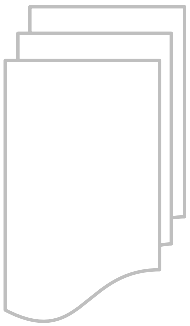
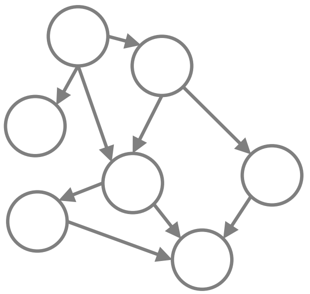
Part 1: Knowledge Graphs



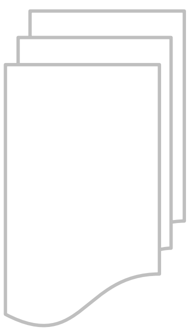
Part 2: Knowledge Extraction

Part 3: Graph Construction



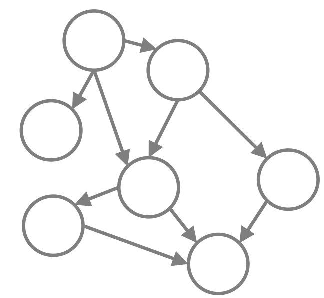
Part 4: Critical Analysis

Part 1: Knowledge Graphs



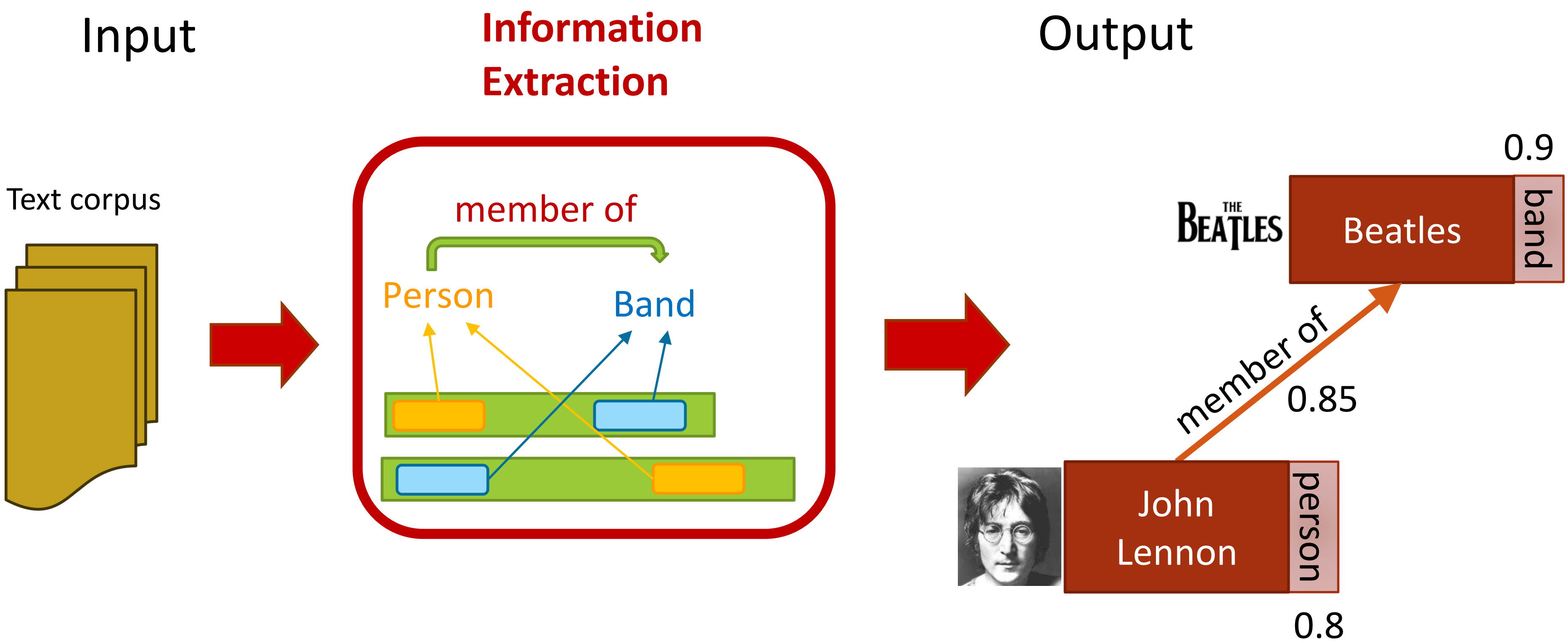
Part 2: Knowledge Extraction

Part 3: Graph Construction



Part 4: Critical Analysis

Information Extraction



Information Extraction

3 IMPORTANT SUB-PROBLEMS

(DEFINE DOMAIN, LEARN EXTRACTORS, SCORE EXTRACTIONS)

3 LEVELS OF SUPERVISION

(MANUAL, SEMI-SUPERVISED, UNSUPERVISED)

KNOWLEDGE FUSION WITH MULTIPLE EXTRACTORS

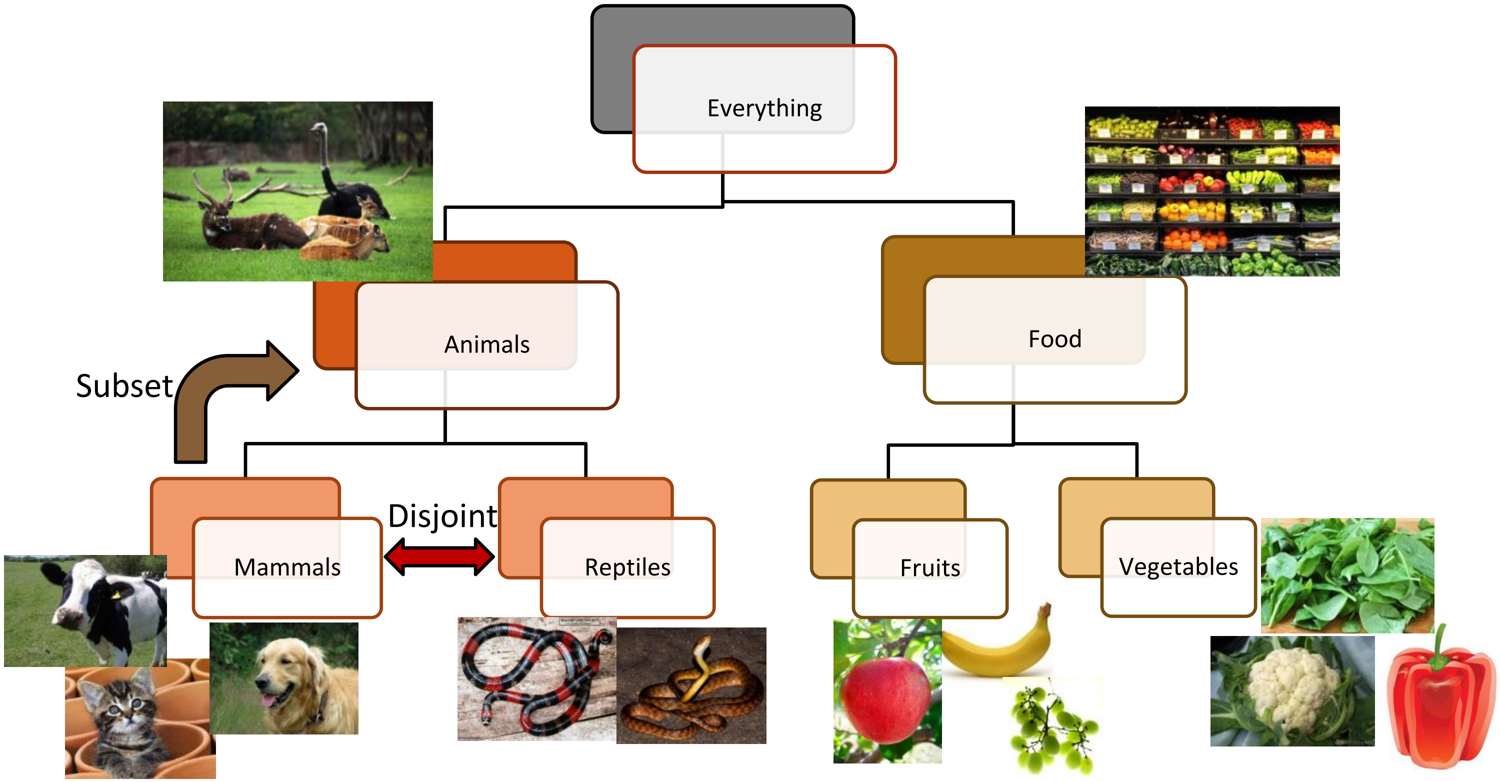
(CO-TRAINING, MULTI-VIEW LEARNING)

EXAMPLE IE SYSTEMS

Information Extraction

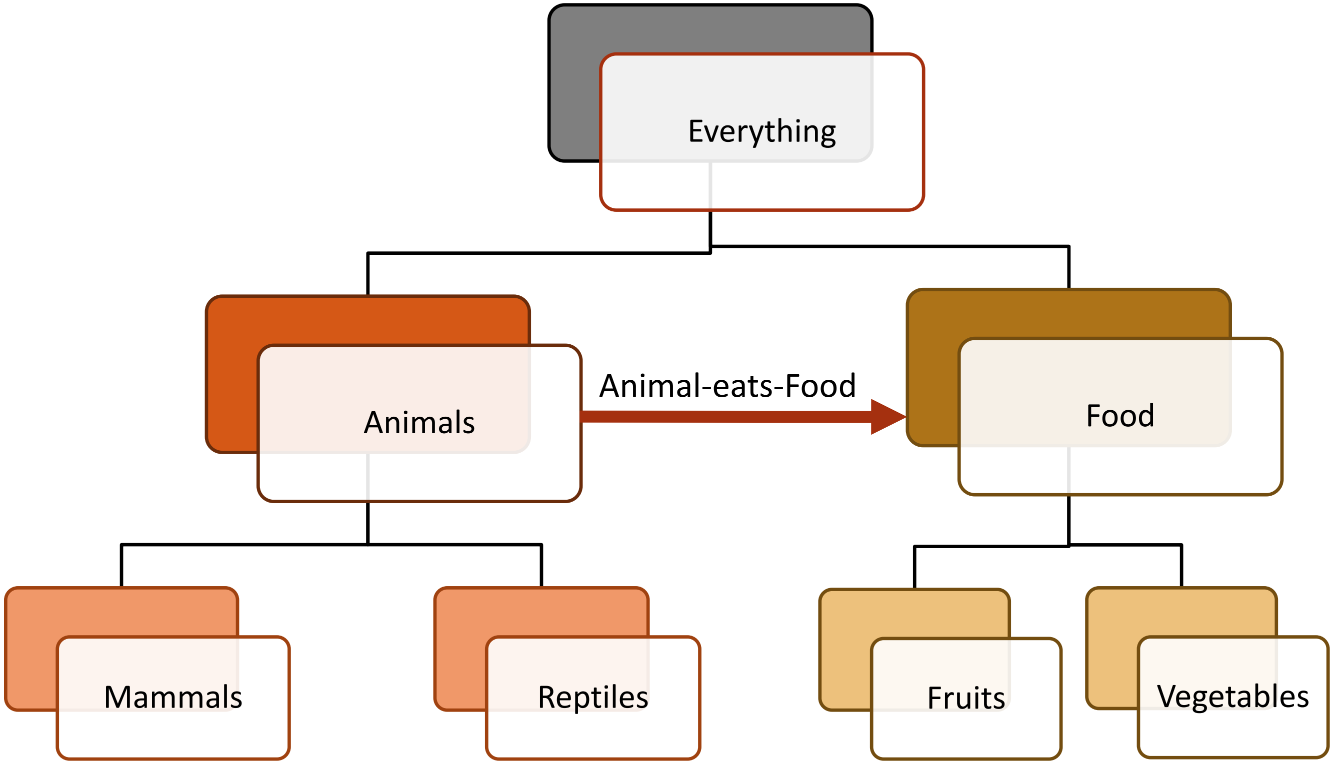
Defining domain: types/relations of interest

Defining Domain: Manual



*[**Toward an Architecture for Never-Ending Language Learning**, Carlson et al. AAAI 2010]*

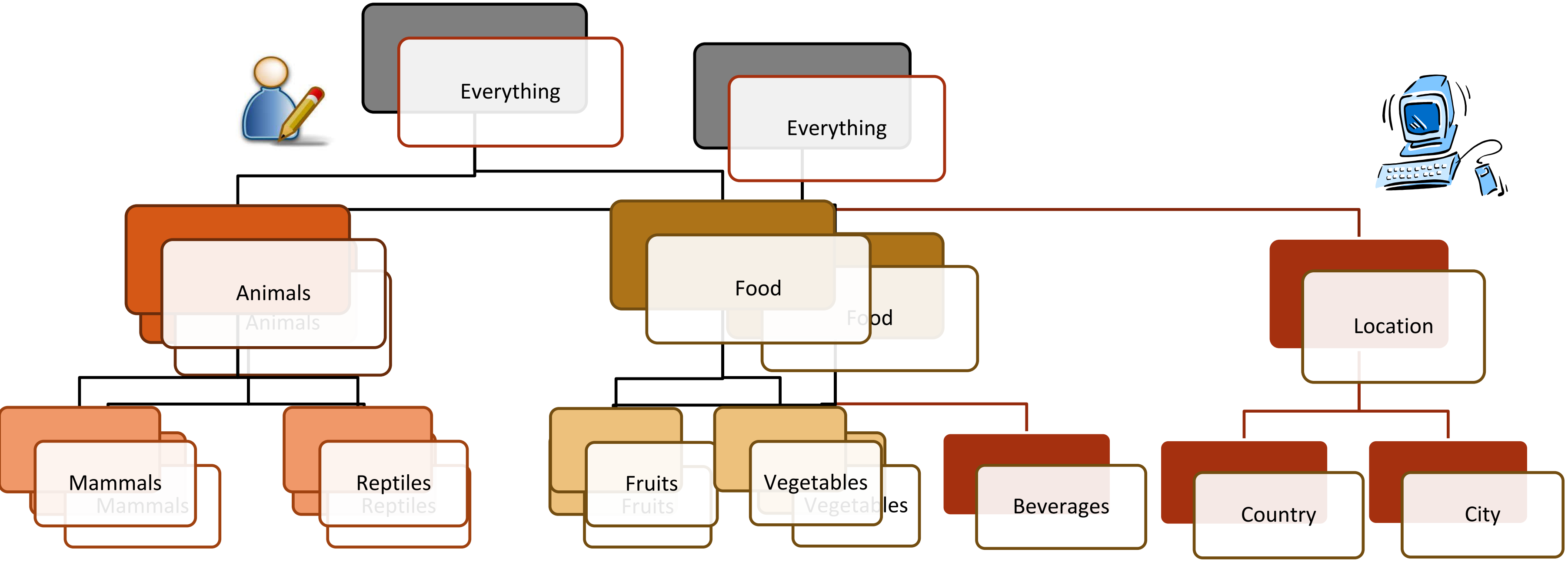
Defining Domain: Manual



- **Highly semantic ontology**
- **Leads to high precision extractions**
- **Expensive to create**
- **Requires domain experts**

Defining Domain: Semi-automatic

- Subset of types are manually defined
- More types are discovered from data



[**Exploratory Learning**, Dalvi et al., ECML 2013]
[**Hierarchical Semi-supervised Classification with Incomplete Class Hierarchies, Dalvi et al., WSDM 2016**]

Defining Domain: Semi-automatic

- Types and type hierarchy is manually defined
  E.g. River, City, Food, Chemical, Disease, Bacteria
- Relations are automatically discovered using clustering methods

Discovered relation	Patterns	Seed instances
River -in heart of- City	“in heart of” “in the center of” “which flows through”	“Seine, Paris”, “Nile, Cairo” “Tiber river, Rome” “River arno, Florence”
Food -to produce- Chemical	“to produce” “to make” “to form”	“Salt, Chlorine” “Sugar, Carbon dioxide” “Protein , Serotonin”
Disease -caused by- Bacteria	“caused by” “is the causative agent of” “is the cause of”	“pneumonia, legionella” “mastitis, staphylococcus aureus” “gonorrhea, neisseria gonorrhoeae”

- **Easier to derive types using existing resources**
- **Relations are discovered from the corpus**
- **Leads to moderate precision extractions**
- **Partially semantic ontology**

[Discovering Relations between Noun Categories, Mohamed et al., EMNLP 2011]

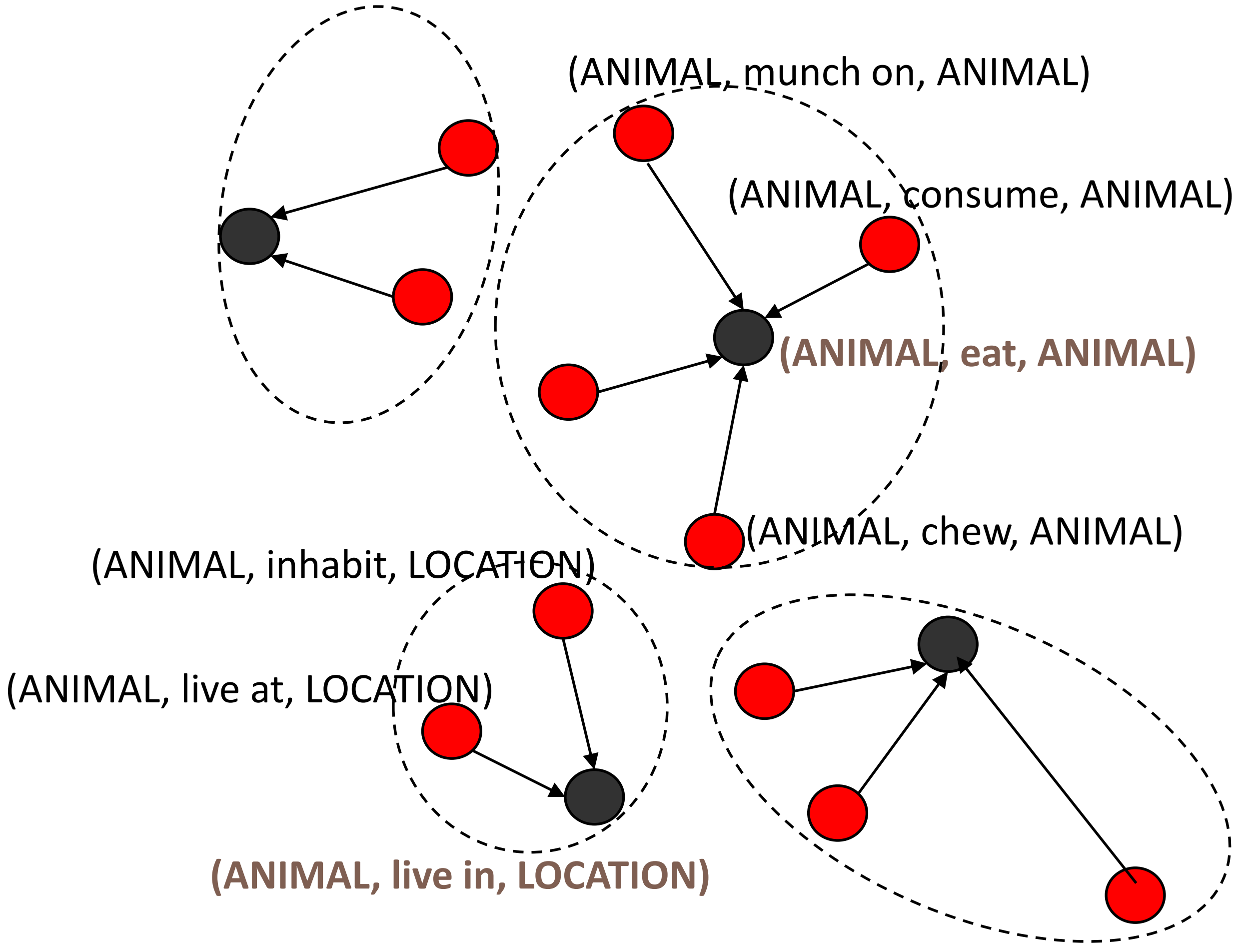
Defining Domain: Automatic

- Any noun phrase is a candidate entity
- Any verb phrase is a candidate relation

- **Cheapest way to induce types/ relations from corpus**
- **Little/no expert annotations needed**
- **Limited semantics**
- **Leads to noisy extractions**

*[**Open Information Extraction from the Web**, Banko et al., IJCAI 2007]*

Unsupervised relation induction
(Relation clustering)



*[**Canonicalizing Open Knowledge Bases, Galárraga at al.,** CIKM 2014]*

Extractors for each relation of interest

Learning Extractors: Manual

- Human defined high-precision extraction patterns for each relation

Person-member of-Band

<PERSON> works for <BAND>
<PERSON> is part of <BAND>

Extract relation instances
(John Lennon, The Beatles)
(Brian Jones, The Rolling Stones)

Learning Extractors: Semi-supervised

Person-member of-Band

Seed instances

Relation instances
(John Lennon, Beatles)
(Brian Jones, The Rolling Stones)

Learn patterns

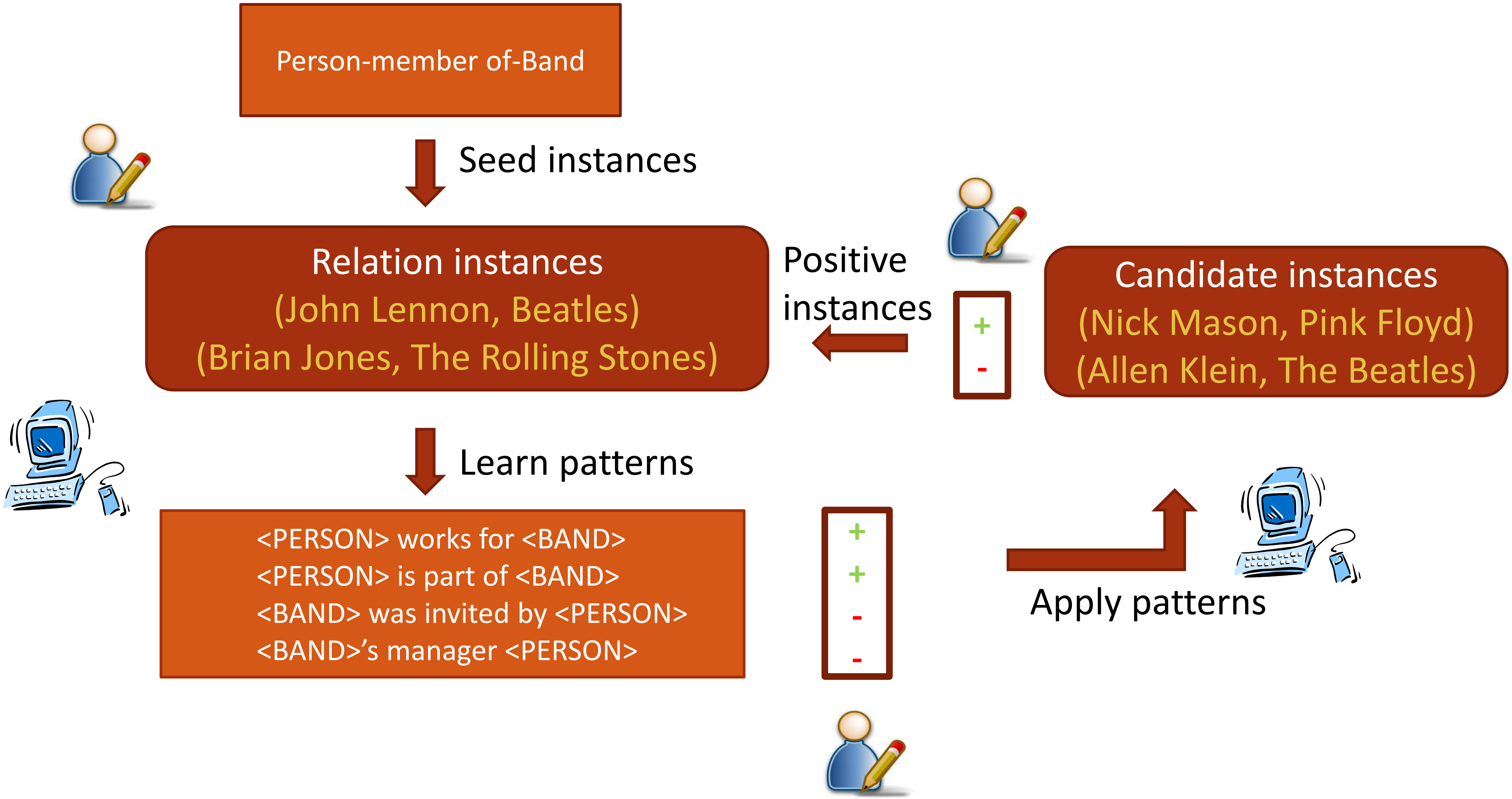
<PERSON> works for <BAND>
<PERSON> is part of <BAND>
<BAND> includes <PERSON>
<BAND>'s manager <PERSON>

Apply patterns

Candidate instances
(Ringo Starr, The Beatles)
(Nick Mason, Pink Floyd)

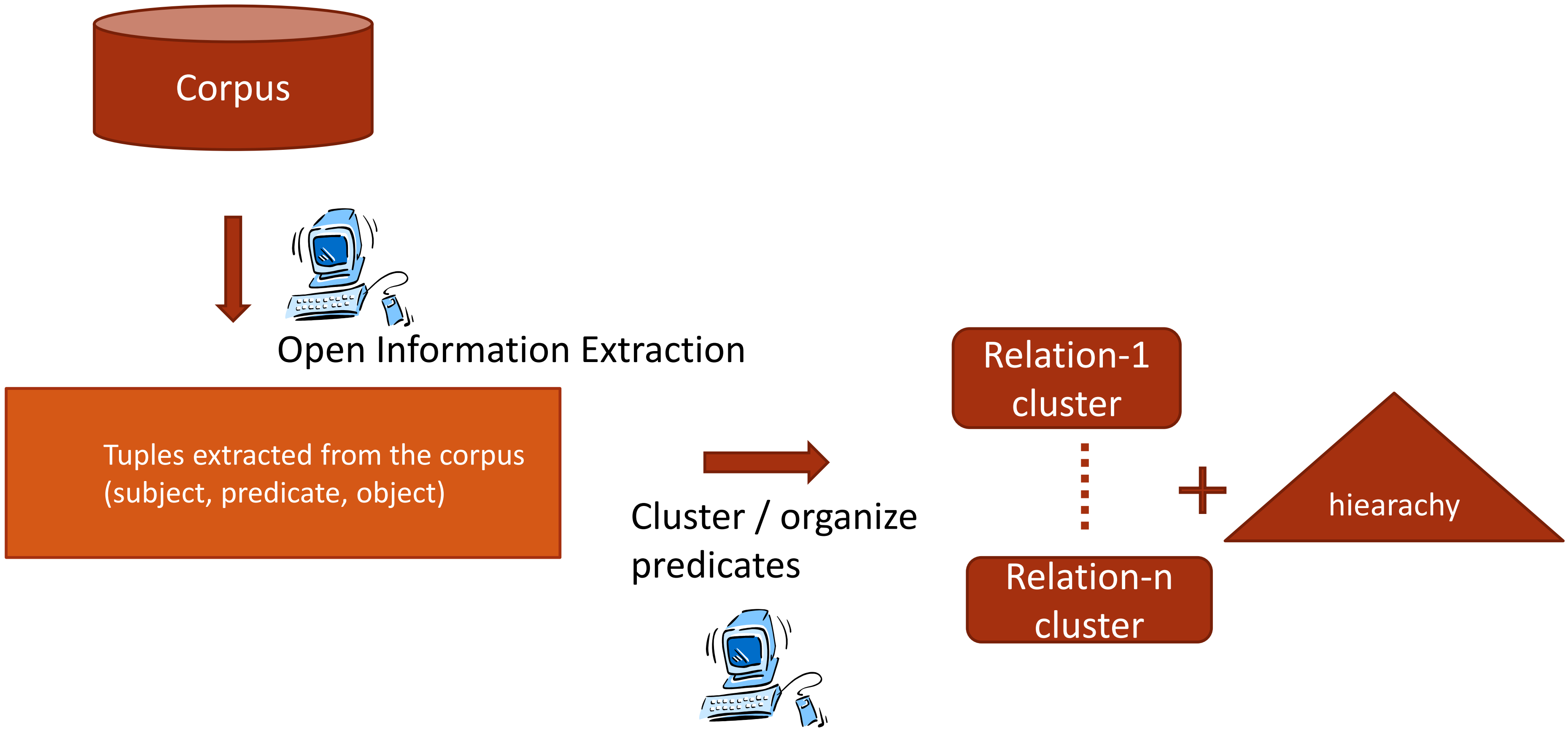
Add top-k instances

Learning Extractors : Interactive



*[**Open information extraction to KBP relations in 3 hours**, Soderland et al., TAC KBP 2013]*

Learning Extractors : Unsupervised



*[***Discovering Semantic Relations from the Web and Organizing them with PATTY***, SIGMOD 2013]*

Scoring the candidate extractions

Scoring the candidate extractions

- Human defined scoring function
  (expensive, high precision, low recall)

- Expert comes up with features
  Crowdsourced true/false evaluation of training data
  Scoring function is learnt using standard ML

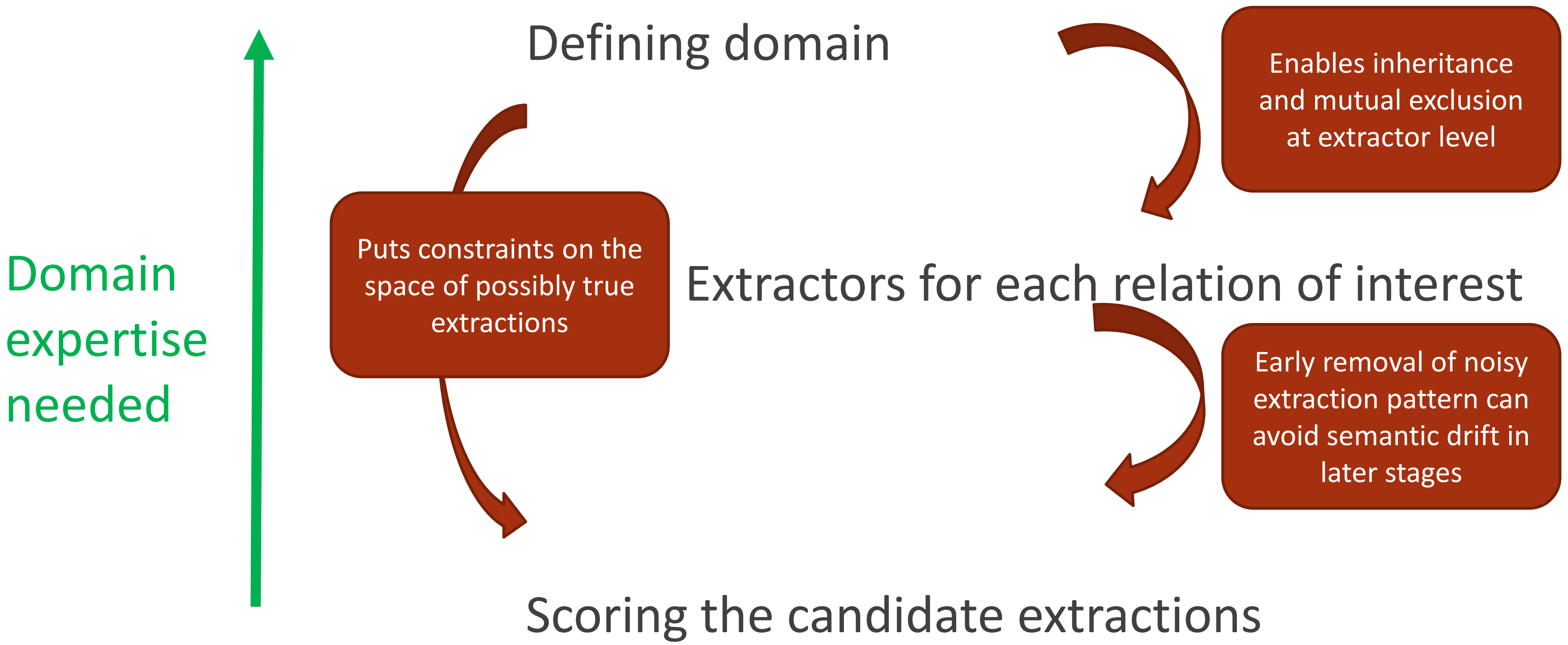
- Completely automatic (Self-training)
  Updated set of instances → weights of extraction patterns → more instances → ....
  (cheap, leads to semantic drift)

Effect of supervision on extractions

Precision,
Human efforts

Recall,
Speed

Impact of early supervision



Examples: Information Extraction Techniques

(1) Narrow domain patterns

Defining domain	Learning extractors	Scoring extractions
		

(1) Narrow domain patterns

Use the collection of rules as the system itself

if “X was born in Y” then predict “X birthplace Y”

High precision: when it fires, it’s correct

Easy to explain predictions

Easy to fix mistakes

However…

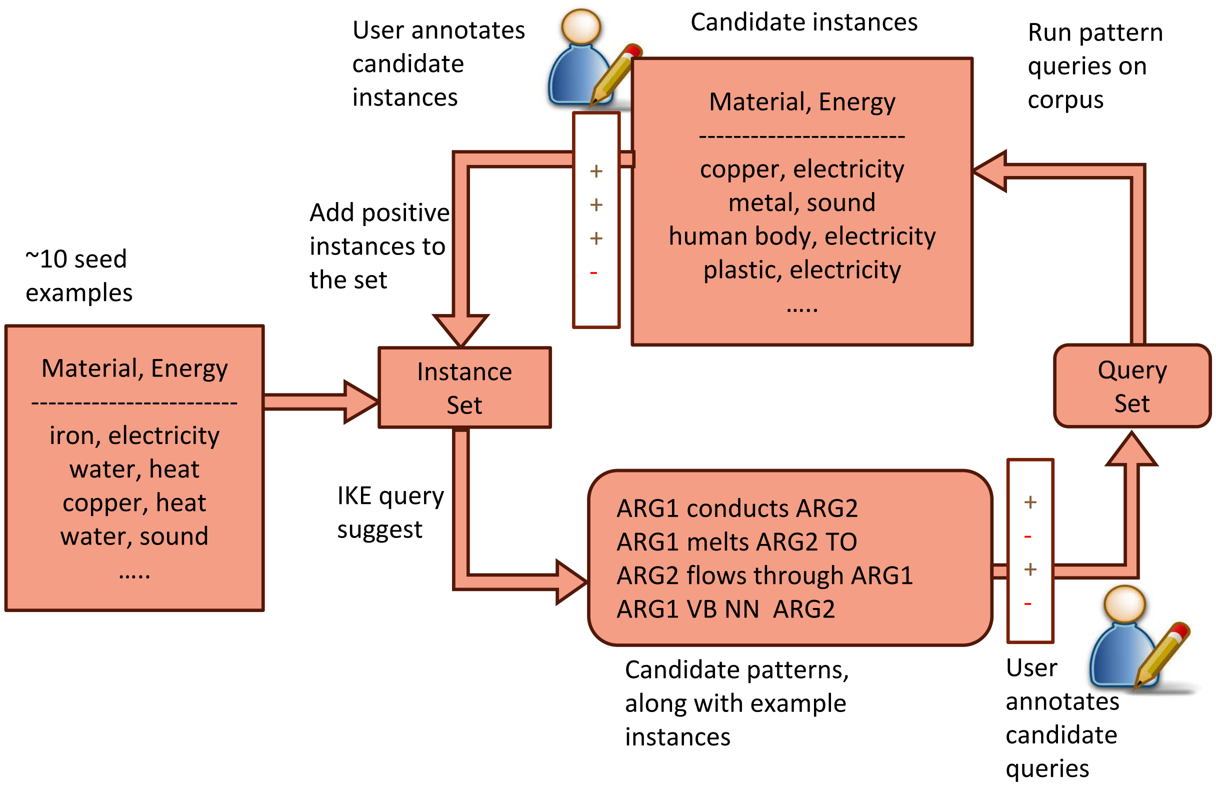
Only work when the rules fire

Do not generalize!

(2) Interactive Bootstrapping (IKE)

Defining domain	Learning extractors	Scoring extractions
		

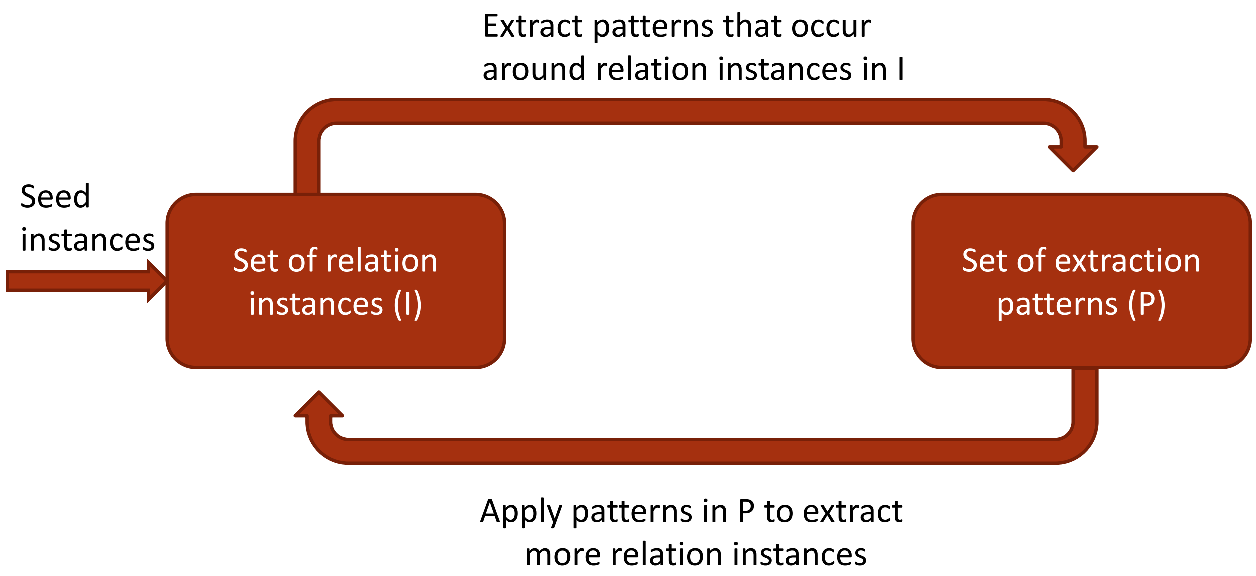
(2) Interactive Bootstrapping (IKE)



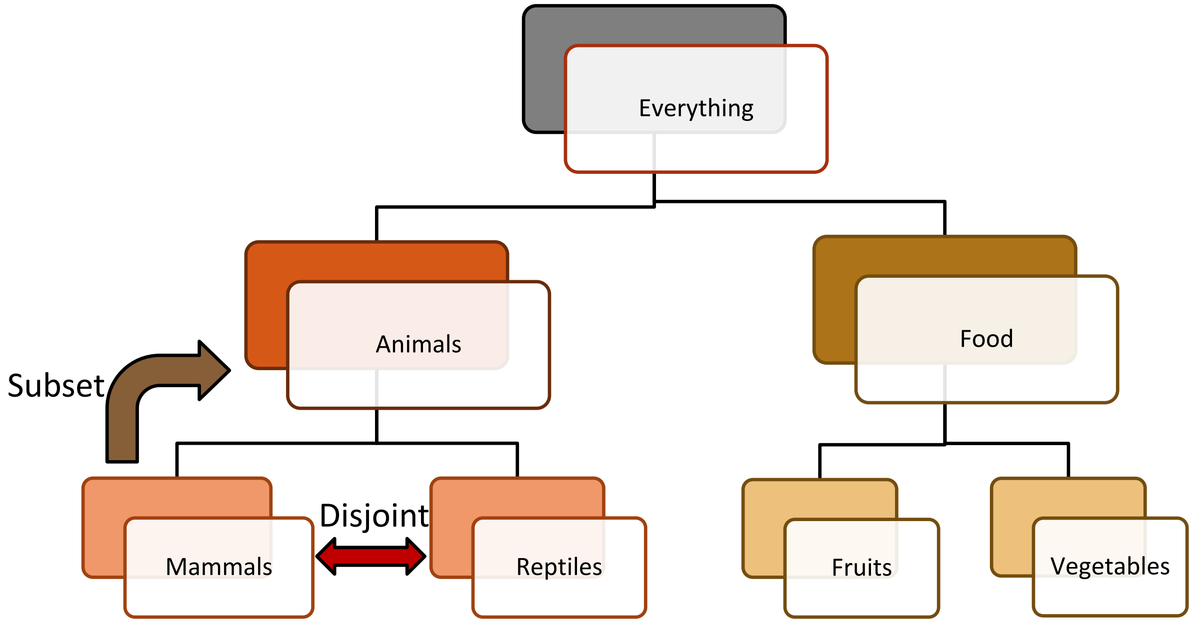
(3) Ontology based extraction

Defining domain	Learning extractors	Scoring extractions
		

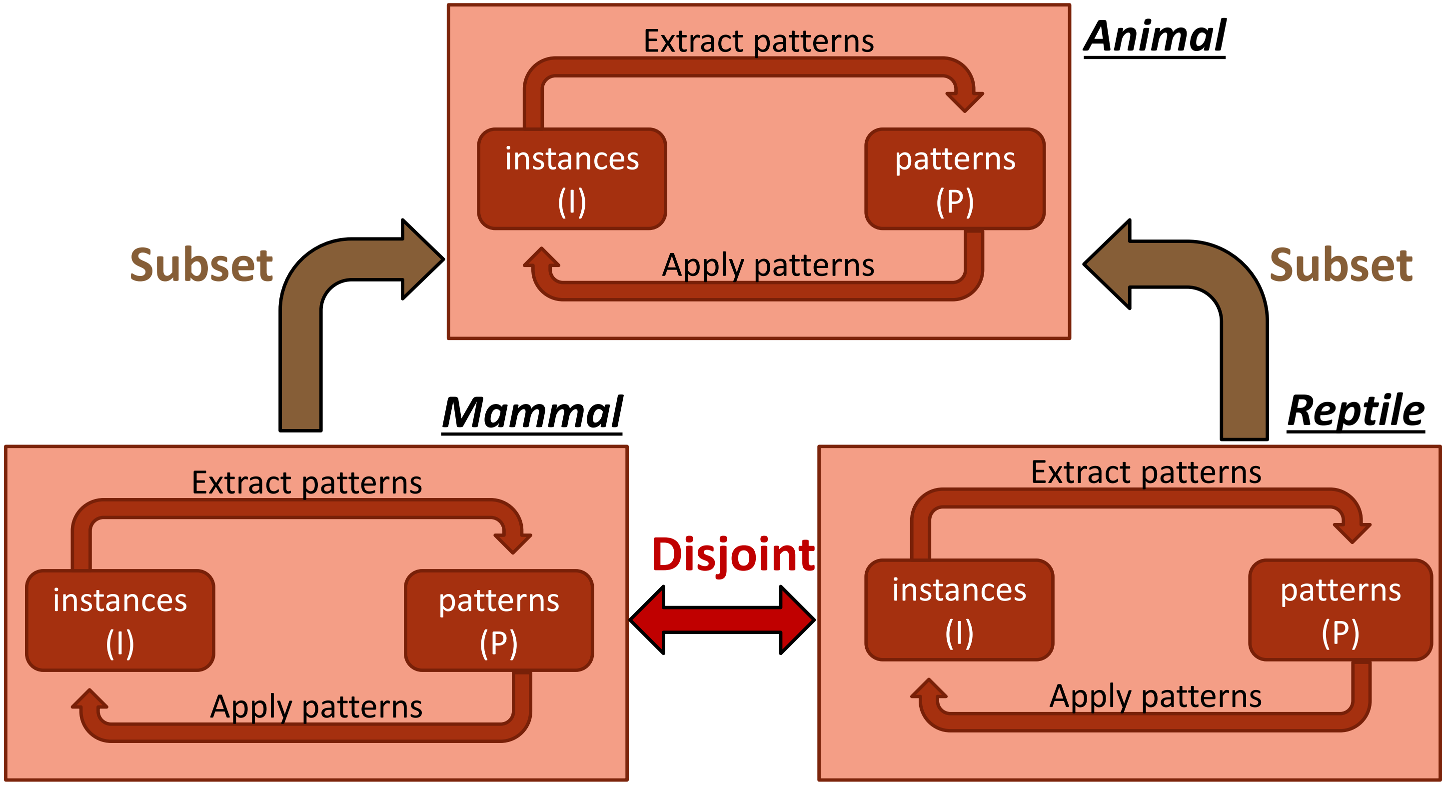
Semi-supervised learning (bootstrapping)



Coupling Constraints (Ontology)



Coupled bootstrap learning



*[**Toward an Architecture for Never-Ending Language Learning**, Carlson et al. AAAI 2010]*

(4) Open Domain IE

Defining domain	Learning extractors	Scoring extractions
		

(4) Open domain IE

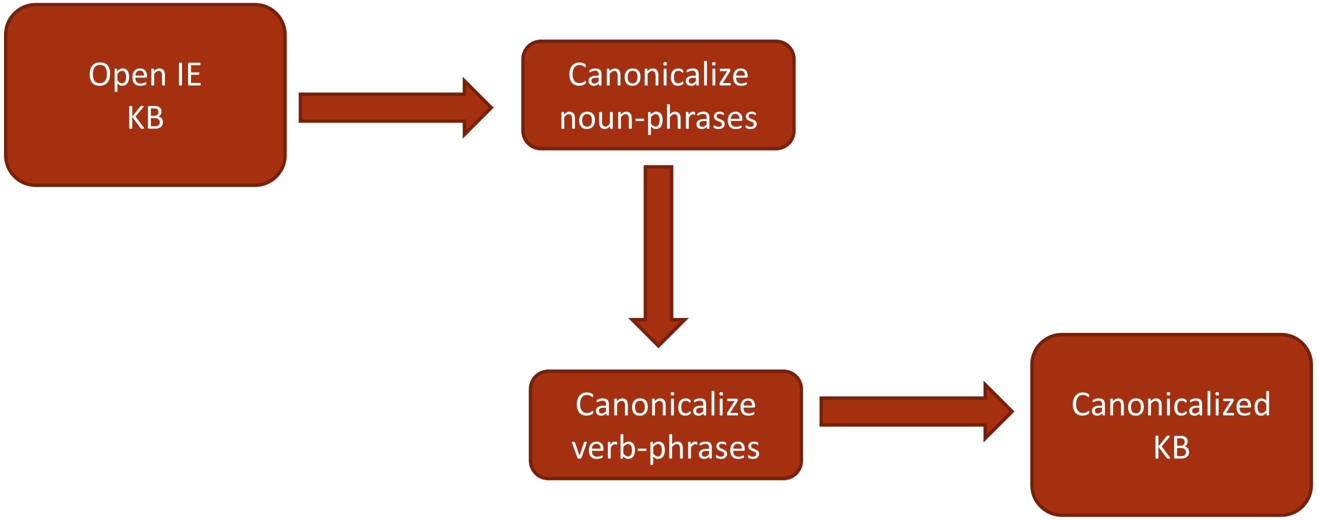
- Any noun phrase is a candidate entity
- Any verb phrase is a candidate relation
- Sentence: "John Lennon was an English music artist who gained worldwide fame as one of the members of the Beatles."
  Open IE extractions:
  - 0.95 (John Lennon; **was**; an English music artist)
  - 0.94 (an English music artist; **gained**; L:worldwide; fame; as one of the members of the Beatles)

(5) Hybrid approach

Adding structure to Open KB

Defining domain	Learning extractors	Scoring extractions
		

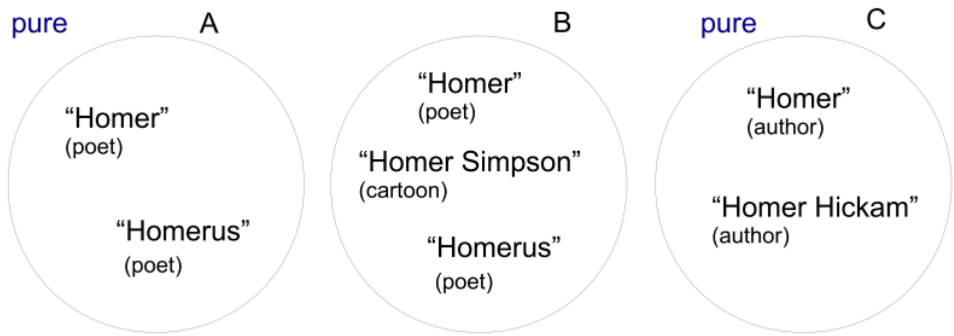
(5) Hybrid approach



*[**Canonicalizing Open Knowledge Bases, Galárraga at al.,** CIKM 2014]*

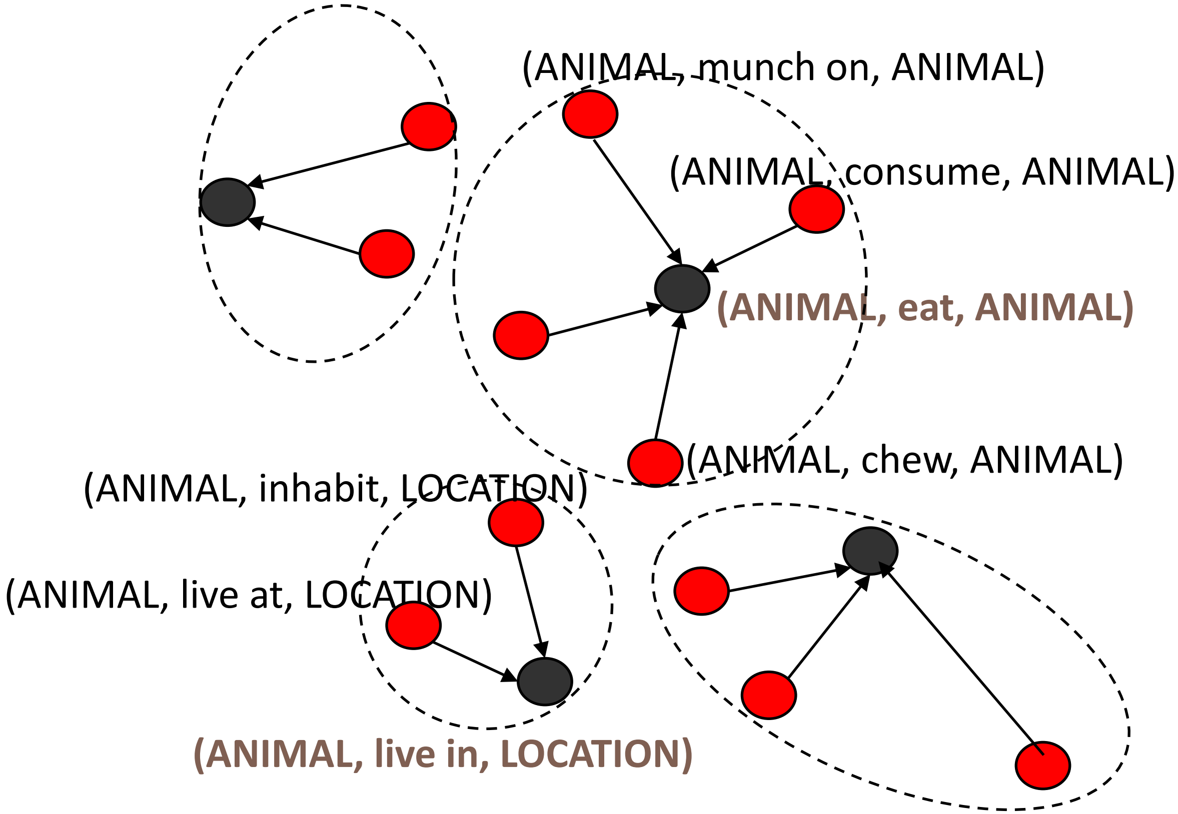
(5) Hybrid approach
(adding structure to Open KB)

- ***Canonicalizing noun phrases***



Canonical schema induction

Verb phrases	Freebase relation
be an abbreviation-for, be known as, stand for, be an acronym for	-
be spoken in, be the official language of, be the national language of	location.country.official_language
be bought, acquire	organization.organization.acquired_by



[Canonicalizing Open Knowledge Bases, Galárraga at al., CIKM 2014
Upcoming article in TACL 2017 ``Domain-Targeted, High Precision Knowledge Extraction'']

Knowledge fusion with multiple extractors

VOTING (AND VS OR OF EXTRACTORS)

CO-TRAINING (MULTIPLE EXTRACTION METHODS)

MULTI-VIEW LEARNING (MULTIPLE DATA SOURCES)

MACHINE LEARNING FOR KNOWLEDGE FUSION

Information Extraction

Single extractor

Fusing multiple extractors

Multiple weak extractors

- ***Extractor 1:*** text patterns to extract ISA relations
  e.g. coupled pattern learner in NELL

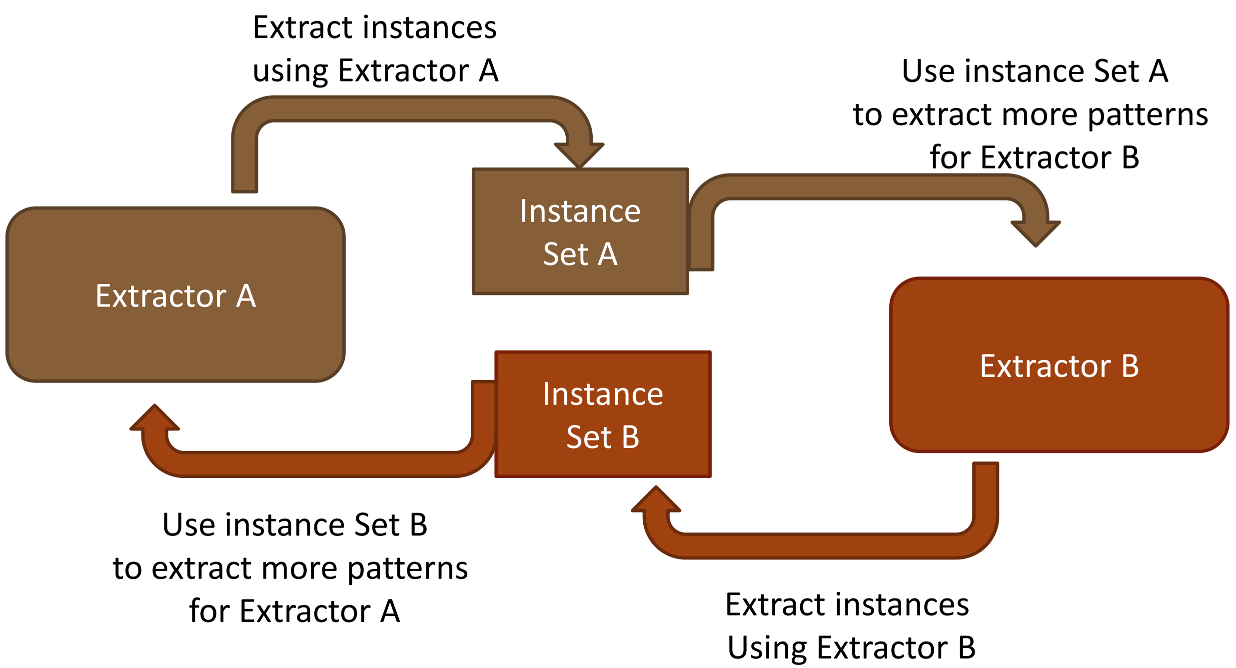
- ***Extractor 2:*** learning wrappers for HTML pages to extract ISA relations from structured text

Voting Schemes

- ***AND of two extractors:***
  - For a candidate extraction to be promoted to a fact in KB, both the extractors should support the fact
  - score(fact) = score_extractor1(fact) * scrore_extractor2(fact)

- ***OR of two extractors***
  - For a candidate extraction to be promoted to a fact in KB, both the extractors should support the fact
  - score(fact) = score_extractor1(fact) * scrore_extractor2(fact)

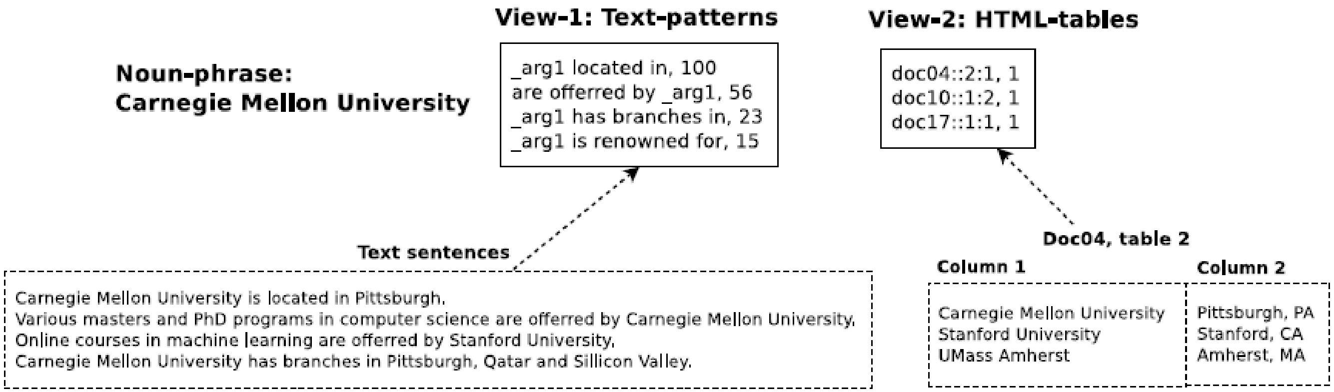
Co-training



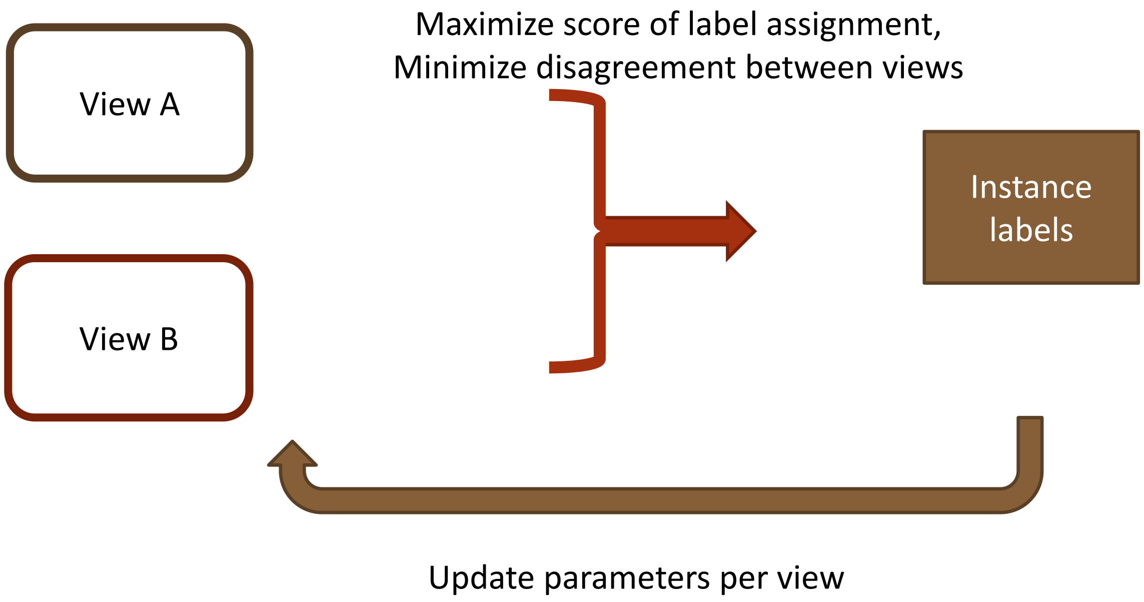
Extract instances
using Extractor A
Use instance Set A
to extract more patterns
for Extractor B
Instance
Set A
Extractor A
Extractor B
Instance
Set B
Use instance Set B
to extract more patterns
for Extractor A
Extract instances
Using Extractor B

Multiple data-views

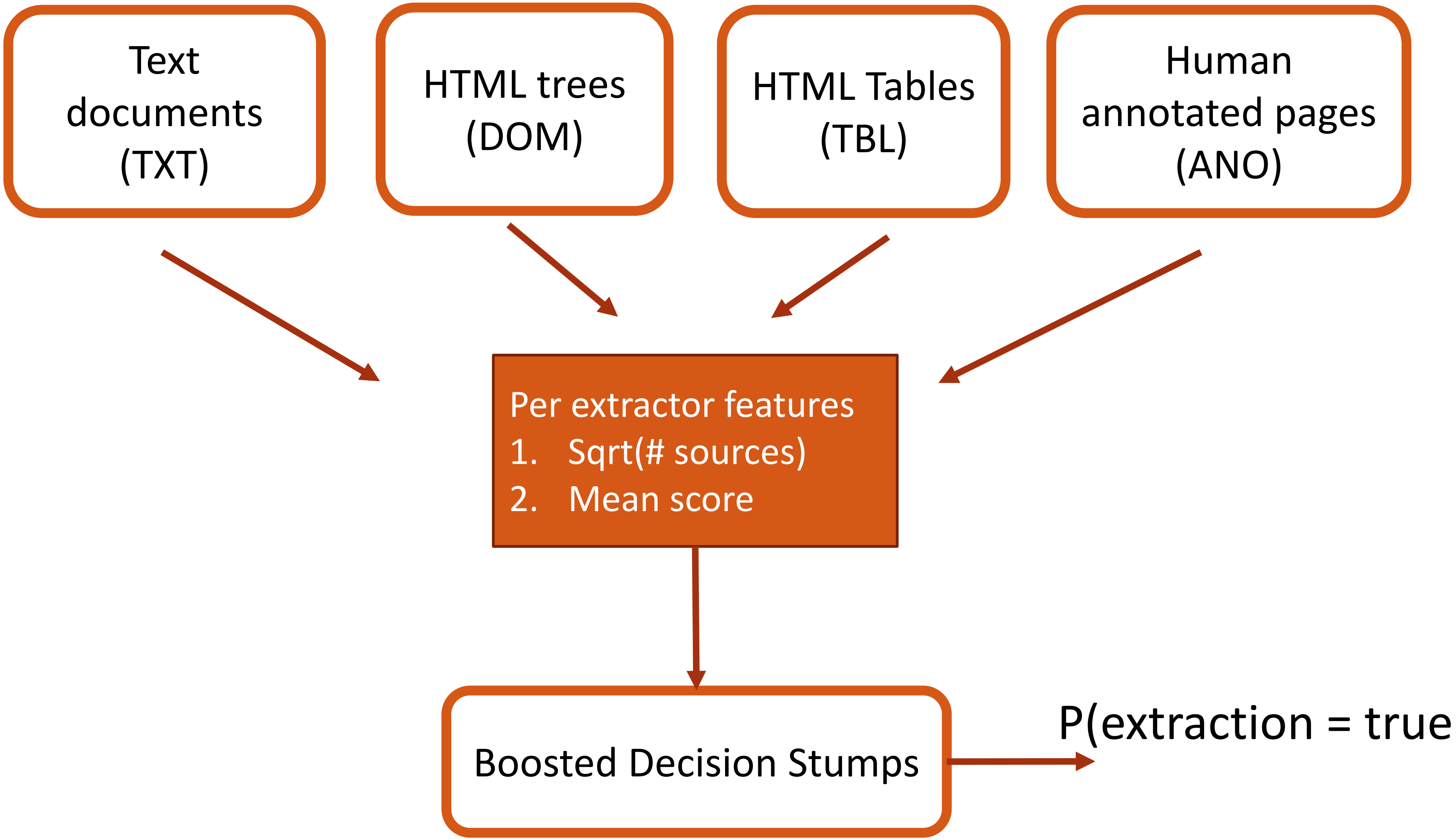
- NP “Carnegie Mellon University” can be represented in two different ways based on its occurrence in text documents and HTML tables.



Multi-view learning



Knowledge vault: fusing the extractors



Example IE Systems

OPEN IE

NELL

KNOWLEDGE VAULT

Open IE (KnowItAll)

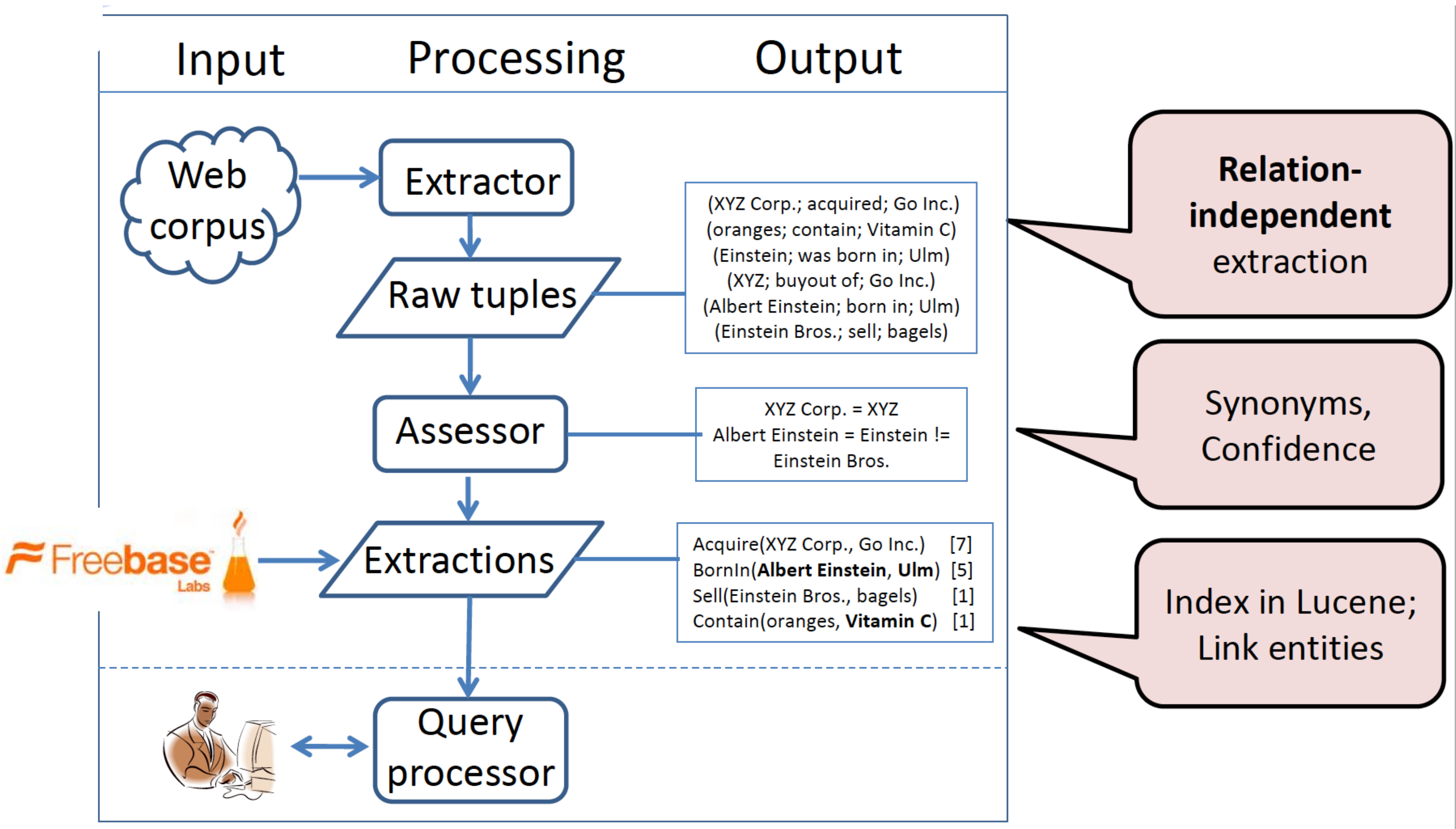
Open Information Extraction

Defining domain	Learning extractors	Scoring extractions
		

[Architecture diagram taken from Oren Etzioni’s slides]

Open IE (KnowItAll)

Open Information Extraction



[Architecture diagram taken from Oren Etzioni's slides]

Never Ending Language Learning (NELL)

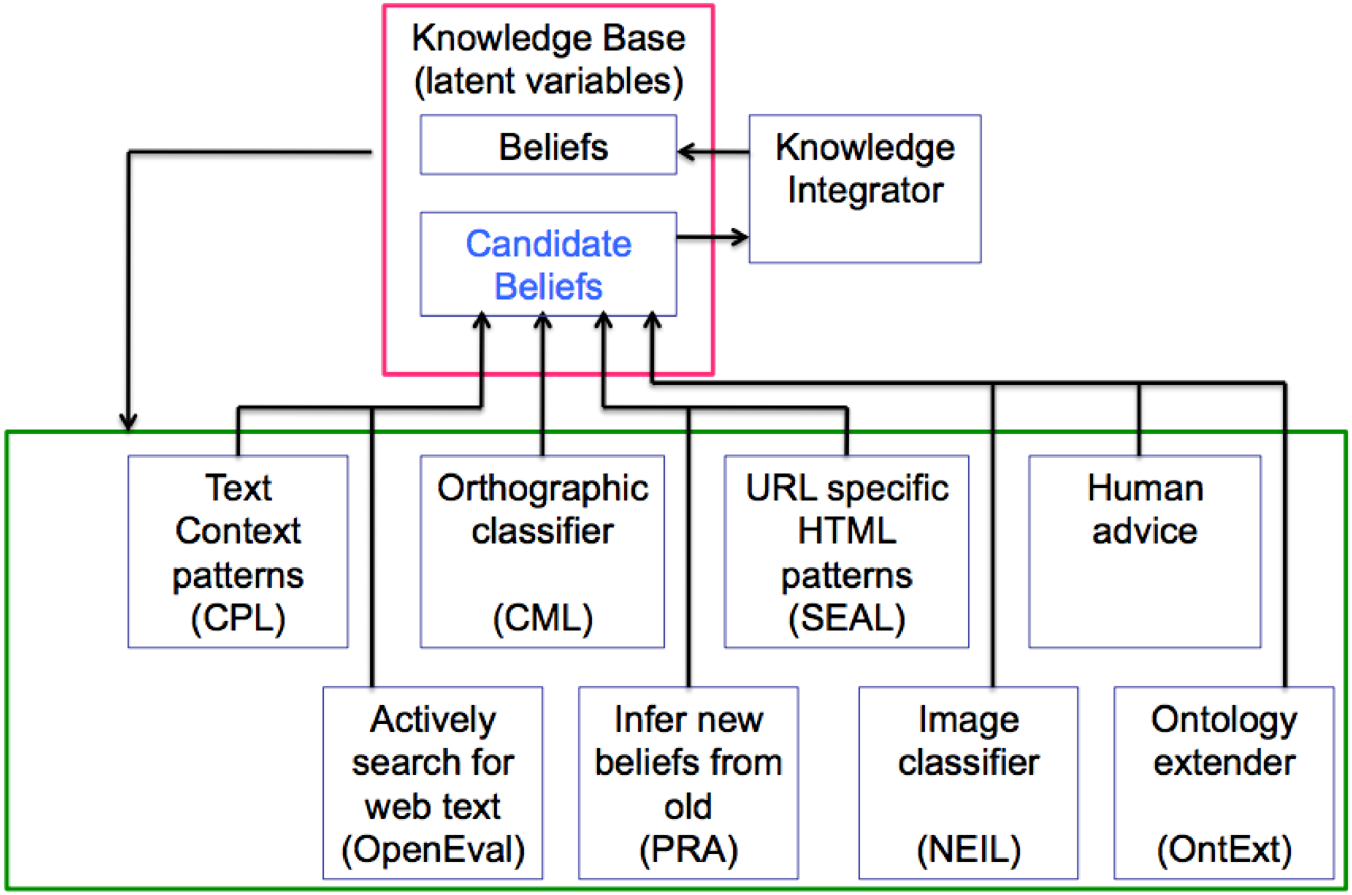
Ontology based extraction

NELL Knowledge Base Browser
CMU Read the Web Project

categories | relations

Defining domain	Learning extractors	Scoring extractions	Fusing extractors
			Voting + local constraint satisfaction

Never Ending Language Learning (NELL)

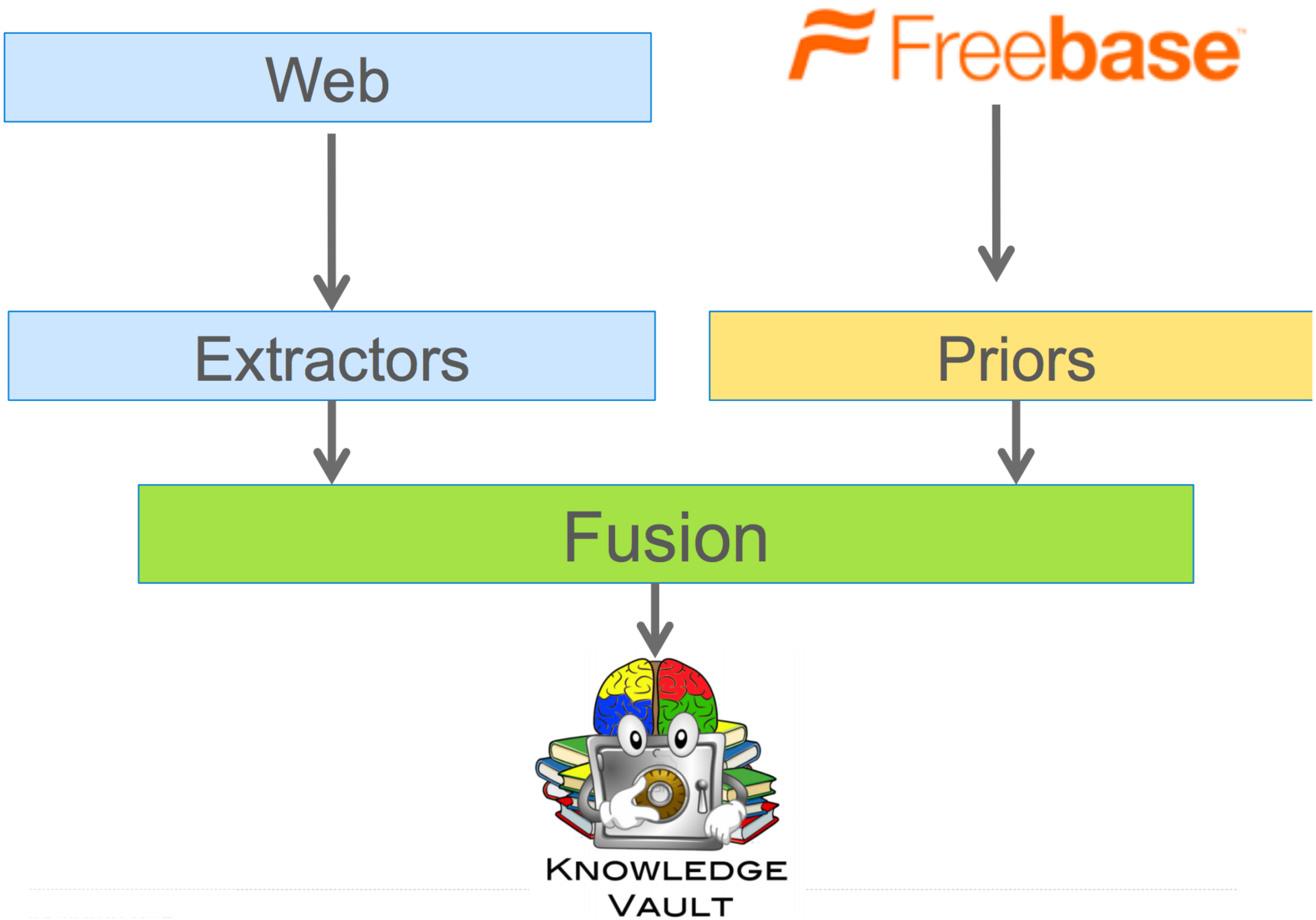


[Never-Ending Learning, *Mitchell et al., AAAI 2015]*

Knowledge Vault

Defining domain	Learning extractors	Scoring extractions	Fusing extractors
			Classifier (Boosted decision stumps)

Knowledge Vault



Summary: Information Extraction

3 IMPORTANT SUB-PROBLEMS

(DEFINE DOMAIN, LEARN EXTRACTORS, SCORE EXTRACTIONS)

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(MANUAL, SEMI-SUPERVISED, UNSUPERVISED)

KNOWLEDGE FUSION WITH MULTIPLE EXTRACTORS

(CO-TRAINING, MULTI-VIEW LEARNING)

EXAMPLE IE SYSTEMS

Thank You

SEE YOU AFTER THE COFFEE BREAK!