Toward a Reading Machine

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Why a Reading Machine?

- The majority of human knowledge is encoded in text
- Much of this text is available in machine-readable formats
- Finding machine operable representations of texts opens the door to the automatic manipulation of vast amounts of knowledge
- There is a big industry awaiting this event.

The goal of Machine Reading

- To build a machine that transforms texts into representations
  - that enable inference and reasoning
- Development of appropriate evaluation methodologies

The goal of Machine Reading

- This goal is not new
  - It is an old dream
- If we failed in the past, why this dream deserves new attention?
- There are two main reasons:

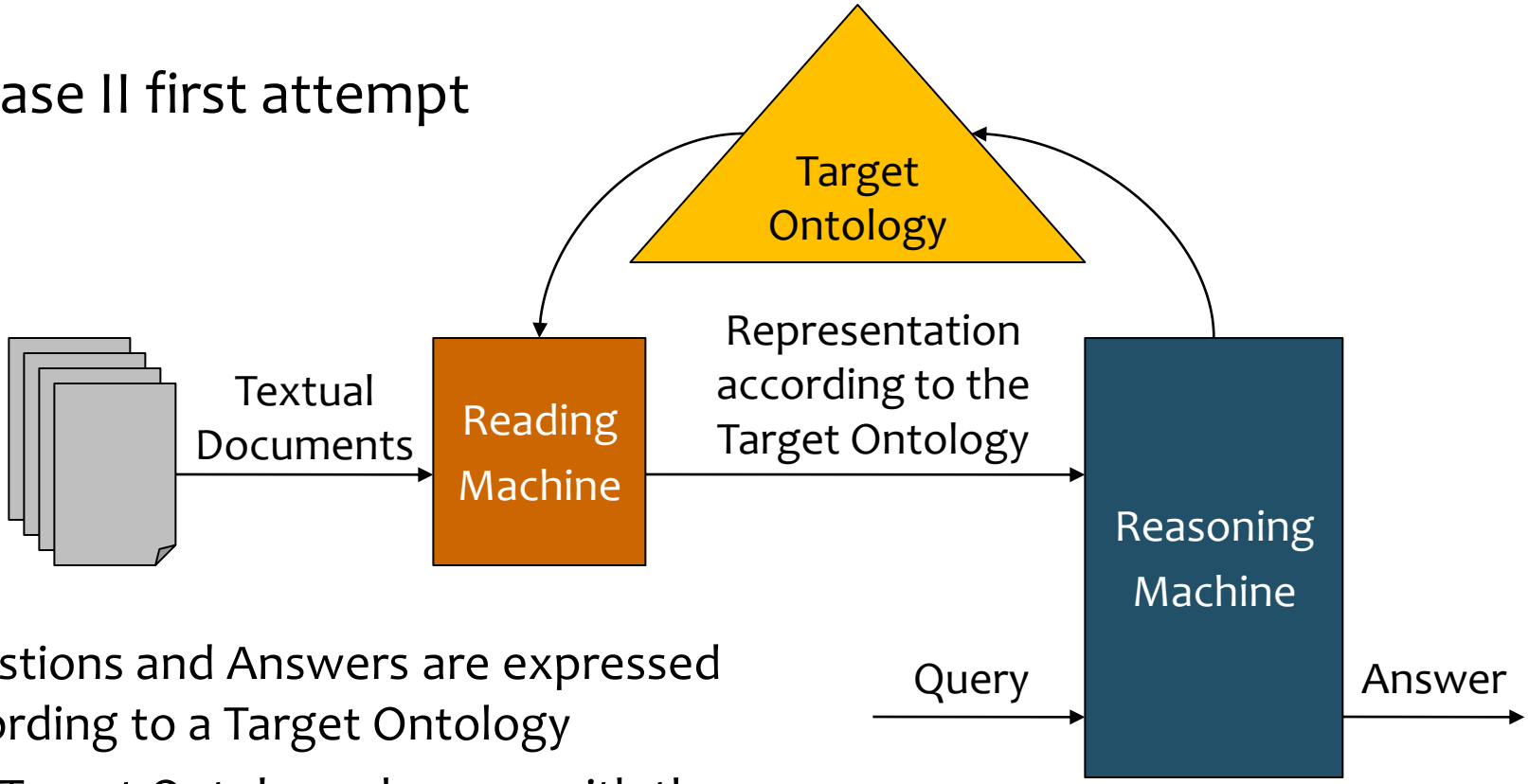
Why now?

1. A change in the paradigms of Computational Semantics
   - Conceptualizing content is not in the form of symbols
   - but in the form of statistical distributions

2. The power to capture the huge amount of background knowledge
   - needed to read a single document

Machine Reading Program

Phase II first attempt



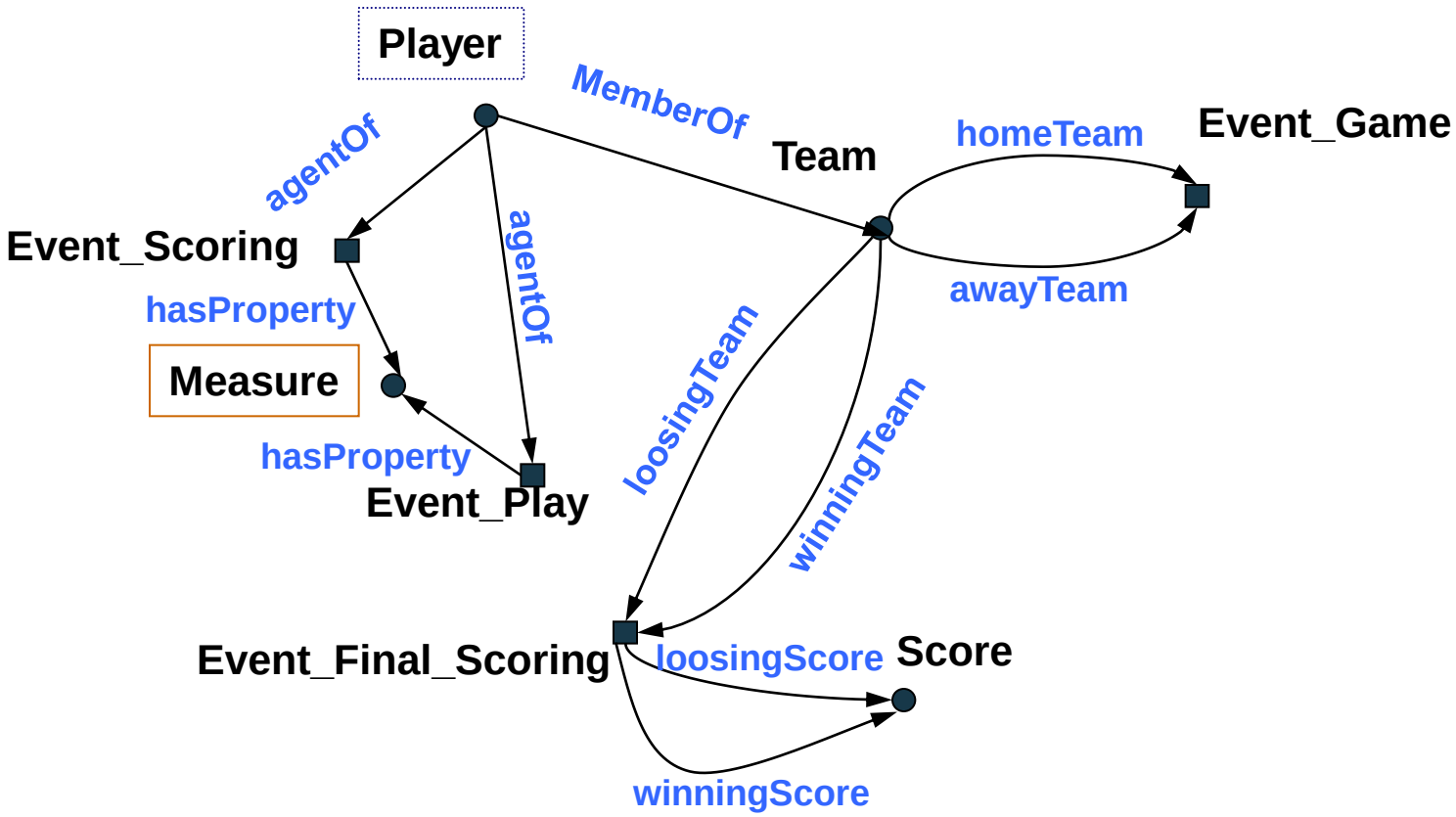
- Questions and Answers are expressed according to a Target Ontology
- The Target Ontology changes with the domain
- Ideally, is an input to the MR system

Query in a Target Ontology

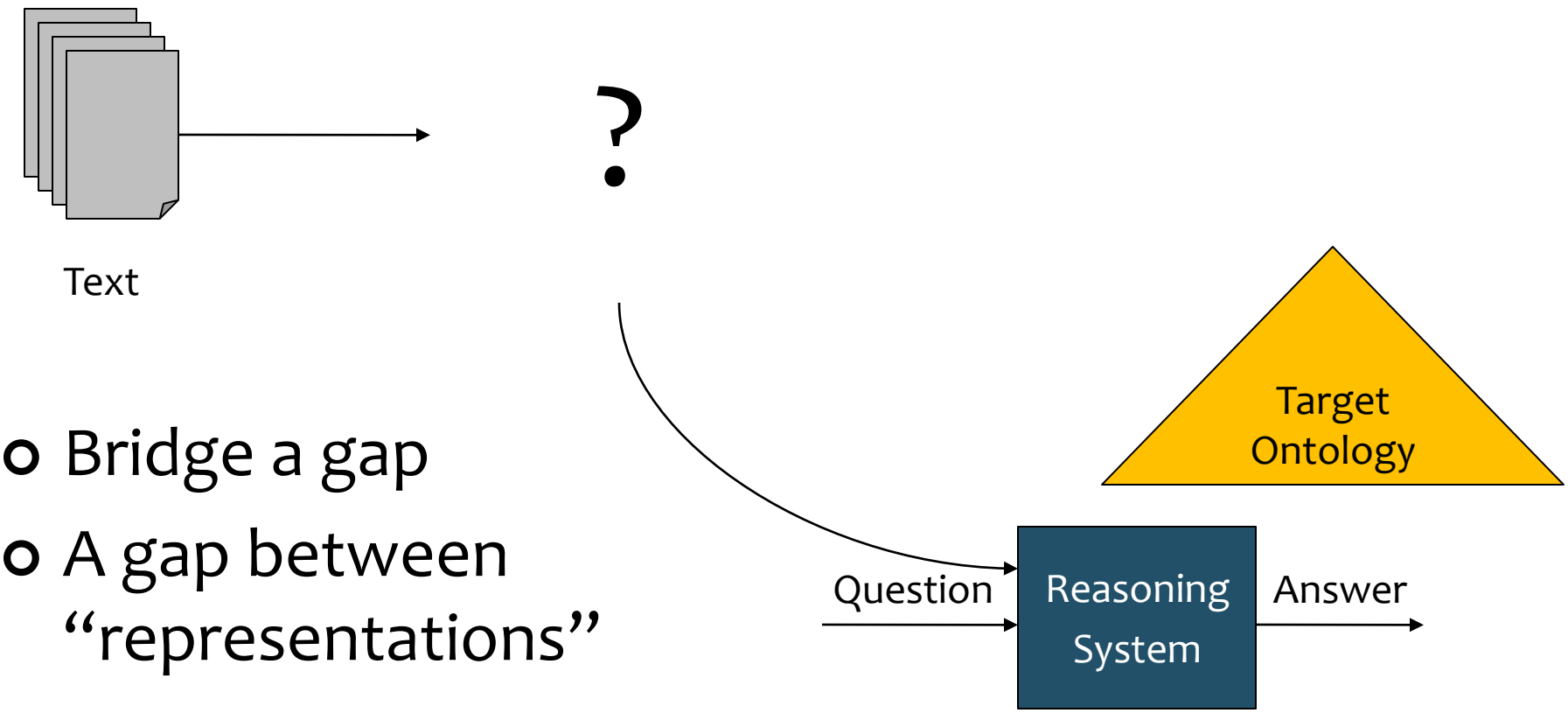
Query 20011: **Who killed less than 35 people in Kashmir?**

```
:-  'HumanAgent'(FileName, V_y),
    killingHumanAgent(FileName, V_x, V_y),

    'HumanAgentKillingAPerson'(FileName, V_x),

    personGroupKilled(FileName, V_x, V_group),
    'PersonGroup'(FileName, V_group),
    'Count'(FileName, V_count),
    value(FileName, V_count, 35),
    numberOfMembersUpperBound(FileName, V_group, V_count),

    eventLocationGPE(FileName, V_x, 'Kashmir').
```

Representation for reasoning



Machine Reading

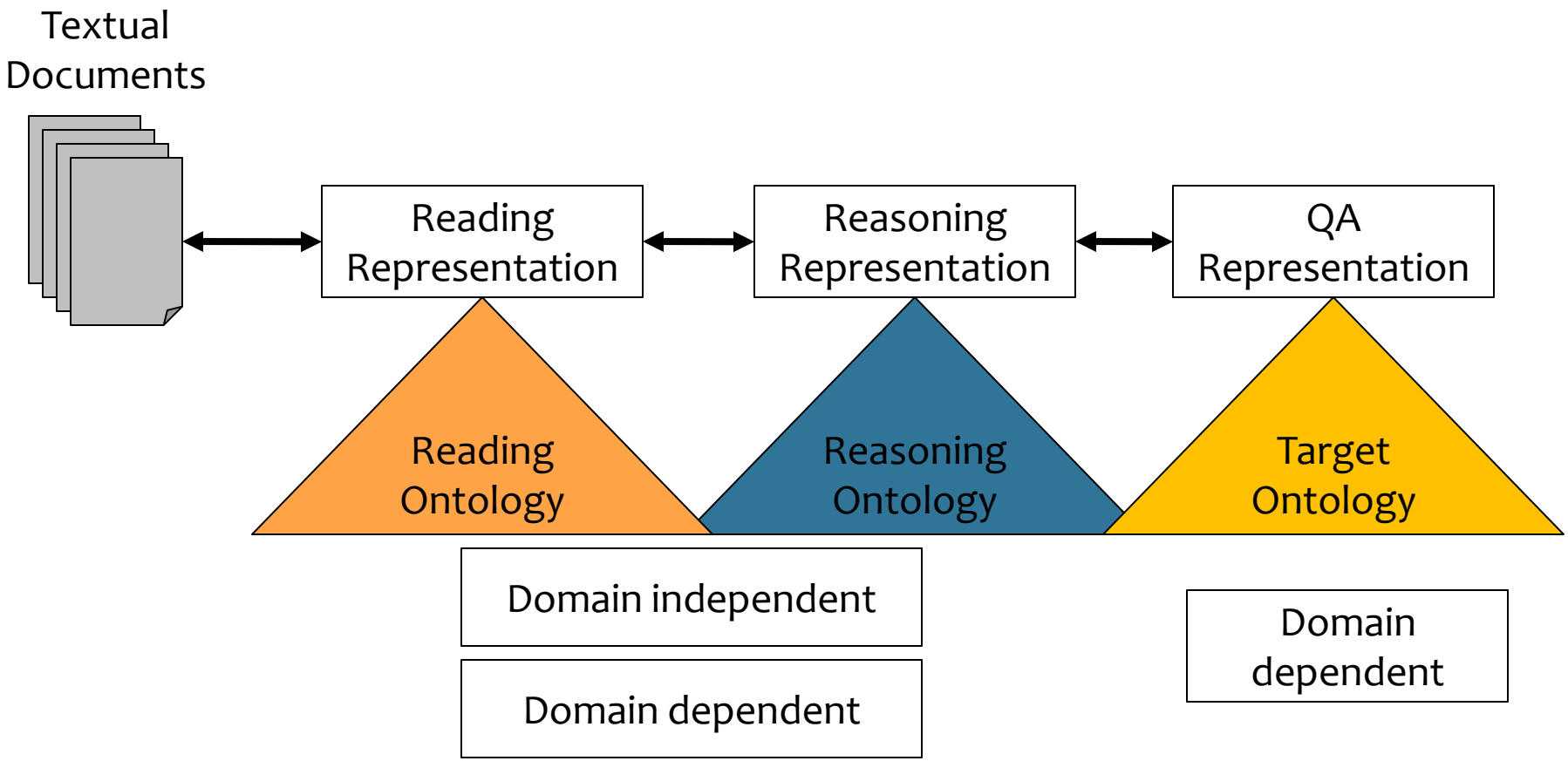


- Bridge a gap
- A gap between "representations"

Representation gap

- **Target Ontology** is oriented to express the QA language
- An extension is needed to enable reasoning: **Reasoning Ontology**
- Both are far from text
- We will several intermediate representations
- And a mapping between them

Mapping between representations



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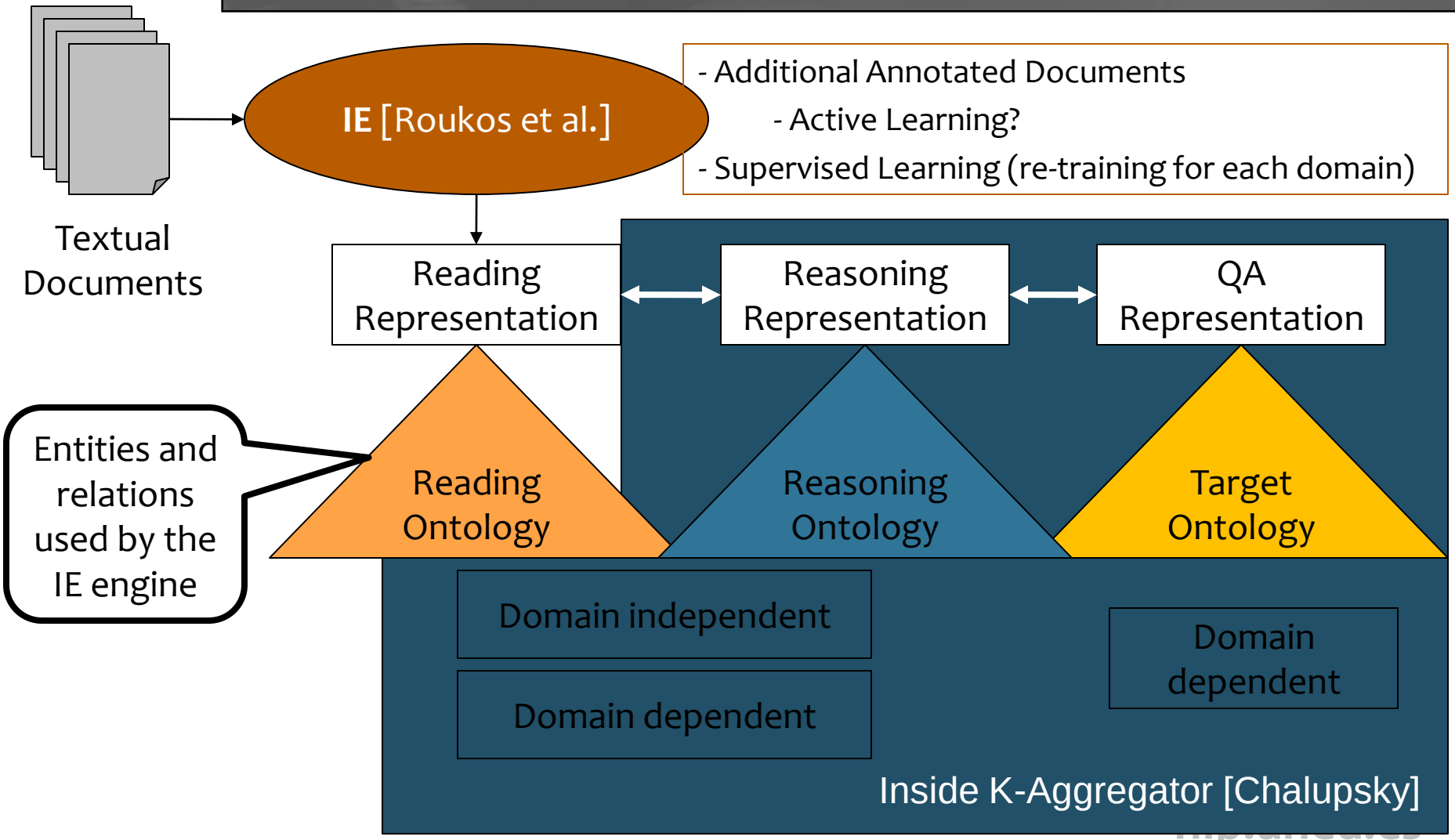
RACR NFL v.1



Not good enough

- Conjunctive queries
- Performance is product of IE performance for each entity and relation in the query

IE F1	Entities and relations in the query
0.9	'HumanAgent'(FileName, V_y),
0.8	killingHumanAgent(FileName, V_x, V_y),
0.9	'HumanAgentKillingAPerson'(FileName, V_x),
0.8	personGroupKilled(FileName, V_x, V_group),
0.9	'PersonGroup'(FileName, V_group), 'Count'(FileName, V_count), value(FileName, V_count, 35), numberOfMembersUpperBound(FileName, V_group, V_count),
0.9	eventLocationGPE(FileName, V_x, 'Kashmir').
0.42	**Upper bound Performance**

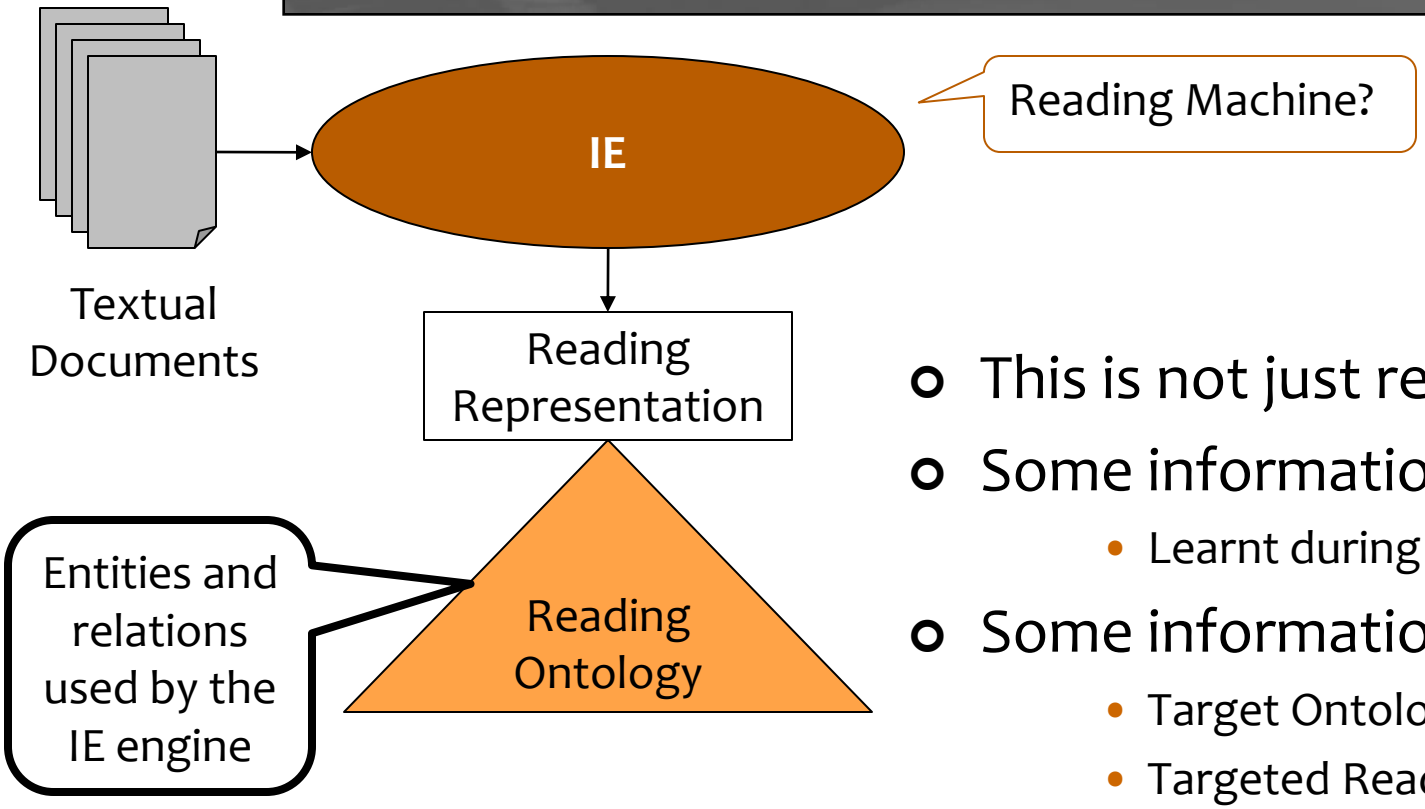
- Will the Reasoning Machine recover from that?

A challenge

- Complex queries
- Almost no training data
- Several different domains
- …
- Many big research questions:
  - System architecture, Background Knowledge acquisition, Inference, Representation, …

Reading Machine

IE approach



- This is not just representation
- Some information is added
  - Learnt during IE training
- Some information is lost
  - Target Ontology
  - Targeted Reading

ISI Reading Machine

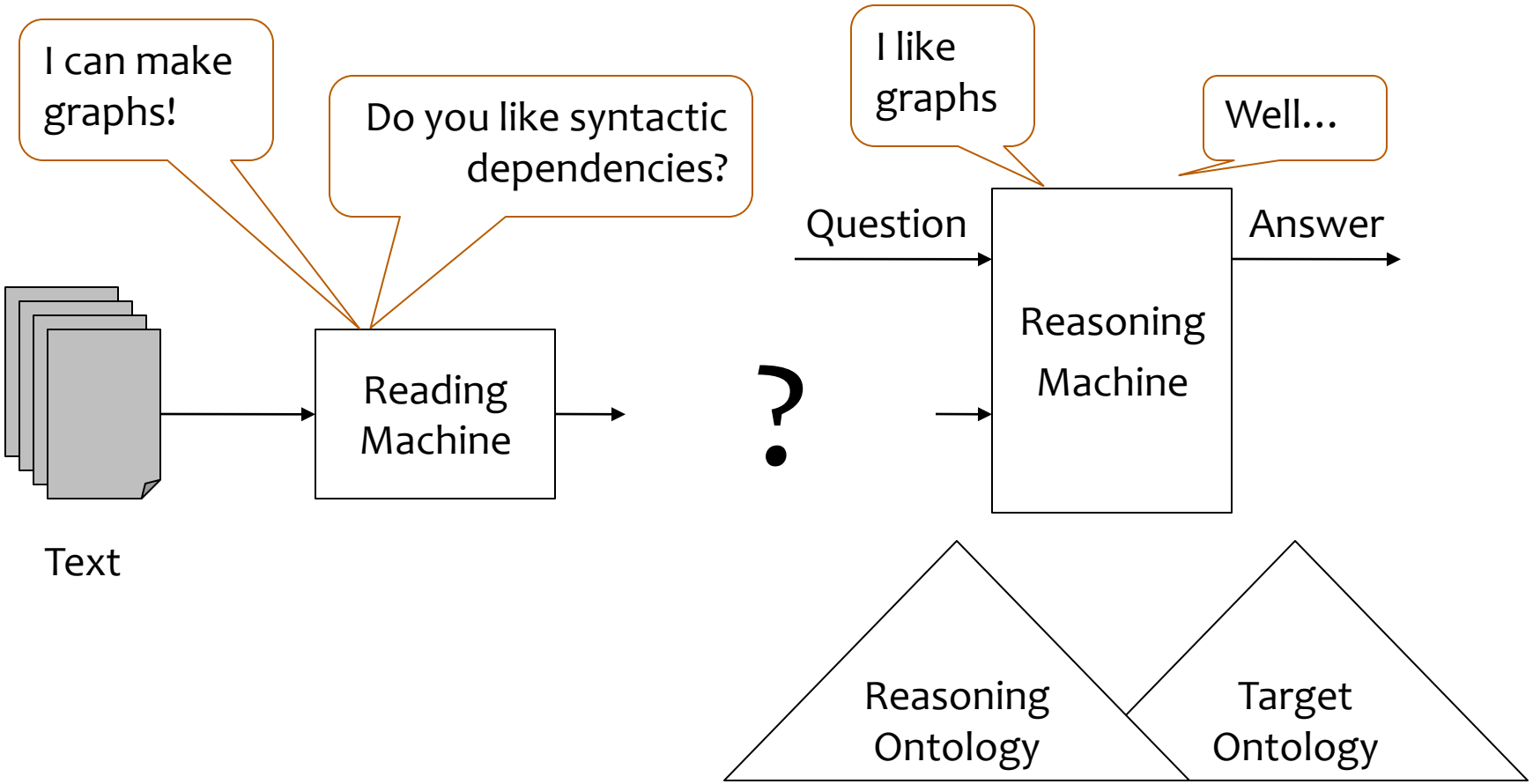
- We need
  - Reading representation
  - Add information
    - Enrichment: Fill the gaps with Background Knowledge
    - Acquire the Background Knowledge from previous readings
  - Targeted reading
    - Closer and closer to the reasoning representation

Bridging the gap

- Reasoning with representations closer to the text

- Representations of text closer to the Reasoning Ontology
- Adding the information needed for reasoning

Representation



Representation

- Can we represent Jerry's Logic Forms as graphs?
- How far would they be from typed syntactic dependencies?
- Can we take advantage of other theories such as Mel'čuk's Meaning Text Theory?
- Can we have a representation of the whole document instead sentence by sentence?

- Just pictures…

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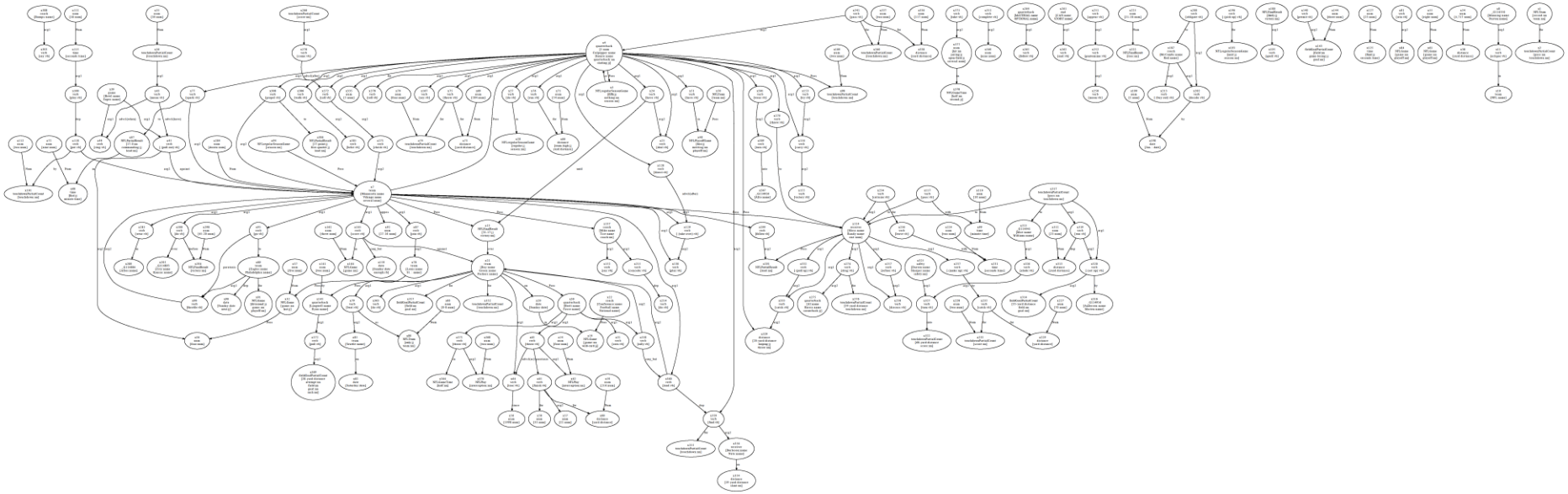
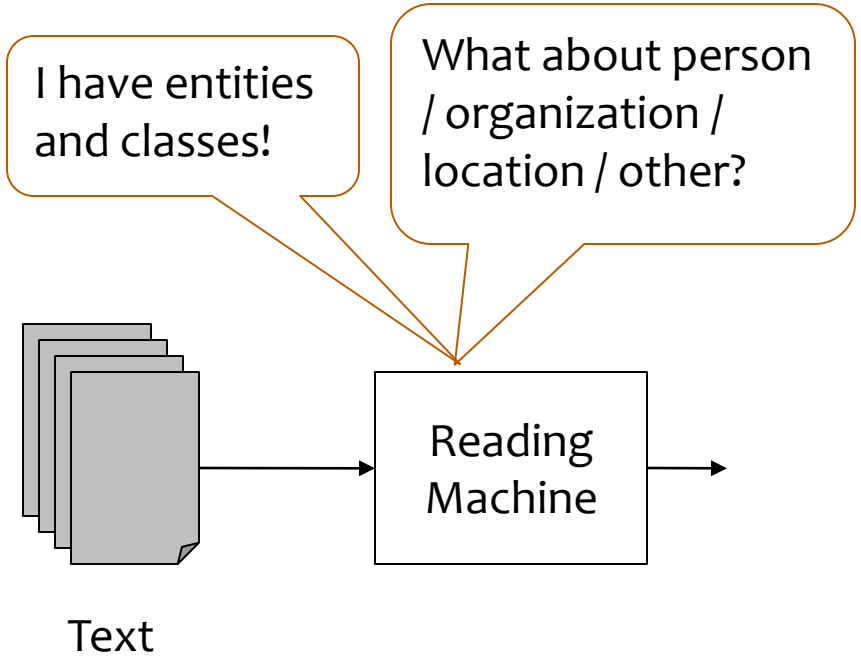
Semantic Dependency Graphs

Let’s call it Semantic Dependency Graph

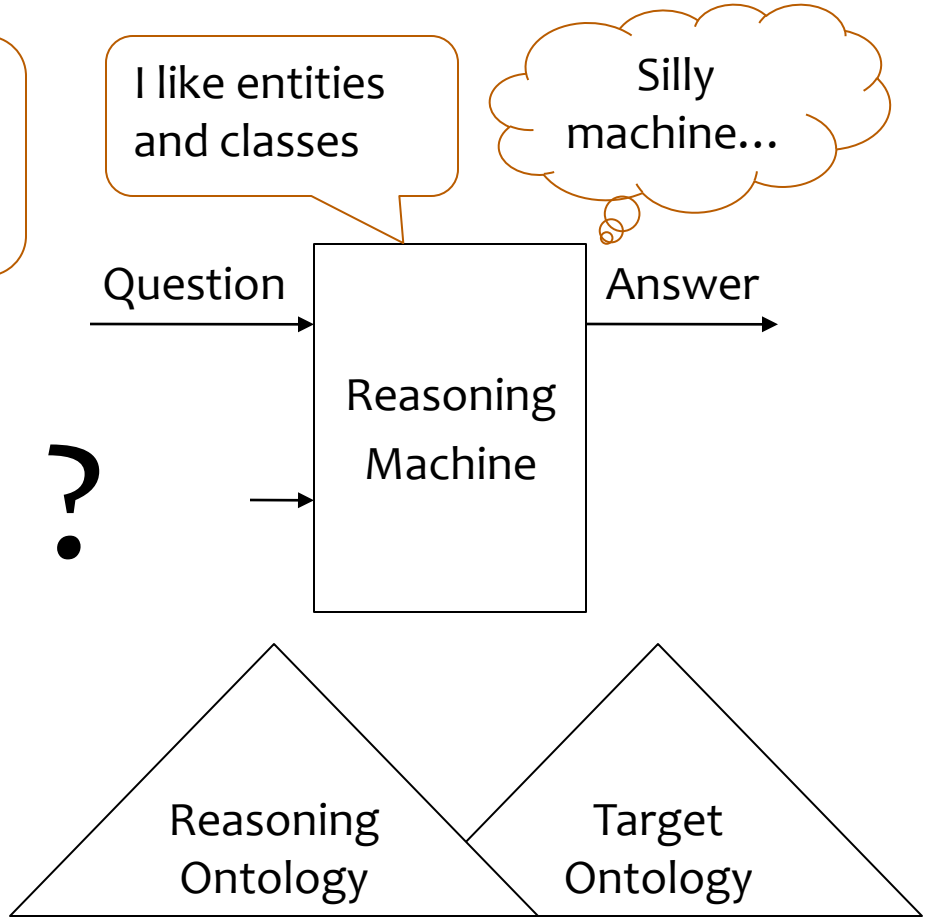


[Research question #1]

What else?


I have entities and classes!
What about person / organization / location / other?
Reading Machine
Text

?


I like entities and classes
Silly machine…
Question
Answer
Reasoning Machine
Reasoning Ontology
Target Ontology

Classes

Easy ones

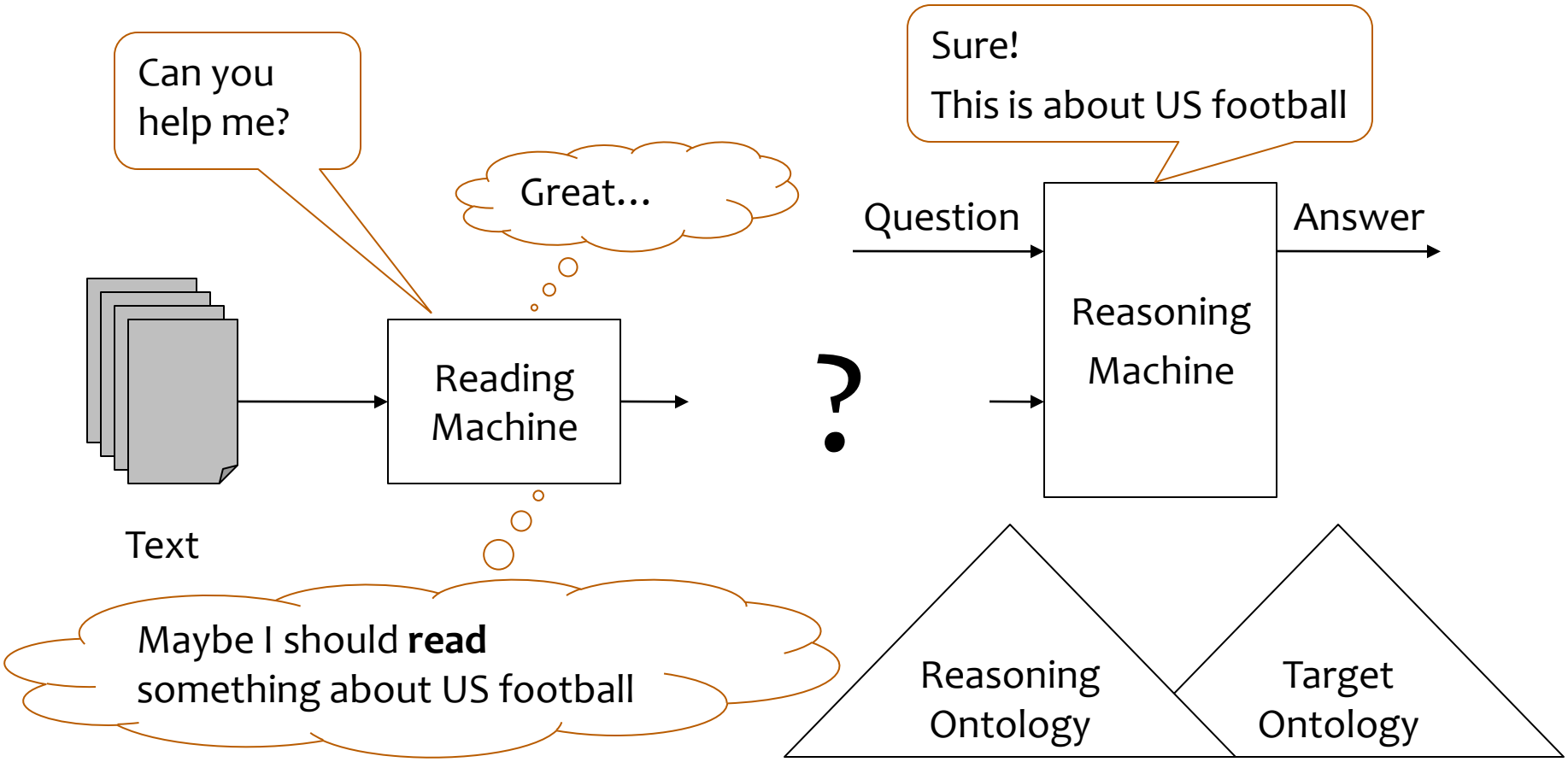
- Entity
  - Named
    - Person
    - Organization
    - Location
    - Other
  - Date
  - Time
  - Measure
    - Distance
    - Weight
    - Height
    - Other
  - …

Not easy ones

- The rest of words
- (almost)

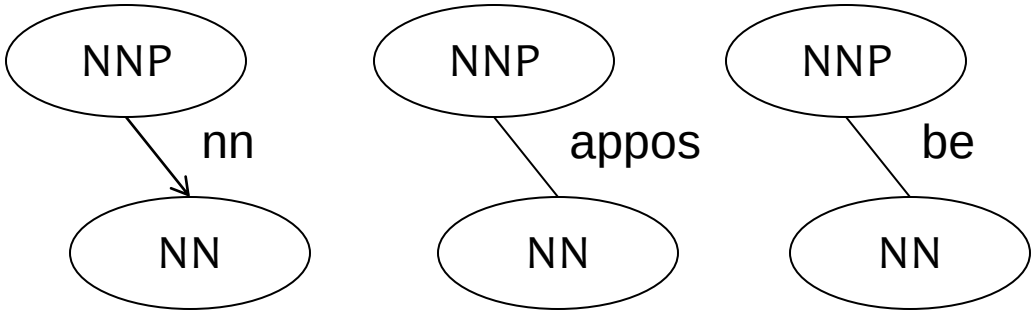
- Skip all philosophical argue

Classes


Can you help me?
Great…
Sure!
This is about US football
Question
Answer
Reading Machine
Reasoning Machine
?
Text
Maybe I should **read** something about US football
Reasoning Ontology
Target Ontology

Classes from text

- Do texts point out classes? Of course
- What classes? The relevant classes for reading
- Uhm… this could be interesting…
- Just small experiment:
  - Parse 30,000 docs. about US football
  - Look for these dependencies



Most frequent has-instance

334:has_instance:[quarterback:n, ('Kerry':'Collins'):name].

306:has_instance:[end:n, ('Michael':'Strahan'):name].

192:has_instance:[team:n, 'Giants':name].

178:has_instance:[owner:n, ('Jerry':'Jones'):name].

151:has_instance:[linebacker:n, ('Jessie':'Armstead'):name].

145:has_instance:[coach:n, ('Bill':'Parcells'):name].

139:has_instance:[receiver:n, ('Amani':'Toomer'):name].

…

Most frequent classes

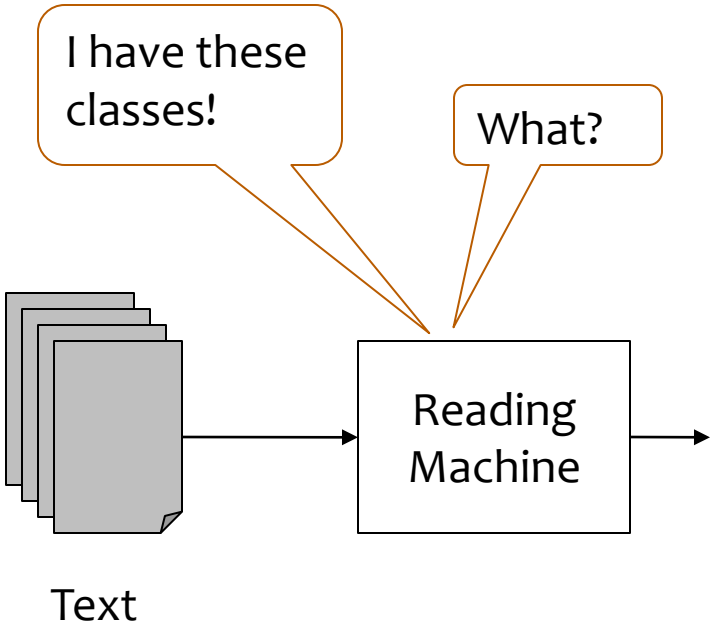
15457 quarterback
12395 coach
7865 end
7611 receiver
6794 linebacker
4348 team
4153 coordinator
4127 player
4000 president
3862 safety
3722 cornerback
3479 (wide:receiver)
3344 (defensive:end)
3265 director
3252 owner
2870 (tight:end)
2780 agent
2291 guard
2258 pick
2177 manager
2138 (head:coach)
2082 rookie
2039 back
1985 (defensive:coordinator)
1882 lineman
1836 (offensive:coordinator)
1832 tackle
1799 center
1776 (general:manager)
1425 fullback
1366 (vice:president)
1196 backup
1193 game
1140 choice
1102 starter
1100 spokesman
1083 (free:agent)
1006 champion
990 man
989 son
987 tailback
...

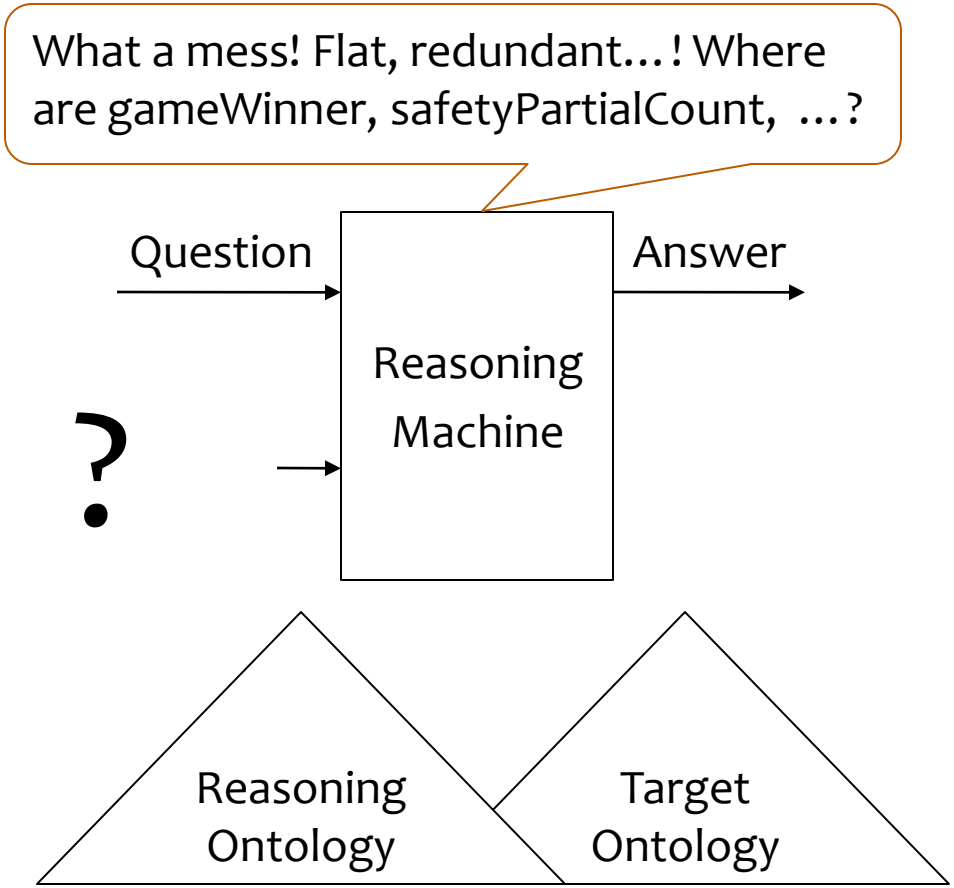
Classes from text

- Find more ways to point out a class in text?
  - Now you have thousands of seeds
  - Bootstrap!

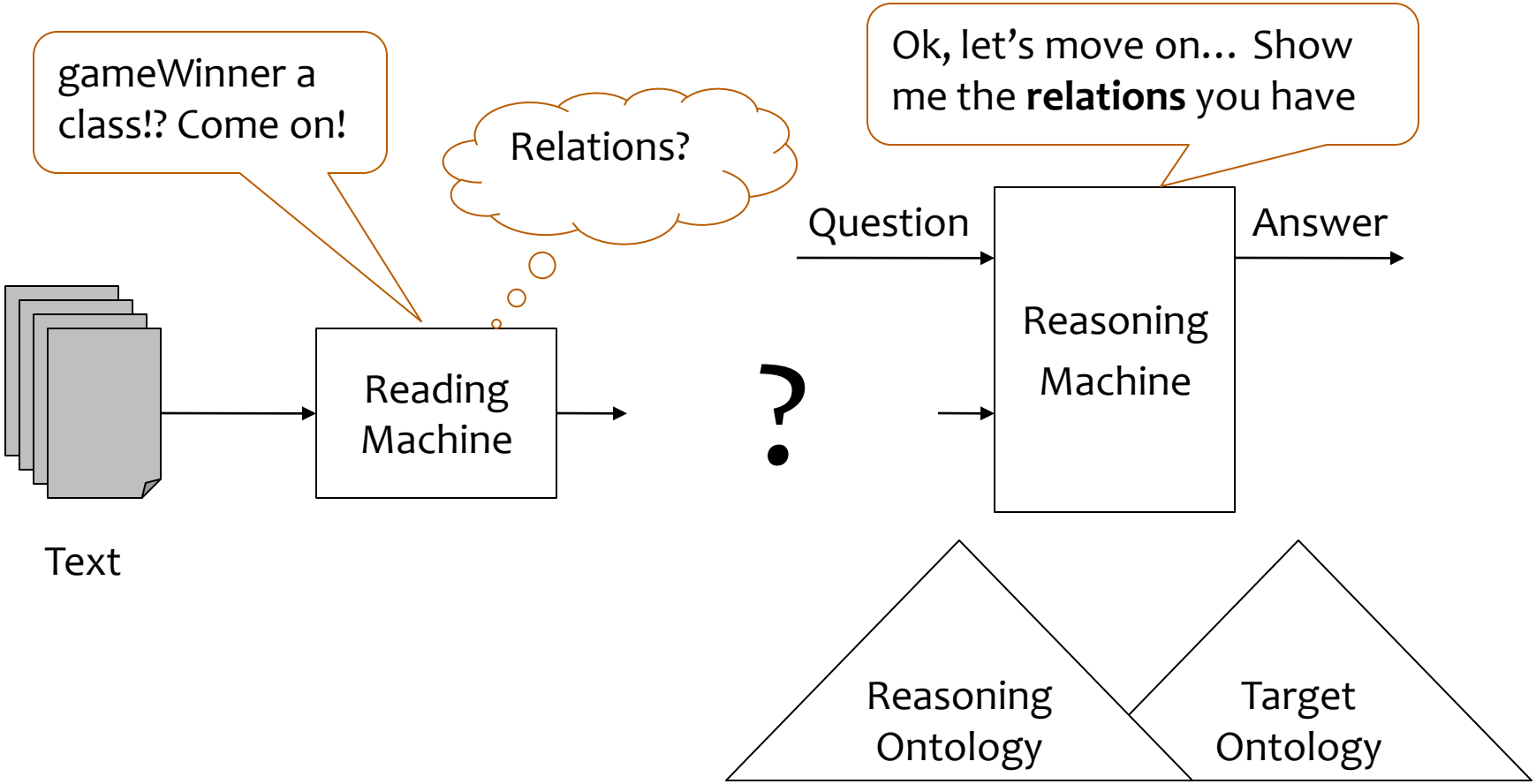
[Research question #2]

Classes


I have these classes!
What?
Reading Machine
Text

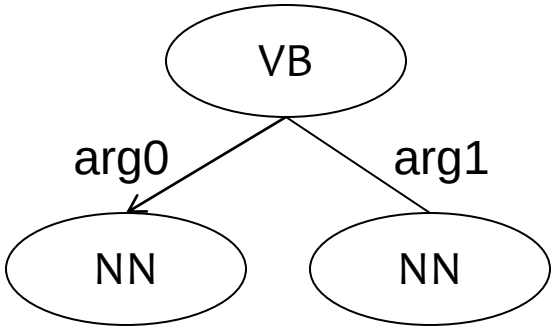

What a mess! Flat, redundant…! Where are gameWinner, safetyPartialCount, …?
Question
Answer
Reasoning Machine
?
Reasoning Ontology
Target Ontology

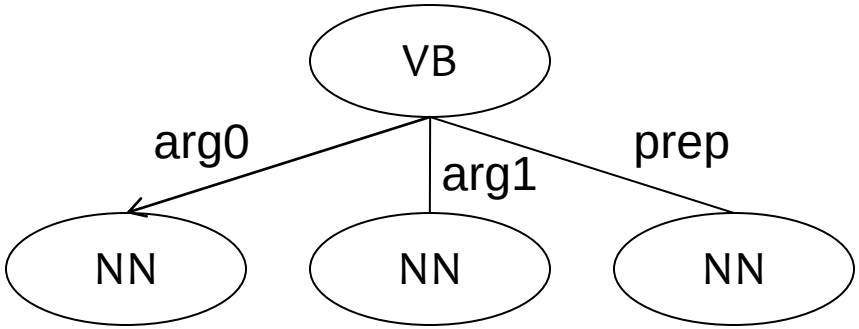
Relations


gameWinner a class!? Come on!
Relations?
Ok, let's move on… Show me the **relations** you have
Question
Answer
Reading Machine
Reasoning Machine
?
Text
Reasoning Ontology
Target Ontology

Relations

- Tom, ehm… What's a relation?
- Well… certainly, a relation is a n-tuple…
- … n-tuple…
- Like verb structures?
- Uhm… this could be interesting…
- Just small experiment:
  - Take the 30,000 docs. about US football and look for:





Most frequent propositions

nvn:[person:n, do:v, thing:n]:1530.
nvn:[group:n, do:v, thing:n]:1264.
nvn:[group:n, win:v, game:n]:960.
nvn:[person:n, tell:v, person:n]:902.
nvn:[person:n, catch:v, pass:n]:814.
nvn:[group:n, have:v, chance:n]:656.
nvn:[person:n, miss:v, game:n]:580.
nvn:[person:n, throw:v, pass:n]:567.
nvn:[group:n, have:v, lot:n]:551.
nvn:[person:n, do:v, job:n]:490.
nvn:[group:n, lose:v, game:n]:482.
nvn:[person:n, have:v, problem:n]:479.
nvn:[person:n, tell:v, group:n]:473.
nvn:[person:n, throw:v, interception:n]:465.
nvn:[group:n, play:v, game:n]:464.

Considering pronouns

Most frequent propositions

nvn:[team:n, win:v, game:n]:297.
nvn:[team:n, have:v, record:n]:212.
nvn:[team:n, lose:v, game:n]:166.
nvn:[touchdown:n, give:v, lead:n]:160.
nvn:[team:n, play:v, game:n]:154.
nvn:[goal:n, give:v, lead:n]:154.
nvn:[(field:goal):n, give:v, lead:n]:150.
nvn:[team:n, make:v, playoff:n]:146.
nvn:[team:n, win:v, championship:n]:136.
nvn:[touchdown:n, give:v, ((0: - : 0):lead):n]:135.
nvn:[goal:n, give:v, ((0: - : 0):lead):n]:124.
nvn:[(field:goal):n, give:v, ((0: - : 0):lead):n]:123.
nvn:[offense:n, score:v, touchdown:n]:118.

Ignoring pronouns

Most frequent "relations"

- A **relation** is a n-tuple between instances of certain type
  - I was playing with NNPs as instances…
- Let's generalize and aggregate:
  - Marino -> NAME
  - Bulger -> NAME
  - Jones -> NAME
  - …

Most frequent “relations”

nvn:['NAME', beat:v, 'NAME']:3884.
nvn:['NAME', catch:v, pass:n]:2567.
nvn:['NAME', play:v, 'NAME']:2382.
nvn:['NAME', lead:v, 'NAME']:2285.
nvn:['NAME', score:v, touchdown:n]:2261.
nvn:['NAME', throw:v, pass:n]:2107.
nvn:['NAME', win:v, game:n]:2010.
nvn:['NAME', replace:v, 'NAME']:1971.
nvn:['NAME', say:v, 'NAME']:1945.
nvn:['NAME', have:v, 'NAME']:1866.
nvn:['NAME', win:v, 'NAME']:1747.
nvn:['NAME', sign:v, 'NAME']:1740.
nvn:['NAME', defeat:v, 'NAME']:1663.
nvn:['NAME', hit:v, 'NAME']:1446.
nvn:['NAME', kick:v, goal:n]:1433.

Now

- I know instance classes
- I know propositions between instances
- Let’s find the probability of the classes given a proposition

Most probable typed relations

nvn:['NAME', throw:v, pass:n]:[quarterback]:0.00116408907425231.
nvn:['NAME', catch:v, pass:n]:[receiver]:0.000947483419496505.
nvn:['NAME', throw:v, (touchdown:pass):n]:[quarterback]:0.000767205964030132.
nvn:['NAME', throw:v, interception:n]:[quarterback]:0.000415367155661766.
nvn:['NAME', catch:v, pass:n]:[(wide:receiver)]:0.000406047565796885.
nvn:['NAME', say:v, linebacker:n]:[linebacker]:0.000395901727835594.
nvn:['NAME', rank:v, (no:'.'):n]:[(no:'.')]:0.000392502869262291.
nvn:['NAME', rank:v, (0:no:'.'):n]:[(no:'.')]:0.000392502869262291.
nvn:['NAME', complete:v, pass:n]:[quarterback]:0.000390269288924688.
nvn:['NAME', catch:v, (0:pass):n]:[receiver]:0.000346249735543358.
nvn:['NAME', catch:v, pass:n]:[end]:0.00033397730214679.
nvn:['NAME', throw:v, ((0: - : yard):pass):n]:[quarterback]:0.000304392988179183.
nvn:['NAME', have:v, sack:n]:[end]:0.000297055408474171.
nvn:['NAME', intercept:v, pass:n]:[safety]:0.000292011905223431.

Relations between classes

Now I can ask about the relations between classes

Quarterback & receiver

nvn:['NAME', **hit**:v, 'NAME']:[quarterback, receiver]:3.67432997918756e-06.
nvn:['NAME', **find**:v, 'NAME']:[quarterback, receiver]:1.8192935712796e-06.
nvnpn:['NAME', **complete**:v, **pass**:n, **to**:in, 'NAME']:[quarterback, receiver]:1.4512783860507e-06.
nvnpn:['NAME', **throw**:v, **pass**:n, **to**:in, 'NAME']:[quarterback, receiver]:1.37642726590848e-06.
nvnpn:['NAME', **catch**:v, **pass**:n, **from**:in, 'NAME']:[**receiver, quarterback**]:1.16492444555009e-06.
nvnpn:['NAME', **throw**:v, (**touchdown:pass**):n, **to**:in, 'NAME']:[quarterback, receiver]:1.0606850217847e-06.

If there is only one relevant relation between them, they are paraphrases

Relations between classes

But you can have many relevant relations between same classes

Team and game

nvn:['NAME', **win**:v, game:n]:[team]:9.69097313067351e-05.
nvn:['NAME', **lose**:v, game:n]:[team]:5.96928038789563e-05.
nvn:['NAME', **play**:v, game:n]:[team]:2.7232092783388e-05.
nvn:['NAME', **have**:v, game:n]:[team]:2.5404025345459e-05.
nvn:['NAME', **enter**:v, game:n]:[team]:1.32010748425686e-05.
nvn:['NAME', (**not:win**):v, game:n]:[team]:5.77931930517973e-06.
nvn:['NAME', **forfeit**:v, game:n]:[team]:5.30734251201793e-06.
nvn:['NAME', **tie**:v, game:n]:[team]:3.95409472849798e-06.
nvn:['NAME', **reach**:v, game:n]:[team]:3.66152627590672e-06.
nvn:['NAME', **average**:v, game:n]:[team]:3.45676070239657e-06.
nvnpn:['NAME', **extend**:v, **streak**:n, **to**:in, game:n]:[team]:3.29470336174047e-06.

How to cluster different realizations of the same relation?

[Research question #3]

Inferring entity classes

- Now, when I see something (named) doing things, I can guess its class

- Culpepper directed a 15-play drive
  - nvn:['NAME', direct:v, drive:n]:[quarterback]:3.37813951038364e-05.
  - nvn:['NAME', direct:v, drive:n]:[backup]:2.98954603541518e-06.
  - nvn:['NAME', direct:v, drive:n]:[man]:1.56144396948542e-06.
  - nvn:['NAME', direct:v, drive:n]:[freshman]:1.48171220798502e-06.
  - nvn:['NAME', direct:v, drive:n]:[passer]:1.3913157132247e-06.

- And when I see it doing many things in a document, I can aggregate the evidence on its class. How?

[Research question #4]

Propositions into axioms

- "Can we axiomatize this?", asked Jerry
- Why not?
- P(quarterback, throw, pass)=0.0011
  - P(quarterback | throw, pass) = p
  - throw(x,y), pass(y) -> quarterback(x) | p

Relations between events

- “Can you find the ways to express causality?”, asked Rutu

- Why not? Give me a seed

Touchdown & victory

NVN 14 'touchdown':'give':'victory'

NVN 11 'touchdown':'seal':'victory'

NVN 4 'touchdown':'secure':'victory‘

Relations between events

Give

NVN 136 'touchdown':'give':'lead'

NVN 130 'goal':'give':'lead'

NVN 85 'pass':'give':'lead'

Seal

NVN 12 'interception':'seal':'victory'

NVN 11 'touchdown':'seal':'victory'

NVN 6 'pass':'seal':'victory‘

Secure

NVN 5 'victory':'secure':'title'

NVN 4 'group':'secure':'title'

NVN 4 'victory':'secure':'championship'

Relations between events

Set_up

NVN 25 'interception':'set_up':'touchdown'

NVN 20 'pass':'set_up':'touchdown'

NVN 19 'interception':'set_up':'goal'

NVN 14 'pass':'set_up':'goal'

NVN 14 'return':'set_up':'touchdown'

NVN 12 'interception':'set_up':'score'

NVN 11 'fumble':'set_up':'touchdown'

NVN 11 'run':'set_up':'touchdown'

NVN 10 'person':'set_up':'touchdown'

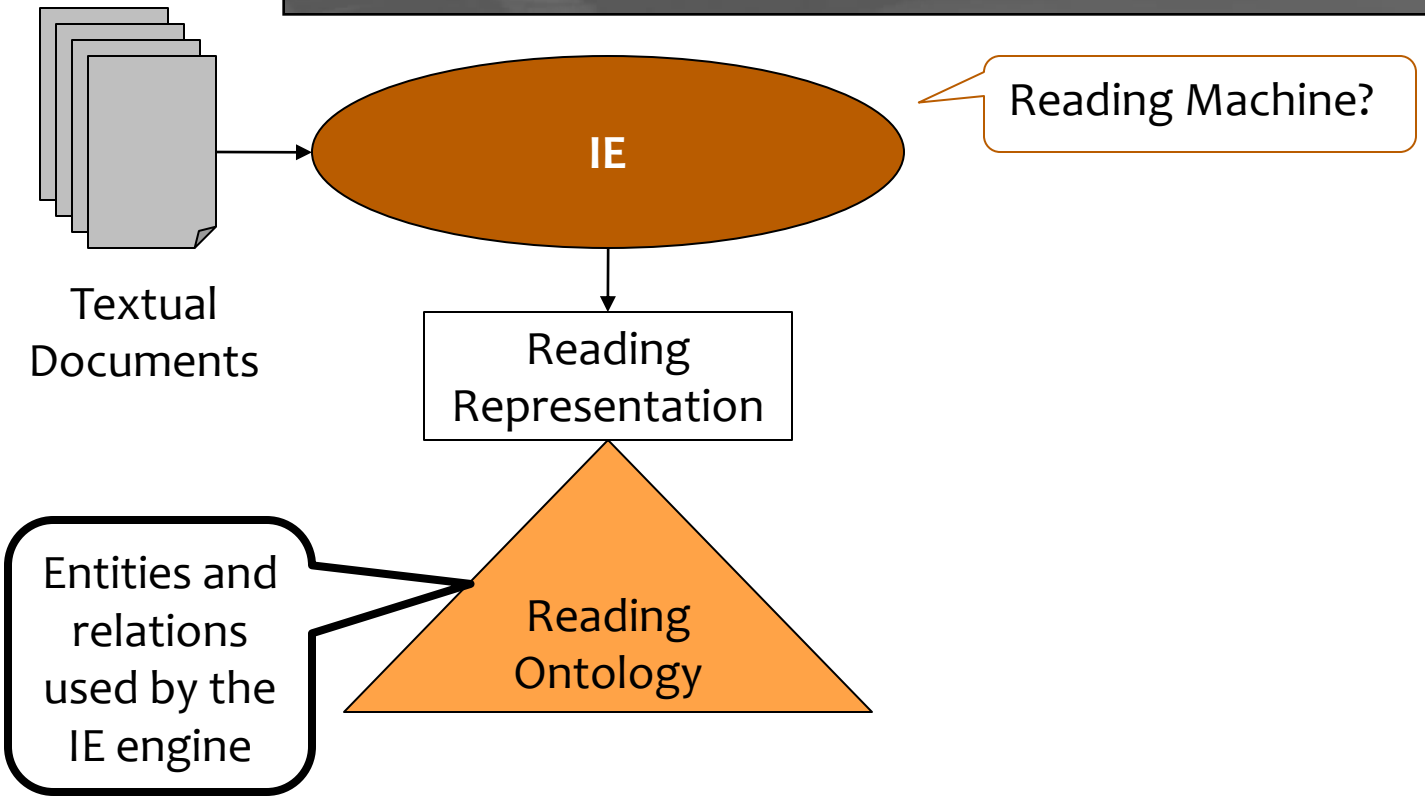
NVN 9 'return':'set_up':'goal'

NVN 9 'pass':'set_up':'run'

NVN 9 'interception':'set_up':'run'

NVN 9 'run':'set_up':'goal'

IE approach


Textual Documents
IE
Reading Machine?
Reading Representation
Reading Ontology
Entities and relations used by the IE engine

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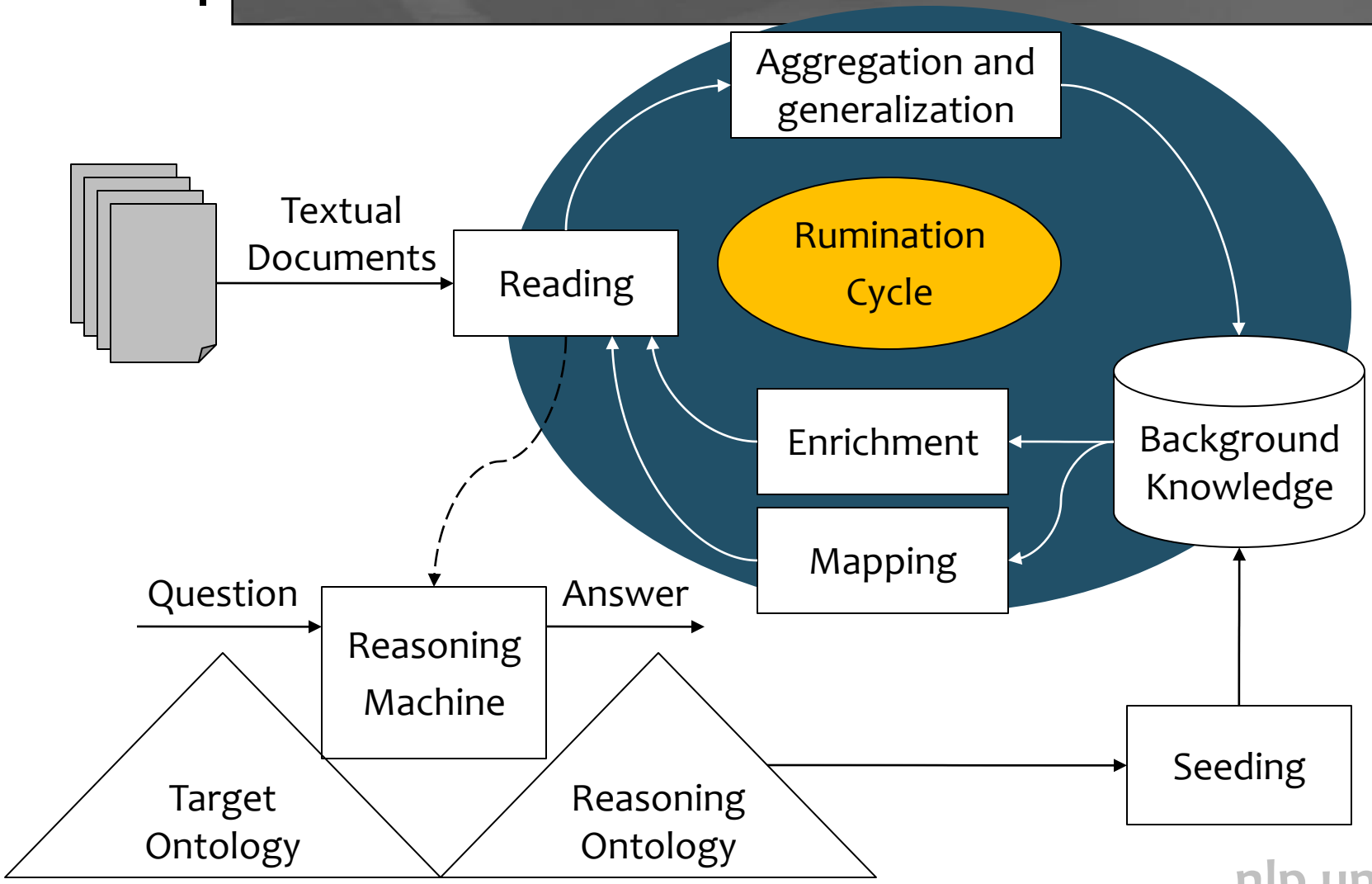
The Reading Machine



The Reading Machine

Iterate over big amounts of text

1. Process texts up to reified logic forms
2. Generalization and aggregation of frequent structures in the logic forms
   1. Estimation of their probability distributions
   2. Dumping intermediate Background Knowledge Bases (BKB)
3. Enrichment of initial text representations (BKBs are then used to fill the knowledge gaps)
4. Repeat with the enriched representation of texts

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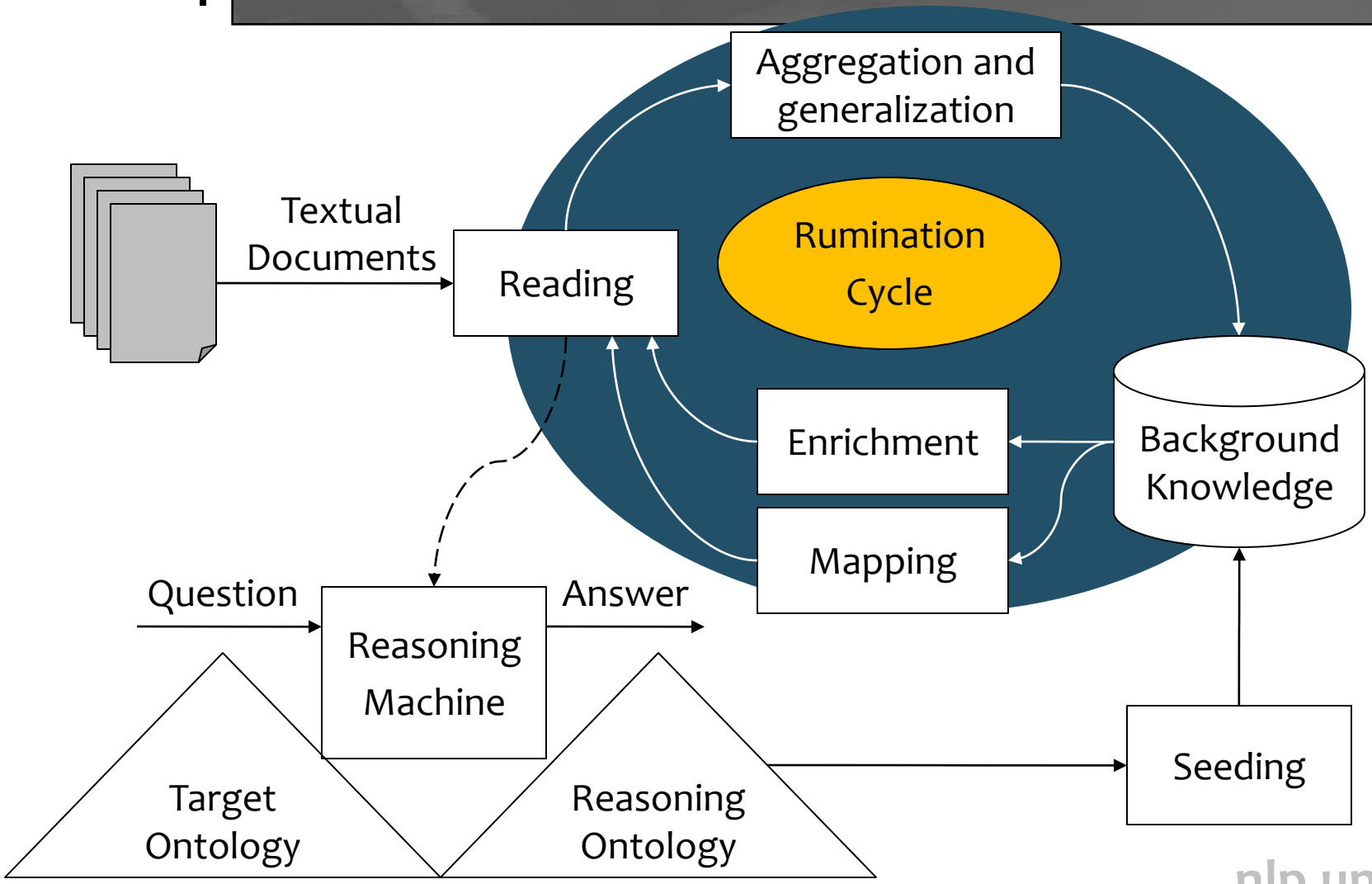
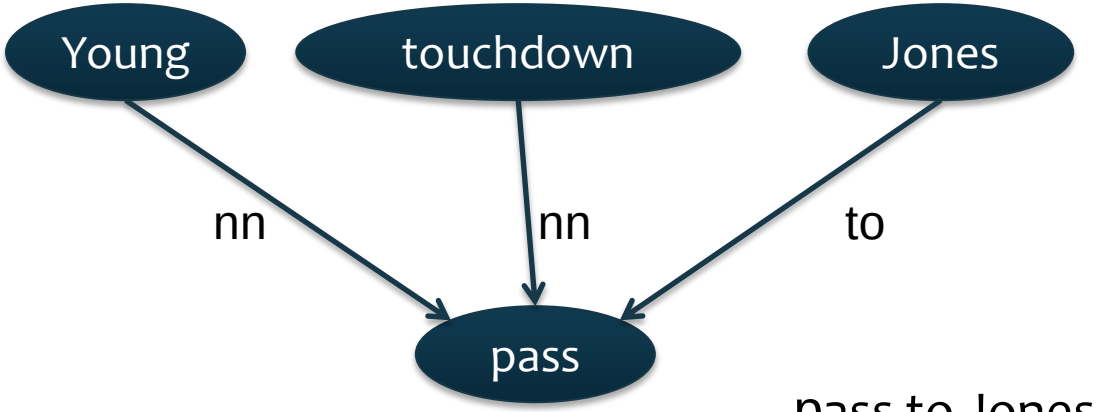
The Reading Machine



Enrichment example (1)

… to set up a 7-yard Young touchdown pass to Brent Jones



Young pass

?> X:has-instance:Young

X=quarterback

?> NVN:quarterback:X:pass

X=throw

X=complete

pass to Jones

?> X:has-instance:Jones

X=end

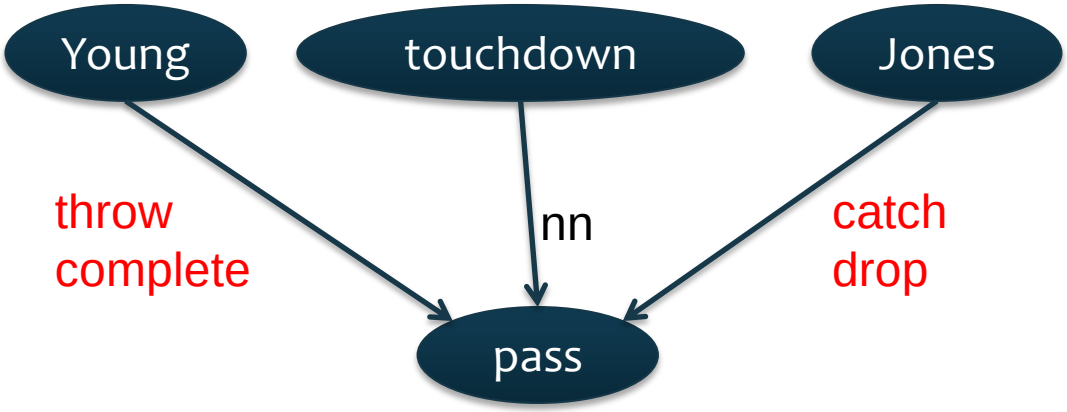
?> NVN:end:X:pass

X=catch

X=drop

Enrichment example (2)

…to set up a 7-yard Young touchdown pass to Brent Jones



touchdown pass

?> NVN touchdown:X:pass

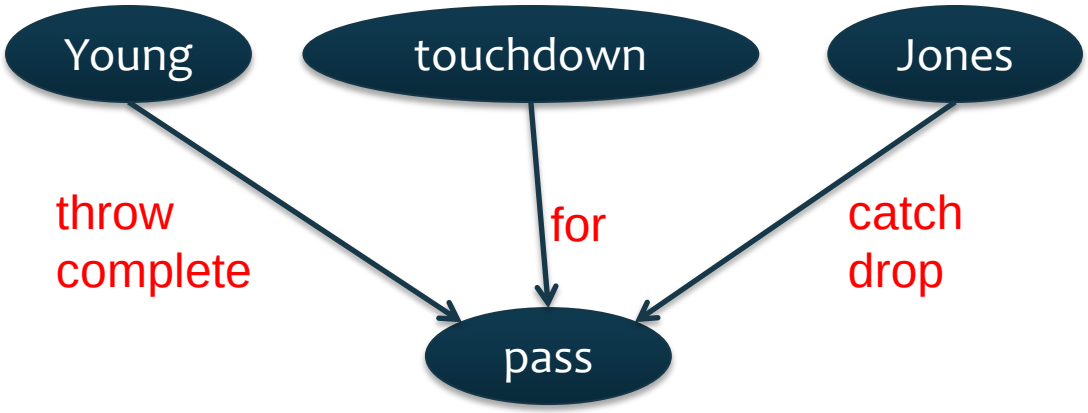
False

?> NPN pass:X:touchdown

X=for

Enrichment example (3)

… to set up a 7-yard Young touchdown pass to Brent Jones



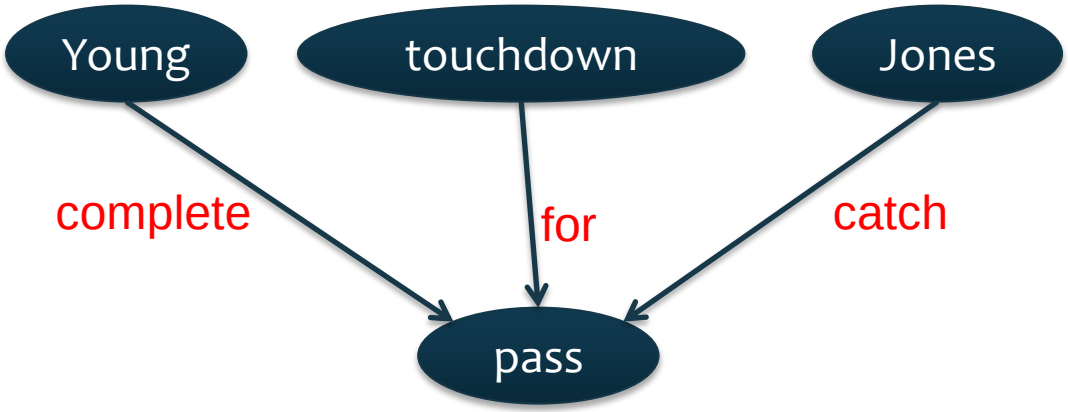
?> NVNPN NAME:X:pass:for:touchdown

X=complete

X=catch

Enrichment example (4)

…to set up a 7-yard Young touchdown pass to Brent Jones



⇒ Young complete pass for touchdown

⇒ Jones catch pass for touchdown

Evaluation

- The evaluation of these machines is an open research question
- It is also an opportunity to consolidate the community around the field
  - Specially in EU
- The development of an international evaluation is part of this proposal

Conclusions

- Machine Reading is a target for CL
- A dream
- Time for a new attempt
  - Concepts are probability distributions
    - Propositions
- New project at UNED
  - Development of a Reading Machine
  - Collect sources of knowledge (text + …)
  - New international evaluation campaign

UNED

References

- Anselmo Peñas and Eduard Hovy. Filling Knowledge Gaps in Text for Machine Reading. 23rd International Conference on Computational Linguistics (COLING 2010), Beijing, 2010.

- Anselmo Peñas and Eduard Hovy. Semantic Enrichment of Text with Background Knowledge. 1st International Workshop on Formalisms and Methodology for Learning by Reading (FAM-LbR), NAACL 2010.

- Alvaro Rodrigo, Anselmo Peñas, Eduard Hovy and Emanuele Pianta. Question Answering for Machine Reading Evaluation. Proceedings of CLEF 2010 Workshop on Question Answering in Multiple Languages (MLQA'10), Padua, September 2010.

- Rodrigo Agerri and Anselmo Peñas. On the Automatic Generation of Intermediate Logic Forms for WordNet Glosses. Computational Linguistics and Intelligent Text Processing, CICLing 2010. Lecture Notes in Computer Science 6008. Springer-Verlag, 2010.

Thanks!

Domain issue

?> person:X:pass

NFL Domain

905:nvn:[person:n, catch:v, pass:n].
667:nvn:[person:n, throw:v, pass:n].
286:nvn:[person:n, complete:v, pass:n].
204:nvnpn:[person:n, catch:v, pass:n, for:in, yard:n].
85:nvnpn:[person:n, catch:v, pass:n, for:in, touchdown:n].

IC Domain

6:nvn:[person:n, have:v, pass:n]
3:nvn:[person:n, see:v, pass:n]
1:nvnpn:[person:n, wear:v, pass:n, around:in, neck:n]

BIO Domain

<No results>

Domain issue

?> X:receive:Y

NFL Domain

55:nvn:[person:n, receive:v, call:n].

34:nvn:[person:n, receive:v, offer:n].

33:nvn:[person:n, receive:v, bonus:n].

29:nvn:[team:class, receive:v, pick:n].

IC Domain

78 nvn:[person:n, receive:v, call:n]

44 nvn:[person:n, receive:v, letter:n]

35 nvn:[group:n, receive:v, information:n]

31 nvn:[person:n, receive:v, training:n]

BIO Domain

24 nvn:[patients:n, receive:v, treatment:n]

14 nvn:[patients:n, receive:v, therapy:n]

13 nvn:[patients:n, receive:v, care:n]

Domain issue

- Limiting to a specific domain provides some powerful benefits
  - Ambiguity is reduced
  - Higher density of relevant propositions
  - Different distribution of propositions across domains
  - Amount of source text is reduced, allowing deeper processing such as parsing
  - Specific tools for specific domains
- Proposition stores seem to be useful
  - Improve parsing, corref, WSD,…
- We presented a new application: ENRICHMENT

Paraphrasing

Cornerback & receiver

nvn(('NNP':'receiver'):'beat':('NNP':'cornerback')):23.
nvn(('NNP':'cornerback'):'cover':('NNP':'receiver')):11.
nvn(('NNP':'cornerback'):'shadow':('NNP':'receiver')):4.
nvn(('NNP':'cornerback'):'shut_down':('NNP':'receiver')):4.
nvn(('NNP':'receiver'):'burn':('NNP':'cornerback')):3.
nvn(('NNP':'cornerback'):'intercept':('NNP':'receiver')):3.
nvn(('NNP':'cornerback'):'face':('NNP':'receiver')):2.
nvn(('NNP':'cornerback'):'trip_up':('NNP':'receiver')):2.
nvn(('NNP':'cornerback'):'hold':('NNP':'receiver')):2.
nvn(('NNP':'cornerback'):'outjump':('NNP':'receiver')):2.
nvn(('NNP':'cornerback'):'limit':('NNP':'receiver')):2.

A quarterback is not a player

Players

nvn(('NNP':'player'):'catch':'pass'):83.
nvn(('NNP':'player'):'miss':'game'):66.
nvn(('NNP':'player'):'have':'yard'):59.
nvn(('NNP':'player'):'gain':'yard'):49.
nvn(('NNP':'player'):'throw':'pass'):43.
nvn(('NNP':'player'):'score':'touchdown'):43.
nvn(('NNP':'player'):'have':'sack'):34.
nvn(('NNP':'player'):'average':'yard'):30.
nvn(('NNP':'player'):'have':'surgery'):28.
nvn(('NNP':'player'):'run':'yard'):27.
nvn(('NNP':'player'):'start':'game'):26.
nvn(('NNP':'player'):'carry':'ball'):26.

They are what they do

Quarterbacks

nvn(('NNP':'quarterback'):'throw':'pass'):1093.
nvn(('NNP':'quarterback'):'complete':'pass'):422.
nvn(('NNP':'quarterback'):'throw':'interception'):407.
nvn(('NNP':'quarterback'):'lead':('NNP':'team')):354.
nvn(('NNP':'quarterback'):'start':'game'):211.
nvn(('NNP':'quarterback'):'replace':('NNP':'quarterback')):208.
nvn(('NNP':'quarterback'):'hit':('NNP':'receiver')):177.
nvn(('NNP':'quarterback'):'have':'pass'):142.

Rephrasing

"Culpepper finds Moss" <-> "Culpepper completes pass to Moss"

1. Hypothesize Entity classes

?> NAME find NAME

nvn:['NAME', find:v, 'NAME']:[**quarterback, receiver**]:1.8192935712796e-06
nvn:['NAME', find:v, 'NAME']:[**quarterback, end**]:8.17538936560293e-07
nvn:['NAME', find:v, 'NAME']:[**quarterback, (wide:receiver)**]:7.94094409104393e-07
nvn:['NAME', find:v, 'NAME']:[**quarterback, (tight:end)**]:7.41880417507334e-07

(in Logic Form)

?> find(e,x1,x2), name(x1,NAME), name(x2,NAME) -> class(x1,c1), class(x2,c2)

c1=quarterback, c2=receiver | Prob(e,c1,c2)=1.8192935712796e-06
c1=quarterback, c2=end | Prob(e,c1,c2)=8.17538936560293e-07
c1=quarterback, c2=(wide:receiver) | Prob(e,c1,c2)=7.94094409104393e-07
c1=quarterback, c2=(tight:end) | Prob(e,c1,c2)=7.41880417507334e-07

Rephrasing

2. Recover other propositions between the classes found

Propositions relating names of **quarterback**s with names of **receivers**

npn:['NAME', **to**:in, 'NAME']:[quarterback, receiver]:5.69990315934166e-06
nvn:['NAME', **hit**:v, 'NAME']:[quarterback, receiver]:3.67432997918756e-06
nvn:['NAME', **find**:v, 'NAME']:[quarterback, receiver]:1.8192935712796e-06
nvpn:['NAME', **throw**:v, **to**:in, 'NAME']:[quarterback, receiver]:1.7055936330989e-06
nvnpn:['NAME', **complete**:v, **pass**:n, **to**:in, 'NAME']:[quarterback, receiver]:1.4512783860507e-06
nvnpn:['NAME', **throw**:v, **pass**:n, **to**:in, 'NAME']:[quarterback, receiver]:1.37642726590848e-06
nvnpn:['NAME', **catch**:v, **pass**:n, **from**:in, 'NAME']:[receiver, quarterback]:1.16492444555009e-06
nvnpn:['NAME', **throw**:v, **(touchdown:pass)**:n, **to**:in, 'NAME']:[quarterback, receiver]:1.0606850e-06
nvpn:['NAME', **pass**:v, **to**:in, 'NAME']:[quarterback, receiver]:9.53837221790507e-07
nvpn:['NAME', **connect**:v, **with**:in, 'NAME']:[quarterback, receiver]:8.9380301215876e-07
npn:['NAME', **on**:in, 'NAME']:[receiver, quarterback]:7.40714092598897e-07
nvpn:['NAME', **look**:v, **for**:in, 'NAME']:[quarterback, receiver]:7.16122012330255e-07