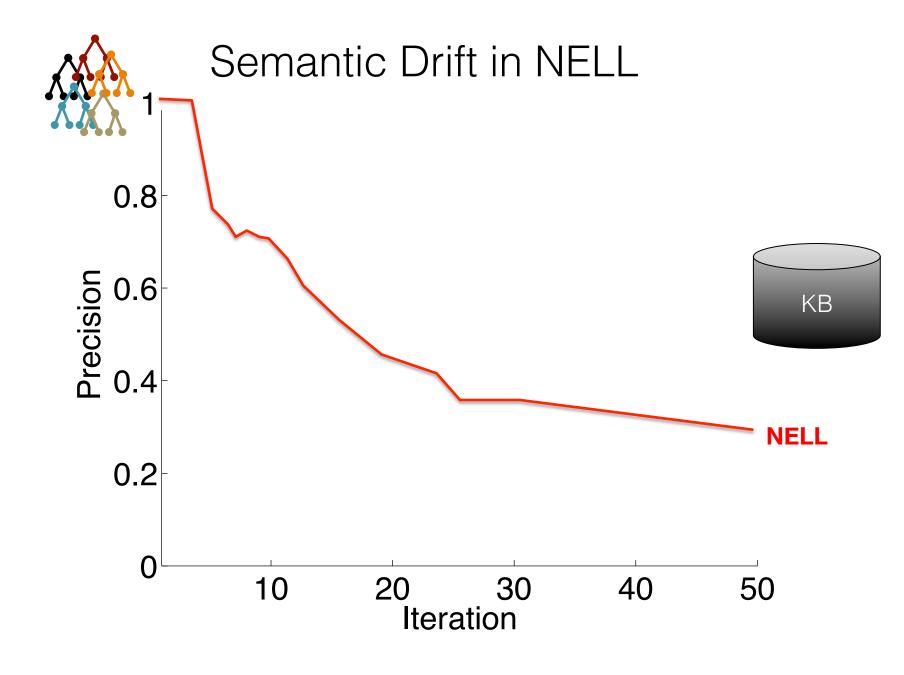
/* comment prediction */



Bootstrap KB Learning for the Biomedical Domain

 Modify KB learning system (NELL) for biomedical domain



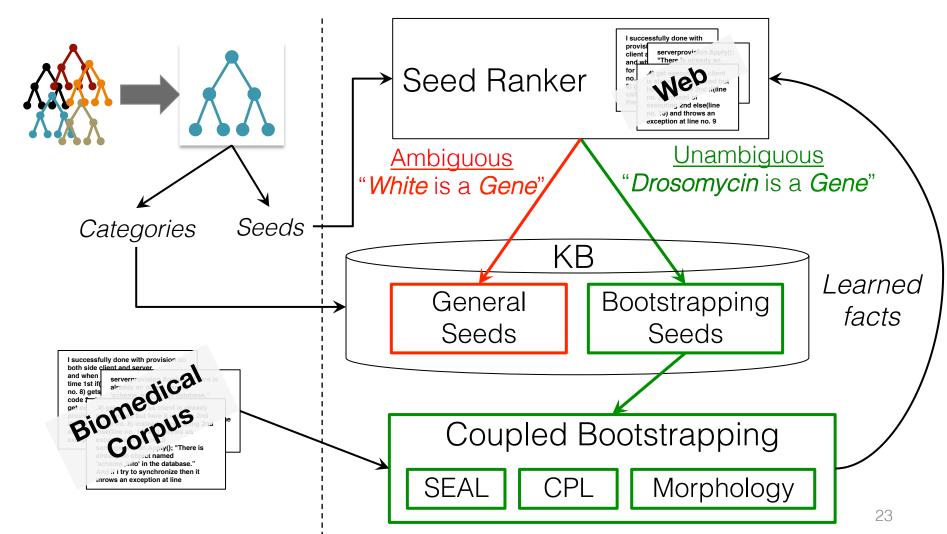


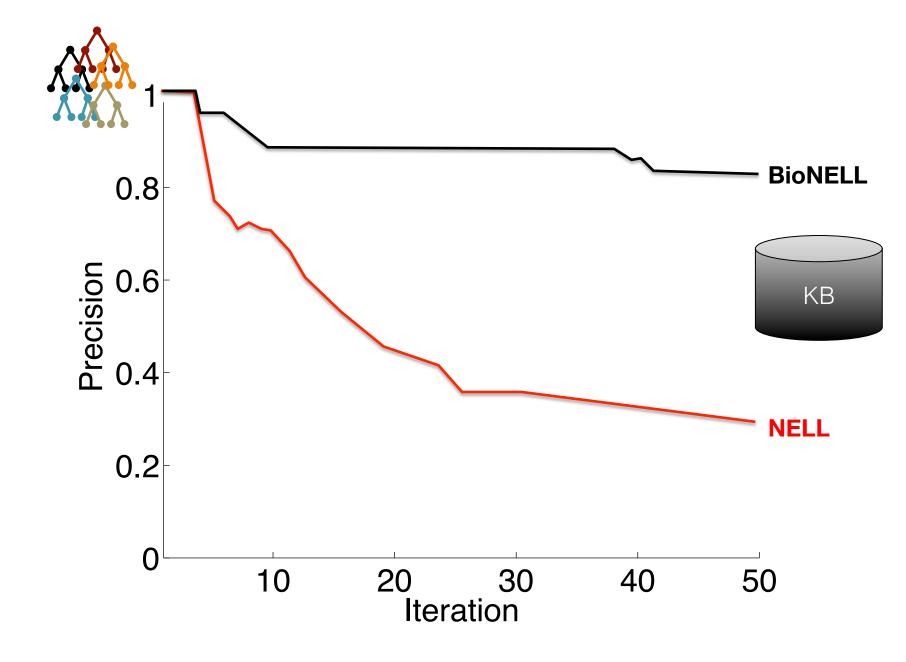
BioNELL



Biomedical Resources

Modified Bootstrapping



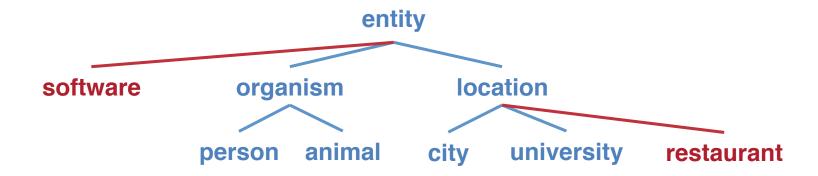


Lessons

BioNELL: Lessons

- Biomedical ontologies + filtering bootstrapping seeds lead to:
 - High-precision biomedical KB
 - Improves domain applications (NER)
- Disadvantage: Relies on input ontologies
 - No existing Software ontologies

Reasoning with Ontologies

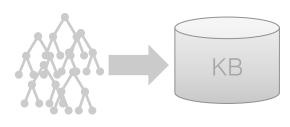


- Ontologies give information context
- Easy to extract domainspecific information
- Ontologies are
 - expensive
 - require prior knowledge
- Manual ontology does not reflect language statistics
- Ontology and facts are often drawn from different sources

Roadmap

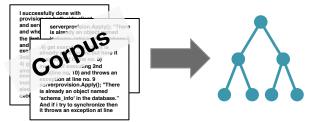
Statistical Language Model for Software Domain Application

/* comment prediction */



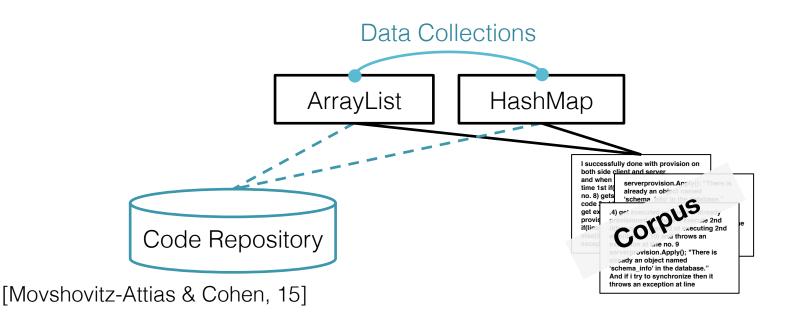
Bootstrap KB Learning for the Biomedical Domain

Grounded Software Ontology Construction

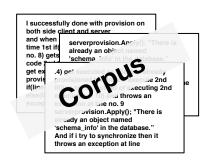


Grounded Software Ontology Construction

- We detect coordinate relations (similarity) between Java classes
 - "This method iterates over <u>ArrayLists</u> and <u>HashMaps</u>"



Grounding



"...Is a root node an internal node?..."

Code Repository

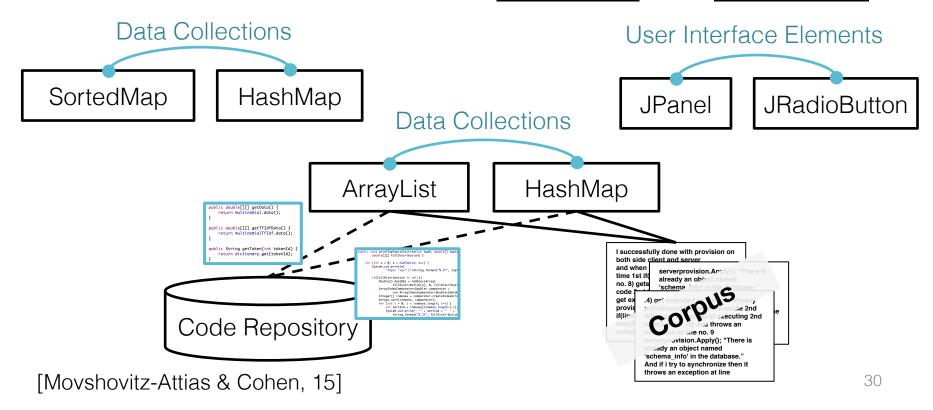
81 implementations of Node

javax.xml.soap.Node
javax.imageio.spi.DigraphNode
javax.swing.tree.TreeNode
javax.swing.tree.MutableTreeNode

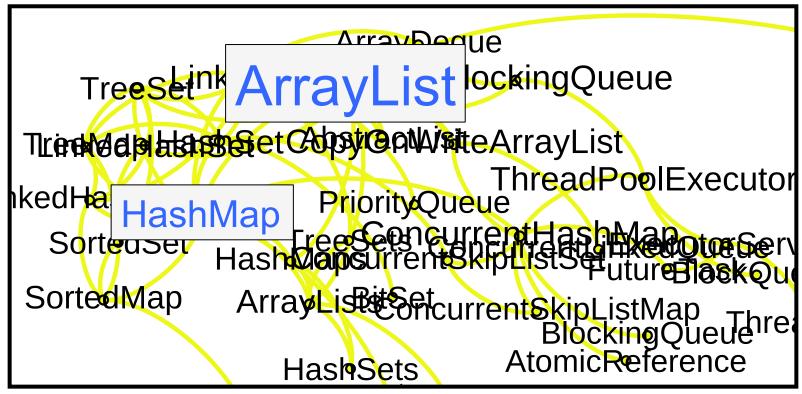
com.sun.org.apache.xerces.internal.dom.NodeImpl

Grounded Software Ontology Construction

- We detect coordinate relations (similarity) between Java classes
 - "This method iterates over ArrayLists and HashMaps"



Utility Classes



- TreeSet
- SortedMap
- SortedSet
- HashSet
- BitSet

- ArrayDeque
- PriorityQueue
- BlockingQueue
- ArrayBlockingQueue
- LinkedHashMap

Nodes: Classes

Edges: Coordinate relations

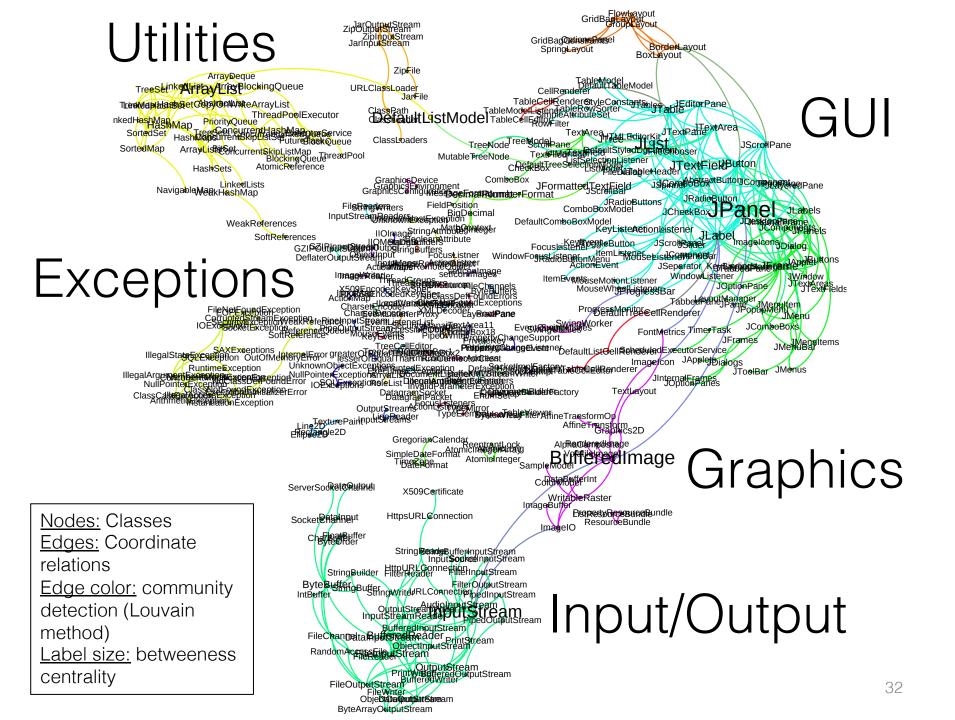
Edge color: community

detection (Louvain method)

Label size: betweeness

centrality

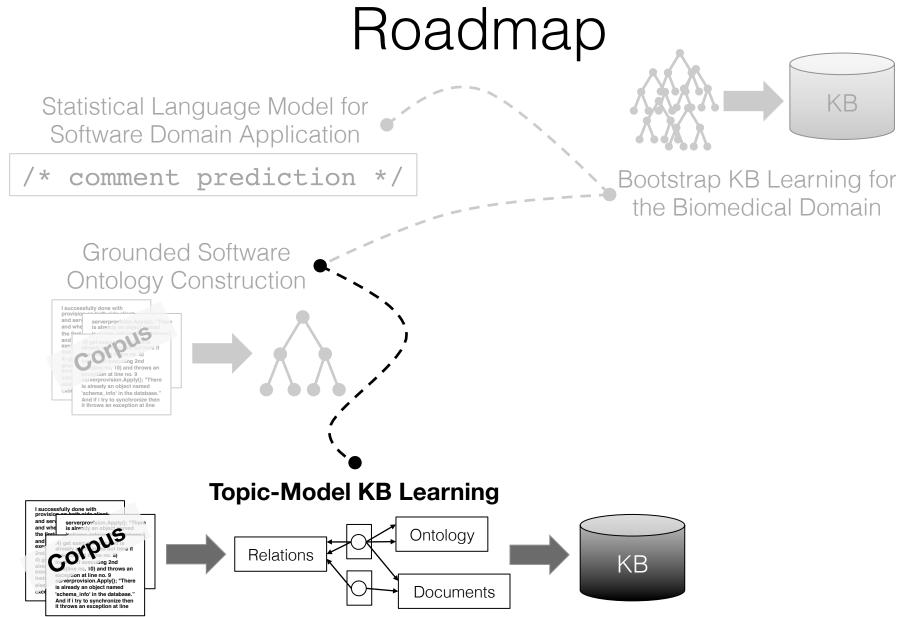
37



Contributions & Lessons

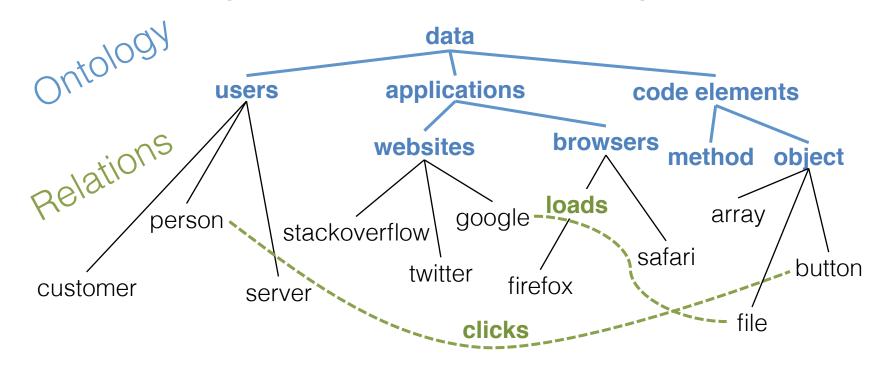
- Linked class entities to code implementation
- Defined distributional similarity for code
- By combining code and text similarities we learned relations (and ontology)
- Advantage: This ontology reflects statistics in language and code
 - In contrast to manually built ontologies
- Grounding to code limits scope of learned ontology to code entities
 - What's missing?

Users
Computer resources
Design patterns

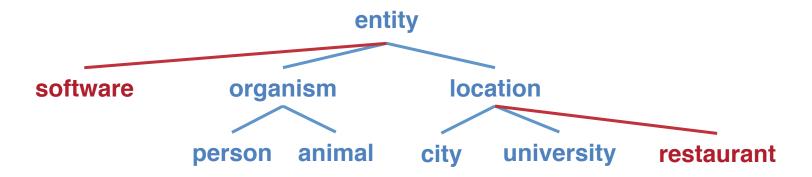


Goal: Corpus-Driven Knowledge Base

- Schema and facts are drawn from corpus
- Unsupervised: learn optimal latent corpus structure together with best-matching facts



Reasoning with Ontologies



- Ontologies give information context
- Easy to extract domainspecific information
- 🕛 Ontologies are
 - expensive
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- U Manual ontology does not reflect language statistics
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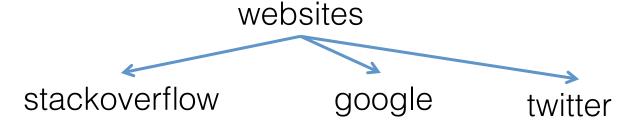
Pattern-based Relation Extraction

1. Hypernym-hyponym

"websites such as stackoverflow"

"websites including google and twitter"

X is a Y
Y including X



2. Subject-Verb-Object

"user clicks button"

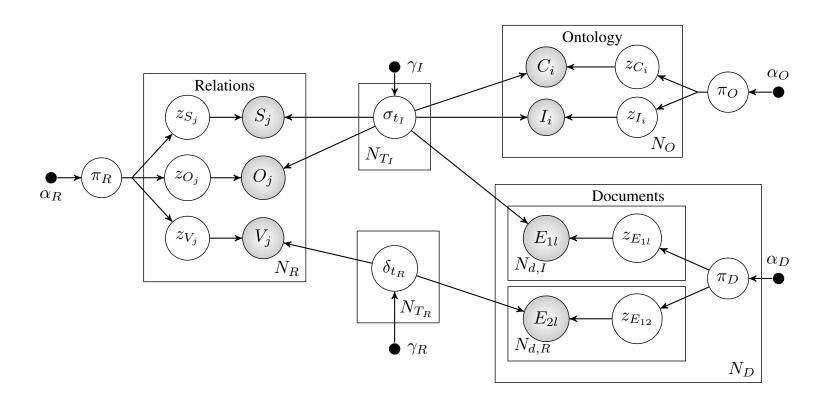
"user clicks form"

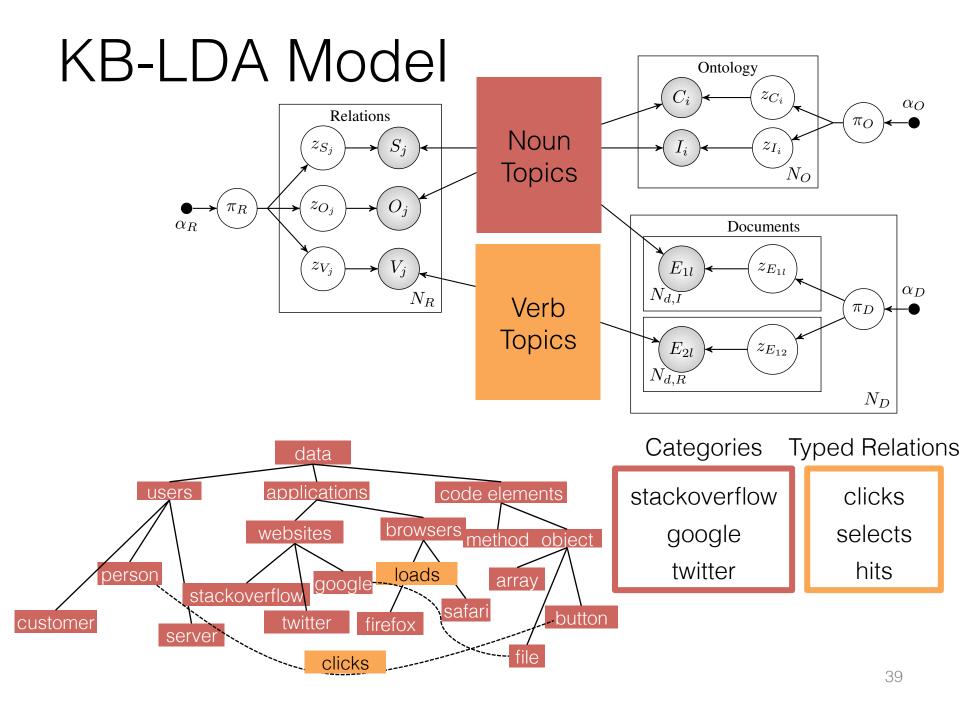
clicks
button

user

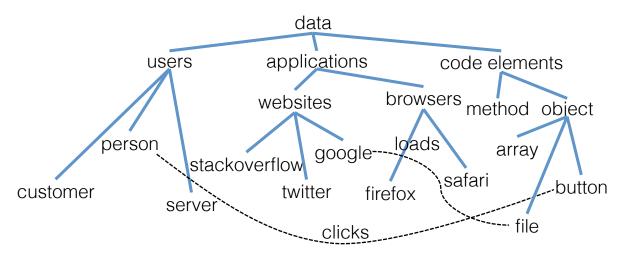
form

KB-LDA Model





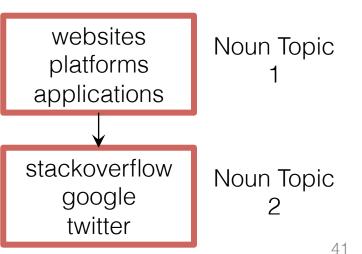
Ontology KB-LDA Model Ontology z_{C_i} γ_I α_O Relations S_{i} σ_{t_I} z_{I_i} N_O N_{T_I} z_{O_j} α_R **Documents** z_{V_j} E_{1l} $z_{E_{1l}}$ α_D $N_{d,I}$ δ_{t_R} N_R π_D N_{T_R} $z_{E_{12}}$ E_{2l} $N_{d,R}$ γ_R N_D

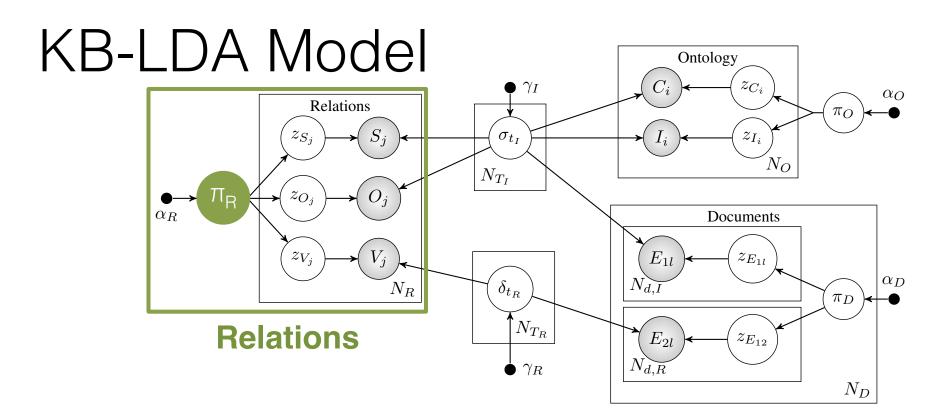


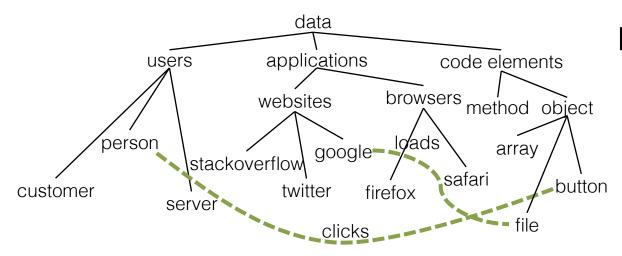
Ontology KB-LDA Model Ontology z_{C_i} γ_I α_O Relations σ_{t_I} S_j z_{I_i} N_O N_{T_I} z_{O_j} **Documents** E_{1l} $z_{E_{1l}}$ α_D N_R δ_{t_R} π_D N_{T_R} $z_{E_{12}}$ E_{2l} $N_{d,R}$ γ_R N_D

Hypernym-hyponym relations:

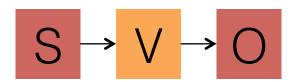
websites → google platforms → stackoverflow







Extracted SVO relation: person, *clicks*, button



KB-LDA Model Ontology z_{C_i} γ_I α_O Relations S_i σ_{t_I} z_{I_i} N_{O} N_{T_I} z_{O_i} α_R **Documents** E_{1l} $z_{E_{1l}}$ α_D $N_{d,I}$ δ_{t_R} N_R π_D N_{T_R} $z_{E_{12}}$ $\widetilde{N_{d,R}}$ γ_R N_D data **Documents** applications users code elements Downloads on websites sometimes have an MD5 browsers method object websites checksum, allowing people to confirm the integrity of the file. I person lo/ads array google--

safari

firefox

-button

file

stackoverflow

server

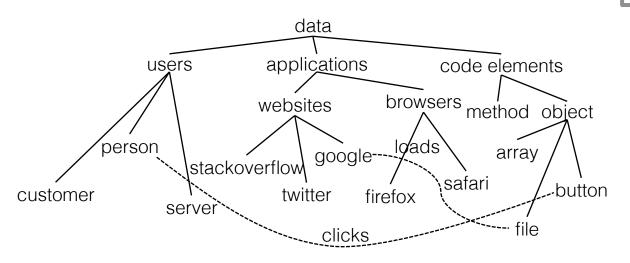
customer

twitter

clicks

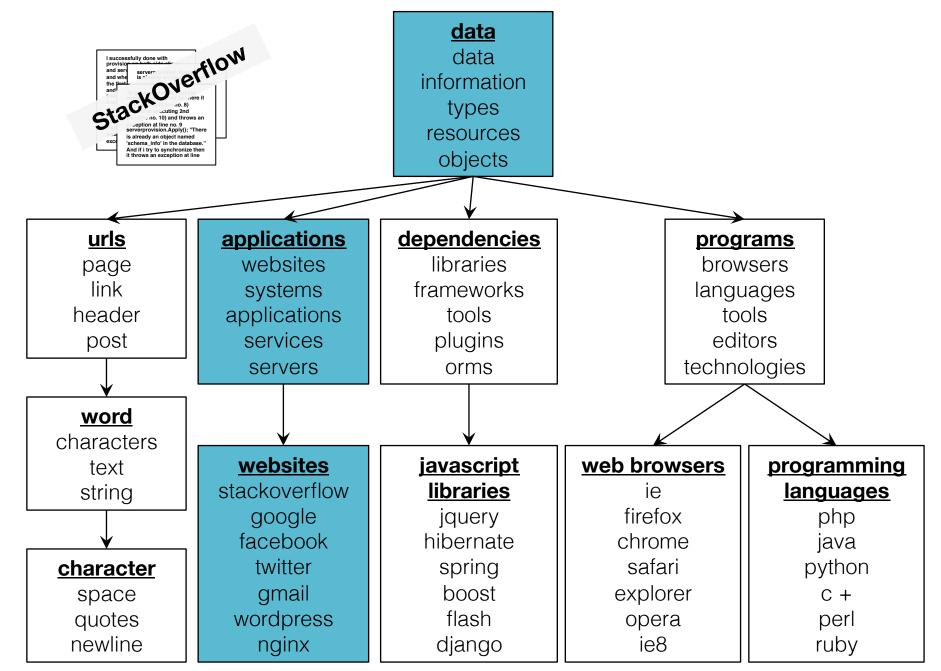
have heard this is to allow not only corrupted files to be instantly identified before they cause a problem but also for for any malicious changes to be easily detected. 43

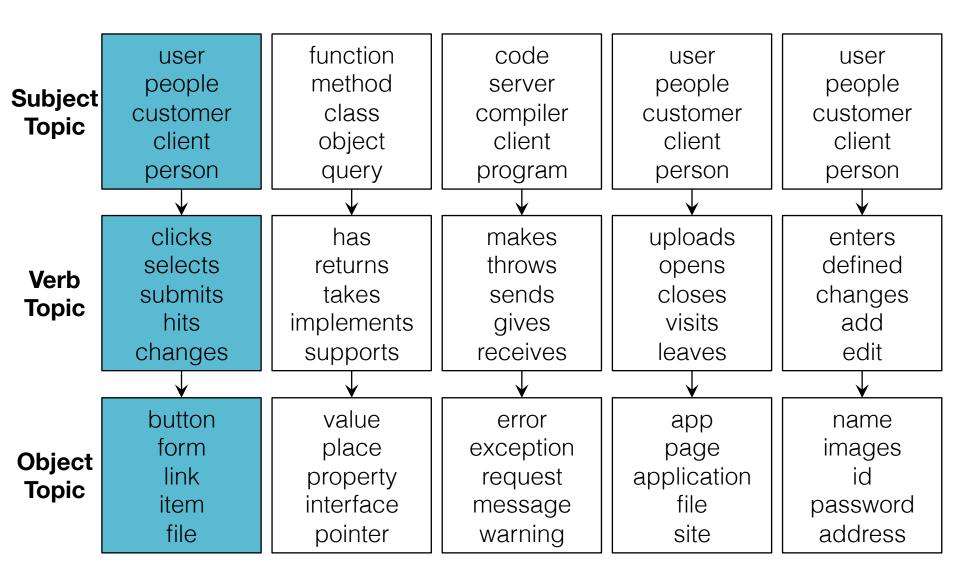
KB-LDA Model Ontology z_{C_i} α_O Relations More in thesis document: Data-driven topic naming α_D N_D



Documents

Downloads on websites sometimes have an MD5 checksum, allowing people to confirm the integrity of the file. I have heard this is to allow not only corrupted files to be instantly identified before they cause a problem but also for for any malicious changes to be easily detected.

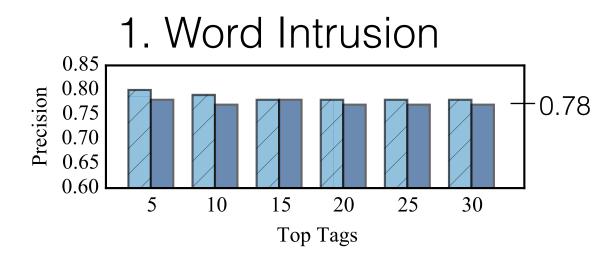


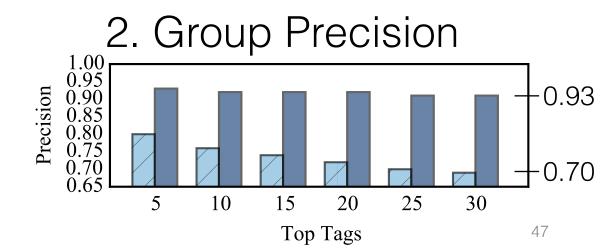


M-Turk Evaluation of Noun Topics

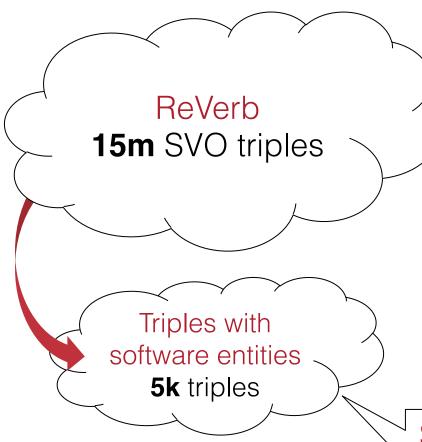
"Which words are **not** related to **programming** languages?"

java
python
javascript
firefox
ruby
perl





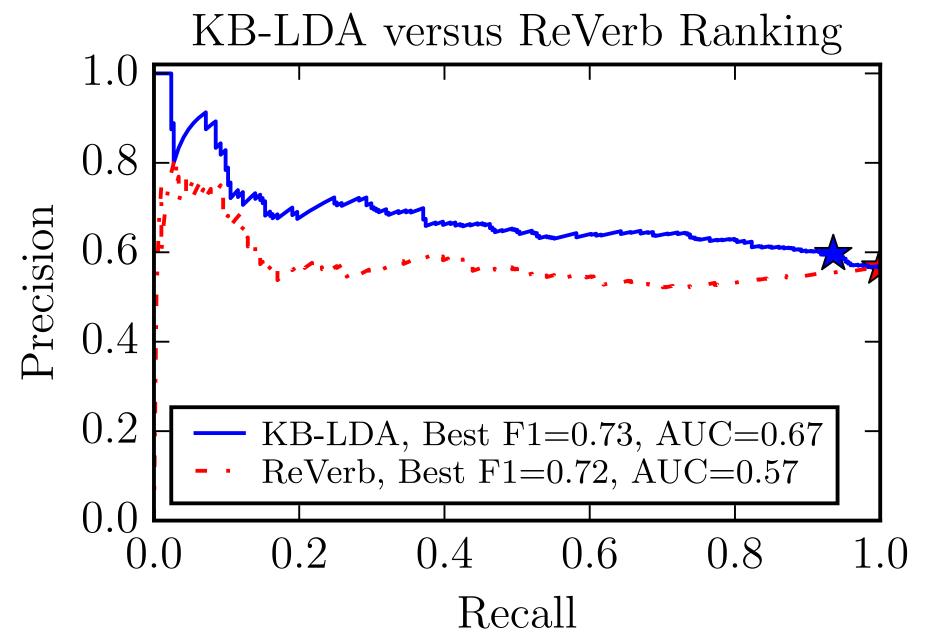
Domain-Specific Extraction from Open IE



- ✓ (safari, supports, svg)
- ✓ (computer, is running, xp)
- ✗ (people, can read, italian)
- ✗ (view, looks, south)

SVOs extracted directly from StackOverflow

37k triples



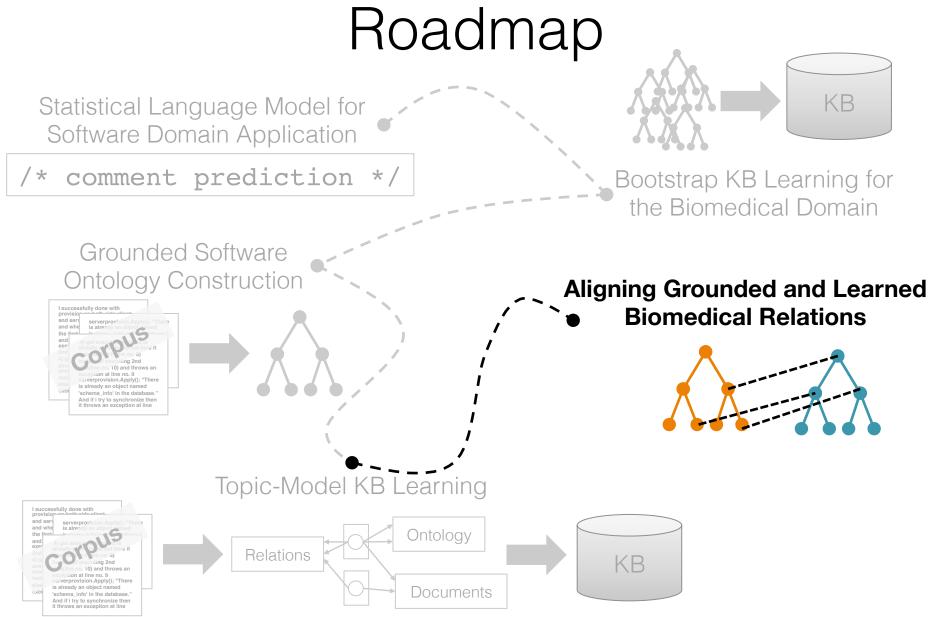
Lessons

KB-LDA Lessons

Corpus-driven KB construction: Jointly optimizes schema and facts

 Unsupervised: Useful for exploration of new domains (Software)

 Can pre-existing domain knowledge improve KB learning? How much? (Biomedical ontologies)



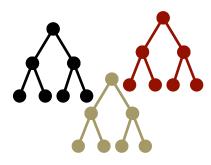
Aligning Grounded and Learned Relations

 Evaluation of KB-LDA relations compared to known relations

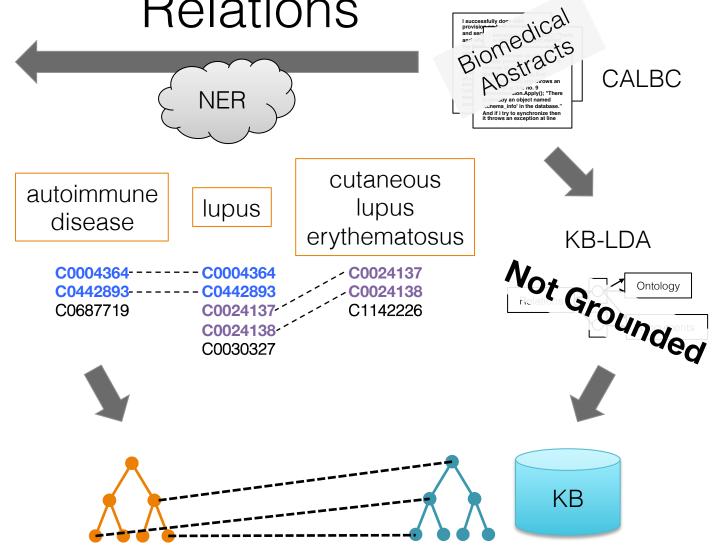
Investigation of the potential of grounding

Aligning Grounded and Learned Relations

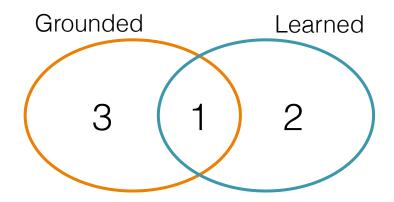
Grounded



- Proteins and Genes (PRGE)
- Chemicals (CHED)
- Diseases and disorders (DISO)
- Living Beings (LIVB)
- Unified Medical Language System (UMLS)
- ...

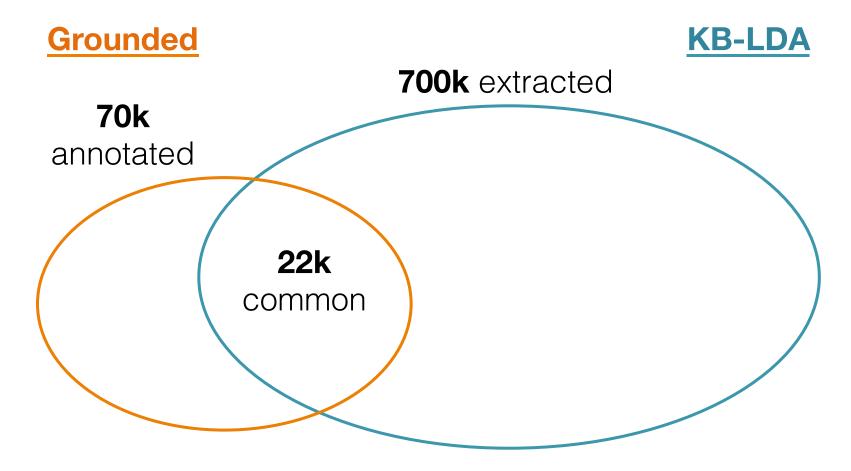


Possible Alignment Outcomes

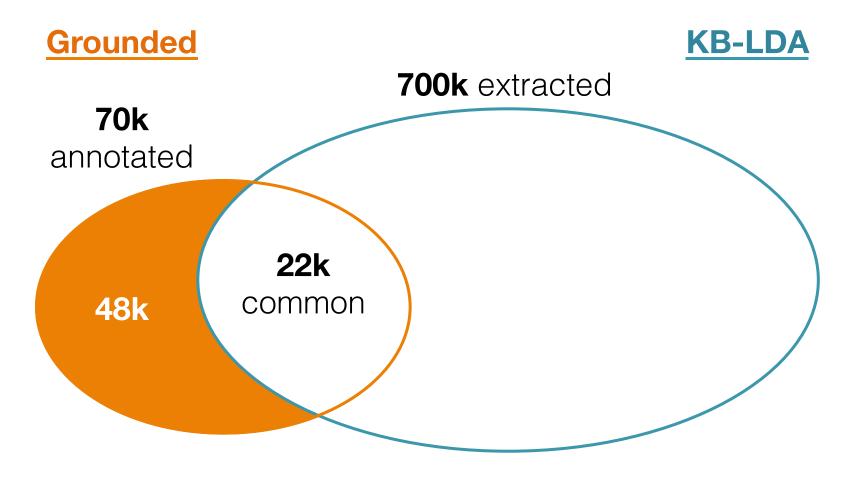


- 1. Does KB-LDA learn existing relations and concepts?
 - Model Validation
- 2. Does KB-LDA discover "new" relations and concepts?
 - Added value of language statistics
- 3. What is missing?
 - Can be added through grounding

Grounded and Learned Entities



Grounded and Learned Entities



Grounded Entities: Manual evaluation of sample

Partial or incorrect parse

35/100

- * bronchial asthma
- pneumoniae
- ✗ beta-1,2-mannotriose

Only in incorrect form **20/35**

Limitation of grounding

Average corpus frequency

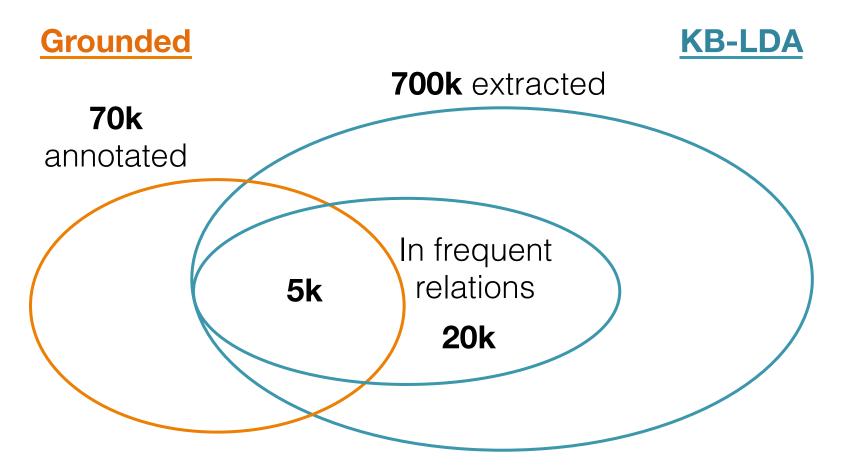
4.87

Frequent entities (f>10)

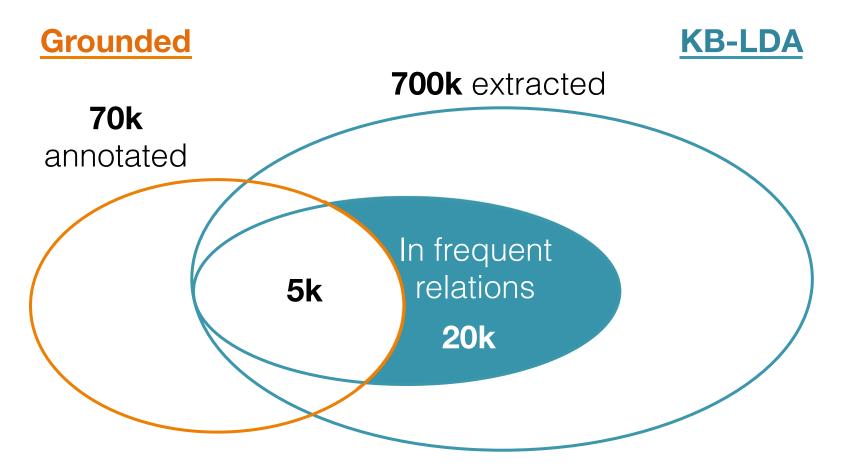
12

Potential advantage of grounding

Grounded and Learned Entities



Grounded and Learned Entities



KB-LDA Entities: Manual evaluation of sample

Correct **97/100**

Added value of language

Parse errors 3/100

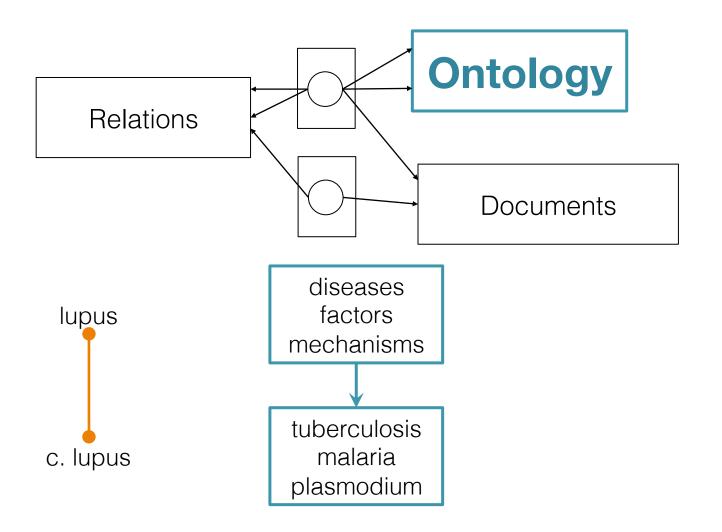
Experimental Terminology **16/100**

- ✓ techniques
- √ samples
- ✓ hapten inhibition experiments
- ✓ sodium dodecyl sulfatepolyacrylamide gel

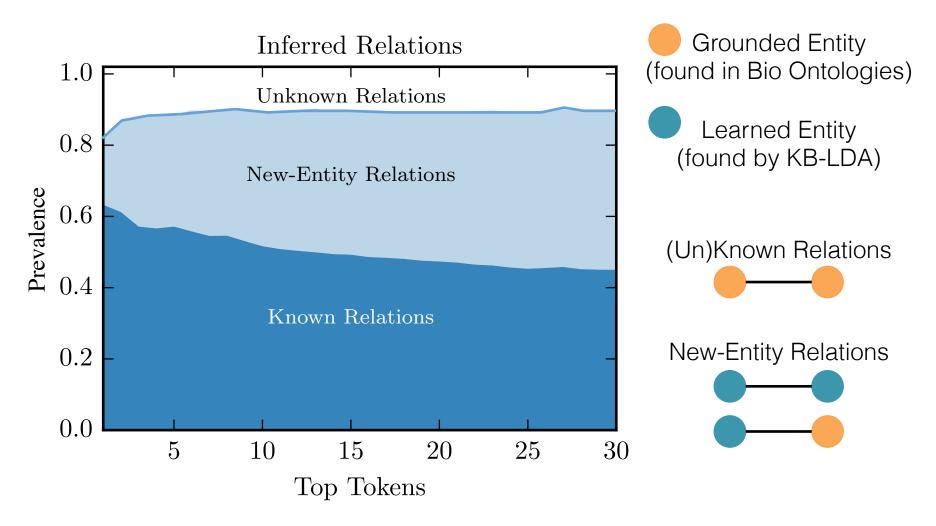
Biological Entities and Processes 81/100

- ✓ linkage
- ✓ leukotoxin
- ✓ chemotactic response
- ✓ plasma cell-associated markers

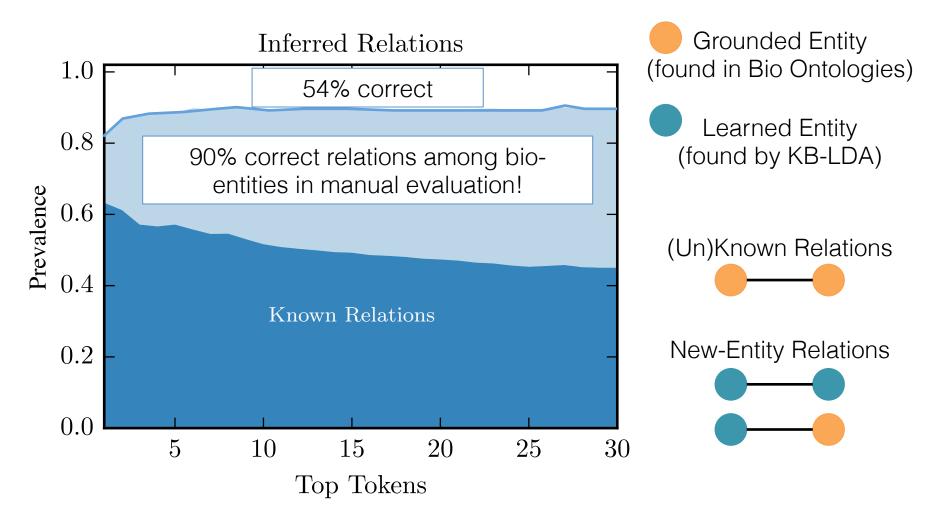
Ontology



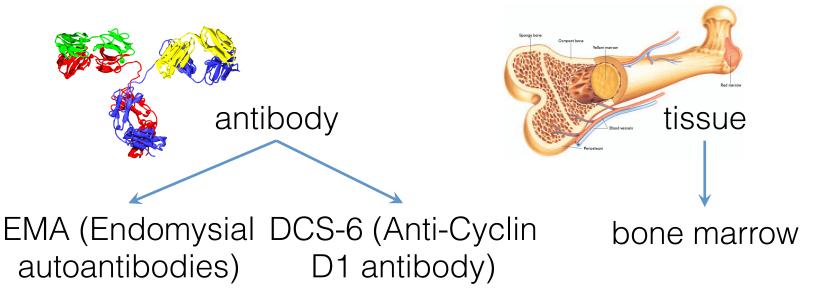
Discovered Ontology Relations

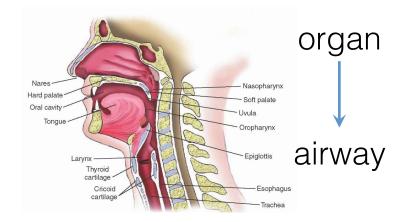


Discovered Ontology Relations

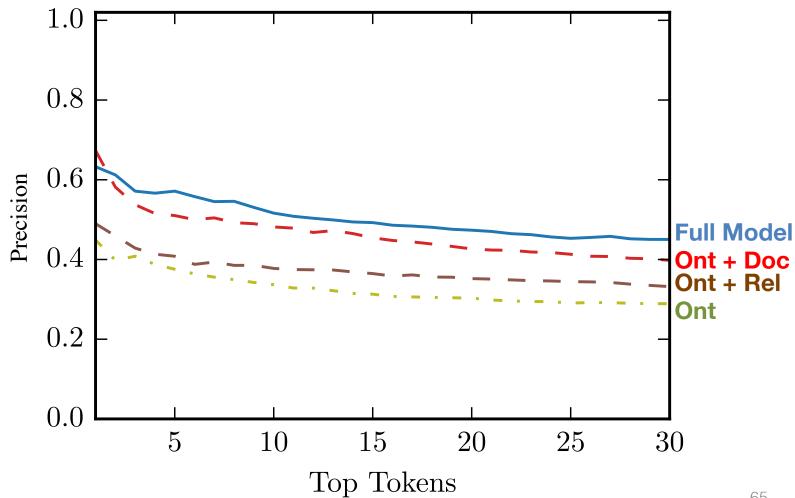


Discovered Ontology Relations

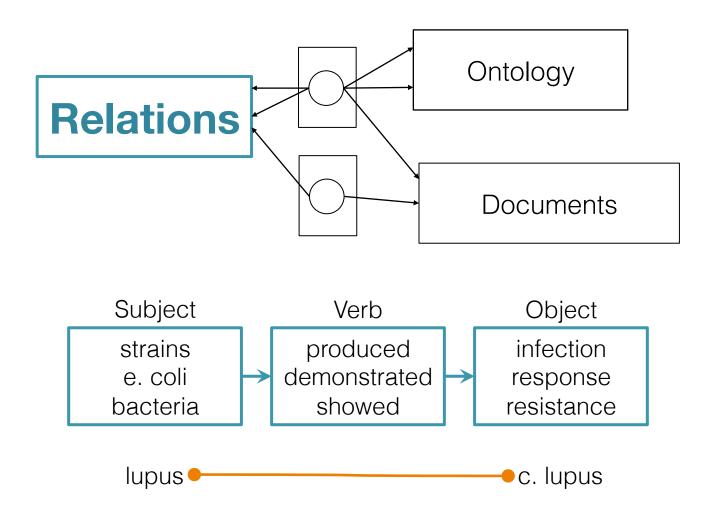




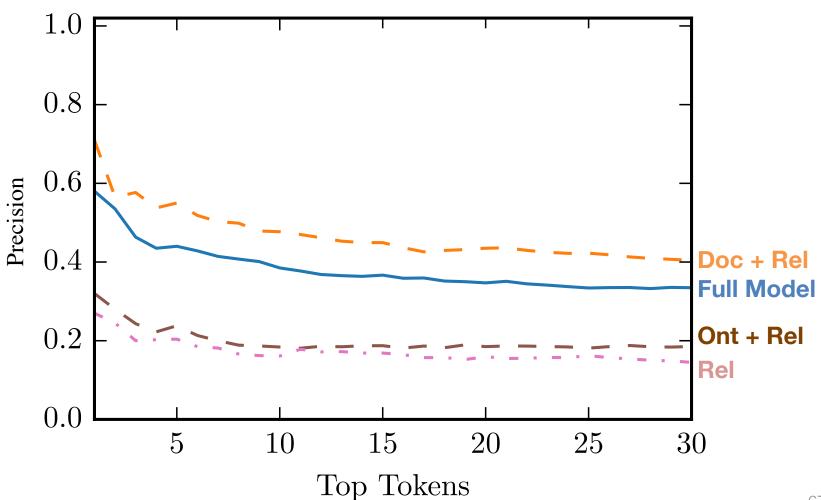
Contribution of Model Components to Learning Ontology



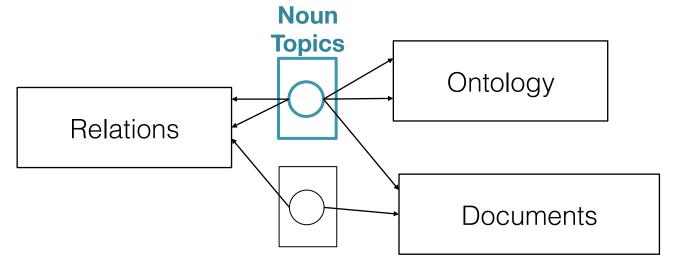
Contribution of Model Components to Learning General Relations

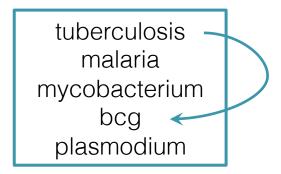


Contribution of Model Components to Learning General Relations

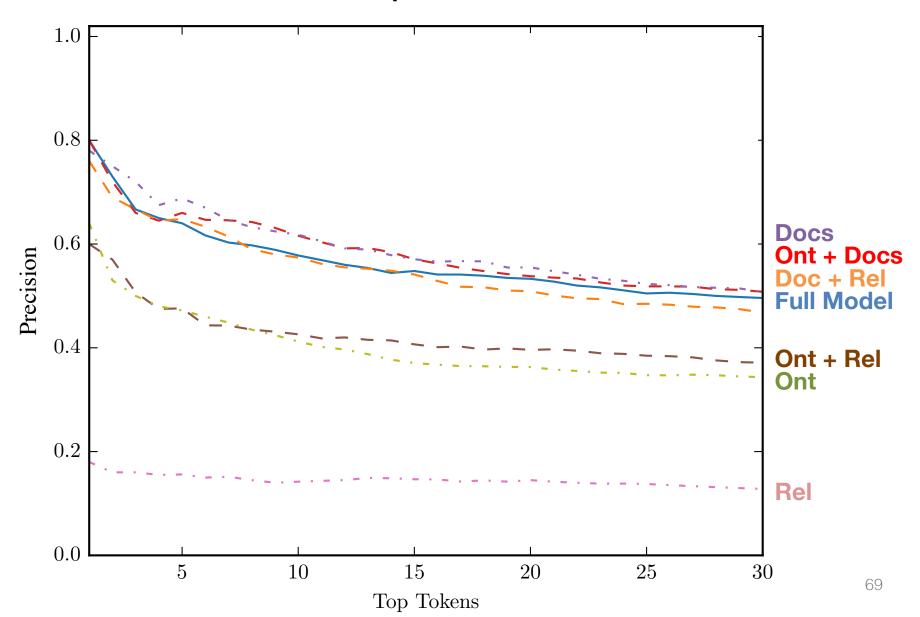


Contribution of Model Components to Learning Intra-Topic Relations



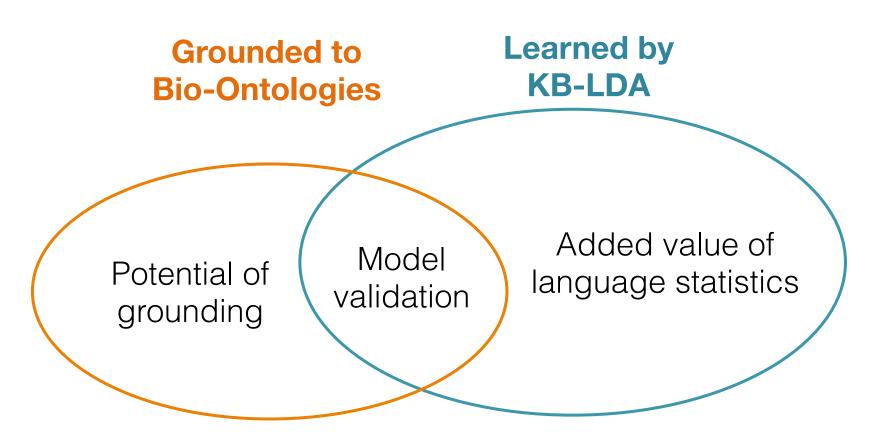


Intra-Topic Relations



Lessons

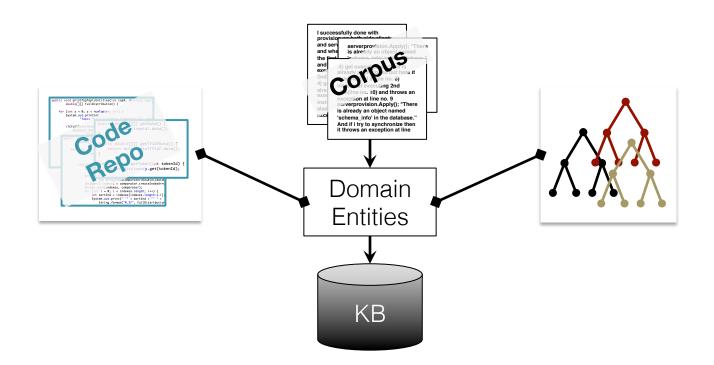
Lessons



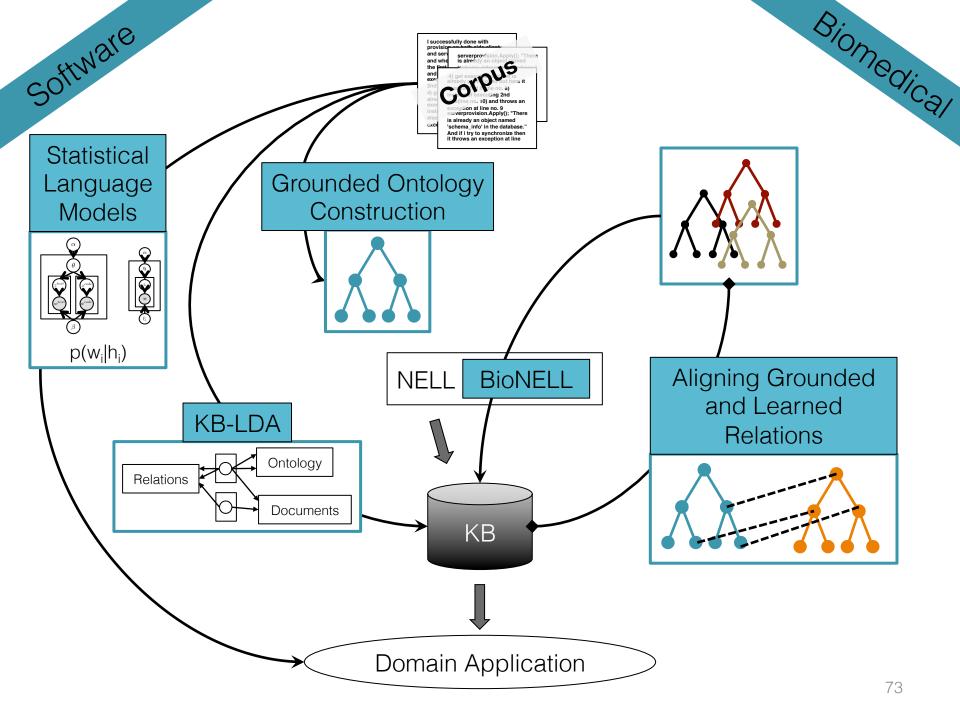
Roadmap KB Statistical Language Model for Software Domain Application comment prediction Bootstrap KB Learning for the Biomedical Domain Grounded Software **Ontology Construction** Aligning Grounded and Learned successfully done with Biomedical Relations And if I try to synchronize then it throws an exception at line Topic-Model KB Learning I successfully done with Ontology Relations KB Documents schema info' in the database Conclusion And if i try to synchronize then it throws an exception at line

Software

Key Idea



"Grounding entities to specialized data from a scientific domain facilitates improved unsupervised and semi-supervised algorithms for Knowledge Base construction for that domain"



What's Next?

Learned Coordinate Terms Coordinate Terms Grounded CT_{1k} Knowledge Base α_{CT} z_{CT_k} π_{CT} Learning N_{T_I} CT_{2k} **Tables** N_{CT} **Tables** N_{T_I} N_T

Revisit application improvement using learned KBs

