Open Information Extraction at Web Scale

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KnowItAll Group (2003 - ?)

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- Janara Christensen
- Tony Fader
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- Prof. Mausam
- Alan Ritter
- Michael Schmitz
- Dr. Stephen Soderland
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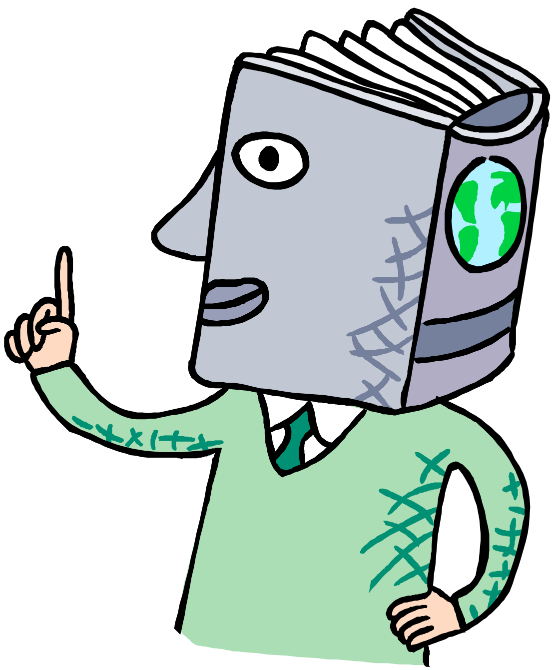
- PhD alumni: Michele Banko, Prof. Michael Cafarella, Prof. Doug Downey, Ana-Maria Popescu, Stefan Schoenmackers, and Prof. Alex Yates.

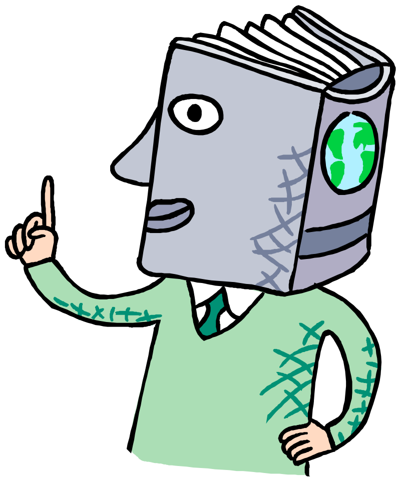


Les Valiant (Turing Award 2011)

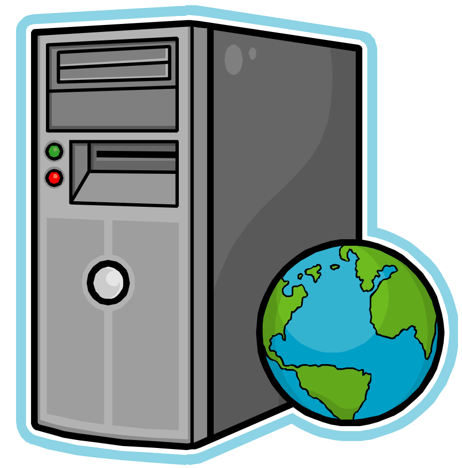
"The most critical choice for a scientist is what problems to work on."

Knowledge Acquisition Bottleneck

1. Massive knowledge is ***necessary*** for AI
   a) Cyc? (Doug Lenat)
   b) Games? (Luis von Ahn)
   c) Volunteers? (OpenMind)
2. Knowledge acquisition has to be ***automatic***
3. **Machine Reading of the Web!**
   (Etzioni et. al, AAAI ’06)
   a) 2009 DARPA MR Program
   b) NELL (Mitchell, AAAI ‘10)
   c) Watson (IBM, ‘11)



What is Machine Reading?



Text → Assertions → Inferences

Micro versus Macro

More Pragmatic Motivation: **Information Overload**

Today a person is subjected to more new information in a day than a person in the middle ages in his entire life!

Paradigm Shift: from retrieval to reading

Key features include…

RevMiner (Huang, Etzioni, Zettlemoyer)

- Extracts key attributes + opinions
- Applied to 400,000 Yelp reviews (Seattle)
- Based on Opine **(Popescu & Etzioni ‘05)**

Extractive UI versus search UI

(Yatani et. al, HCI ‘11)

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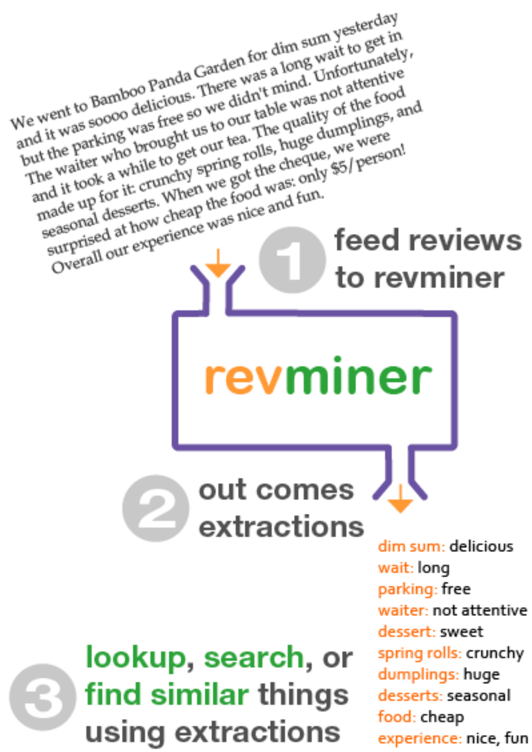
revminer

RevMiner is a University of Washington KnowItAll project by Jeff Huang, Oren Etzioni, Luke Zettlemoyer

RevMiner is an unsupervised extractor for user reviews about places in Seattle, like restaurants and stores

Try these **examples**:
good dim sum
agua verde cafe
cheap indian food
great view clean rooms comfortable bed
great location
elliott bay book
mexican
free parking friendly staff fresh fish



Review Miner - Mozilla Firefox

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Review Miner

http://revminer.com/#umi sake house, seattle

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revminer

umi sake house, seattle

Umi Sake House
Seattle

sushi — freshest (2), incredible, superb (2), amazing (16), fantastic (3), awesome (7), perfect, favorite (5), reasonable, excellent (7), best (62), delicious (16), affordable (2) fancy, worth (2), warm, inexpensive, fresh (40), traditional (7), not solid, tasty (4), huge (2), top (2), prepared, quick, real (3), korean, different (4), full, japanese (6) not bad, decent (3), expensive (4), not great (2), not good, raw, average (2), bad (3), okay (2), alright (2), ok (2), not fresh, mediocre (3), poor

place — freshest, amazing (2), superb (2), awesome (7), glad, favorite (11), perfect (5), intimate, delicious (2), gorgeous, excellent (3), best (7), yummy, classy, great (42), enormous, simple, worth (2), chic, everyday, authentic (2), fresh, impressive, fast, top (2), fun (4), tasty, modern, not loud, clean, entertaining, solid (2), fancy, sou pricier, cute (3), full (2), not small, crazy (3), different (2), packed (13), loyal, latest, central, hot, good (31), big (3), early, bigger, small (3), nice (8), japanese (3), stu pricey, tiny (2), open (4), long (2), popular (2), specific, close, tired (2), late (4), busy (4), cheap, not top, last, trendy (7), typical, not damn, giant, higher, not free, b decent, complete, off (3), loud (7), else, noisy (2), total, raw (2), excited, empty, overpriced, poor, rude, not nasty, not stuffy

rolls — wonderful (2), amazing (14), awesome (5), fantastic (5), perfect, delicious (12), best (3), excellent (2), creative (18), yummy (5), great (13), beautiful (2), super (3), (3), not unique, huge (13), light, tasty (7), large (9), extra (4), japanese (3), good (23), different (11), interesting (3), hot (4), full (3), big (6), fried (11), small, nice (4), better (5), not standard, standard (6), decent (2), fine, not tasty, raw (5), not good (2), average, okay, bad (6), not mediocre

food — fabulous (2), outstanding, amazing (11), wonderful, fantastic (2), awesome (4), pure, favorite (2), professional, excellent (11), affordable, delicious (7), best (7), yu friendly (2), fresh (7), not sweet, inexpensive, worth, generous, classic, authentic, baked, consistent, not delicious, extensive, damn, fast, top, tasty (6), spiced, regular (2), spicy, timely, full (2), japanese (13), smaller, cheap, late (2), enough, whole (2), pricey (5), usual, memorable, typical, not hard, not familiar, standard, b hungry, half, par, fine (3), slow (2), disappointed, cold, average (2), bad (2), okay, ok (3), alright, not impressed, mediocre, passable, overpriced (2), subpar, worst

service — incredible (2), impeccable (4), amazing (2), wonderful (2), superb, fabulous, outstanding (2), awesome (5), fantastic (5), reasonable, helpful (3), excellent (11), exce friendly (12), efficient (2), stellar (3), warm, speedy, attentive (8), top (2), fast (8), prompt (2), consistent, quick (8), large, solid (2), polite (2), full, above (2), good (3 best, usual, not old, standard, better (4), not consistent, spotty (3), decent (9), not great (3), fine, par (2), not hot, not attentive, slow (12), average, pretentious, ba sucked, not mediocre, inattentive, poor, awful, terrible (2), horrible (7), worse (2)

happy hour — incredible, fabulous, amazing (14), awesome (11), fantastic (6), favorite (2), unbeatable, excellent (2), delicious (3), best (19), reasonable, impressed, great (43), h different, low, good (13), big, regular (4), nice (5), late (14), long (4), busy, cheap (2), last (2), not bad, better (3), decent (3), not good (2), bad (3), ridiculous, not me

atmosphere — incredible, fabulous, amazing (2), wonderful, fantastic (3), perfect (2), awesome (2), excellent, relaxed, best, romantic, lovely, unique, classy (2), comfortable (4), lively, modern (2), fun (3), contemporary, attentive (2), cute, large, cool (13), exciting, pleasant, fancy, swanky (3), good (7), different (2), low, nice (20), not small, (2), not terrible, sucks (2)

prices — incredible, awesome, reasonable (17), not crunchy, great (20), worth, fair (4), huge (2), moderate, steeper, sweet, large, small, regular, full (4), spendy, not cheap steep (3), high (7), higher (3), hard, typical (2), sticky, due, better (2), not bad (4), lower (2), standard, decent (5), expensive, not sticky, average, acceptable, dry, overcooked (2), wet

fish — freshest (3), amazing, awesome, delicious (3), best (2), excellent (3), reasonable, flavorful, super (2), great (5), fresh (44), generous, prepared, huge, ideal, top, ta high (2), better, not fishy (2), not nice, fine, fishy, average, bad, not fresh (4), mushy

server — knowledgeable (2), wonderful, amazing, awesome (2), best (2), adorable, excellent, helpful (4), friendly (11), patient (2), super (3), gracious (2), great (4), efficient, pleasant, quick (3), different, nice (8), good (6), busy (3), long (3), whole, not nice, not bad (2), not knowledgeable, fine, slow (2), not friendly, not helpful, terrible, r

menu — incredible, amazing (3), fantastic, massive, delicious, creative (2), unique, super, great (2), inventive, diverse (2), enormous, wide, impressive, fresh (3), tasty, hu large (3), robust, able, nice (2), full, big, regular (8), good (3), crazy, interesting (2), small, long, normal (3), not traditional, typical, special, standard (3), decent, fine

restaurant — incredible, amazing, favorite (2), best, classy (2), romantic, great (3), airy, beautiful (3), worth, authentic, top, spacious, clean, tasty, huge (2), large (3), larger, ple nice, good (2), short, small (2), dark, whole, open, hard, not free, better (2), front (2), not packed, loud (2), fine, average, empty (3), not busy

Outline

I. Twin Motivations for Information Extraction (IE)
   1) Knowledge acquisition bottleneck
   2) New paradigm for search (Extractive UI)

II. Machine Reading = IE + inference
   1) Overview of IE
   2) Open IE
   3) Demo of Open IE
   4) Inference over extractions

III. Lessons and Future Work

1. Information Extraction (IE)

IE(sentence) = Relation instance, probability

"Edison was the inventor of the light bulb."

invented(Edison, light bulb), 0.9

"You shall know a word by the company it keeps" (Firth, 1957)

Context → clues

- …Barcelona mayor…
- …Downtown Barcelona…
- Spanish cities such as Madrid, Barcelona, and..

Where do clues come from?

How to Scale IE?

1970s-1980s: heuristic, hand-crafted clues

- Facts from earnings announcements
- **Narrow** genres; **brittle** clues

1990s: IE as supervised learning

“Mary was named to the post of CFO, succeeding Joe who retired abruptly.”

Learned Extraction Clues

"Mary was named to the post of CFO, succeeding Joe who retired abruptly."

- <New> was named to
- Post of <post>

Does "IE as supervised learning" scale to reading the Web?

No.

Critique of IE=supervised learning

- Relation specific
- Genre specific
- Hand-craft clues →
- Hand-craft training examples

Does not scale to the Web!

Semi-Supervised Learning

- Few hand-labeled examples **per relation!**
- → Limit on the number of relations
- → relations are pre-specified
- **→ Still does not scale to the Web**

Outline

I. Twin Motivations
   1) Knowledge acquisition bottleneck
   2) New paradigm for search
II. Machine Reading
   1) Overview of Information Extraction (IE)
   2) **Open IE**
   3) Demo
III. Inference over Extractions
IV. Lessons and Future Work

2. Open IE (Banko, IJCAI ’07; ACL ‘08)

- Avoid hand-labeling sentences
- Single pass over corpus
- No pre-specified vocabulary (cf. Sekine ’06)
  - Challenge: map relation ***phrase*** to canonical relation
  - E.g., “was the inventor of” ➔ invented

Open versus Traditional IE

	Traditional IE	**Open IE**
Input:	Corpus + Hand-labeled Data	Corpus + Existing resources
Relations:	Specified in Advance	Discovered Automatically
Complexity:	O(*D* * ***R***) *R* relations	O(*D*) *D* documents
Output:	relation-specific	**Relation-independent**

TextRunner

First Web-scale, Open IE system (Banko, IJCAI '07)

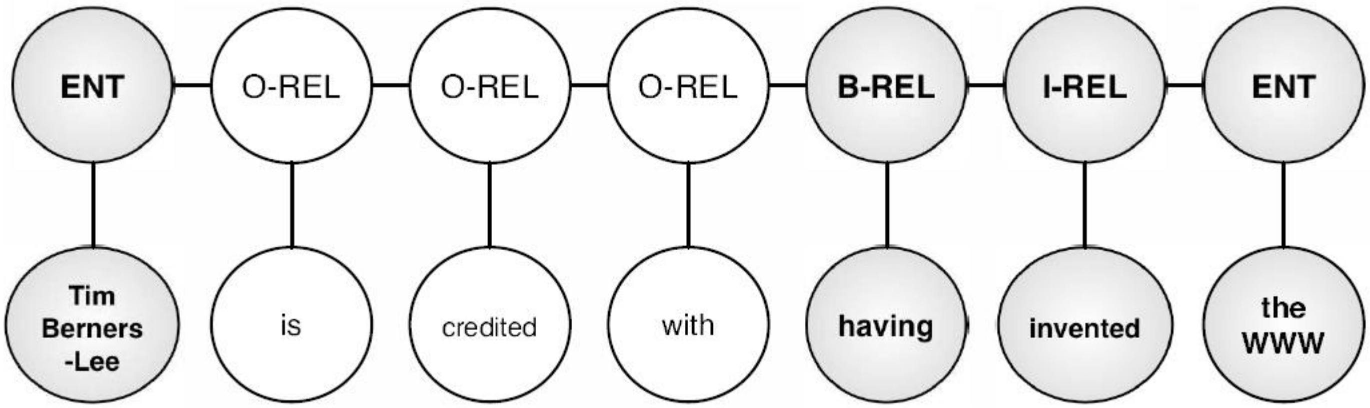
1,000,000,000 distinct extractions

Peak of 0.9 precision (but low recall)

Relation Extraction in TextRunner

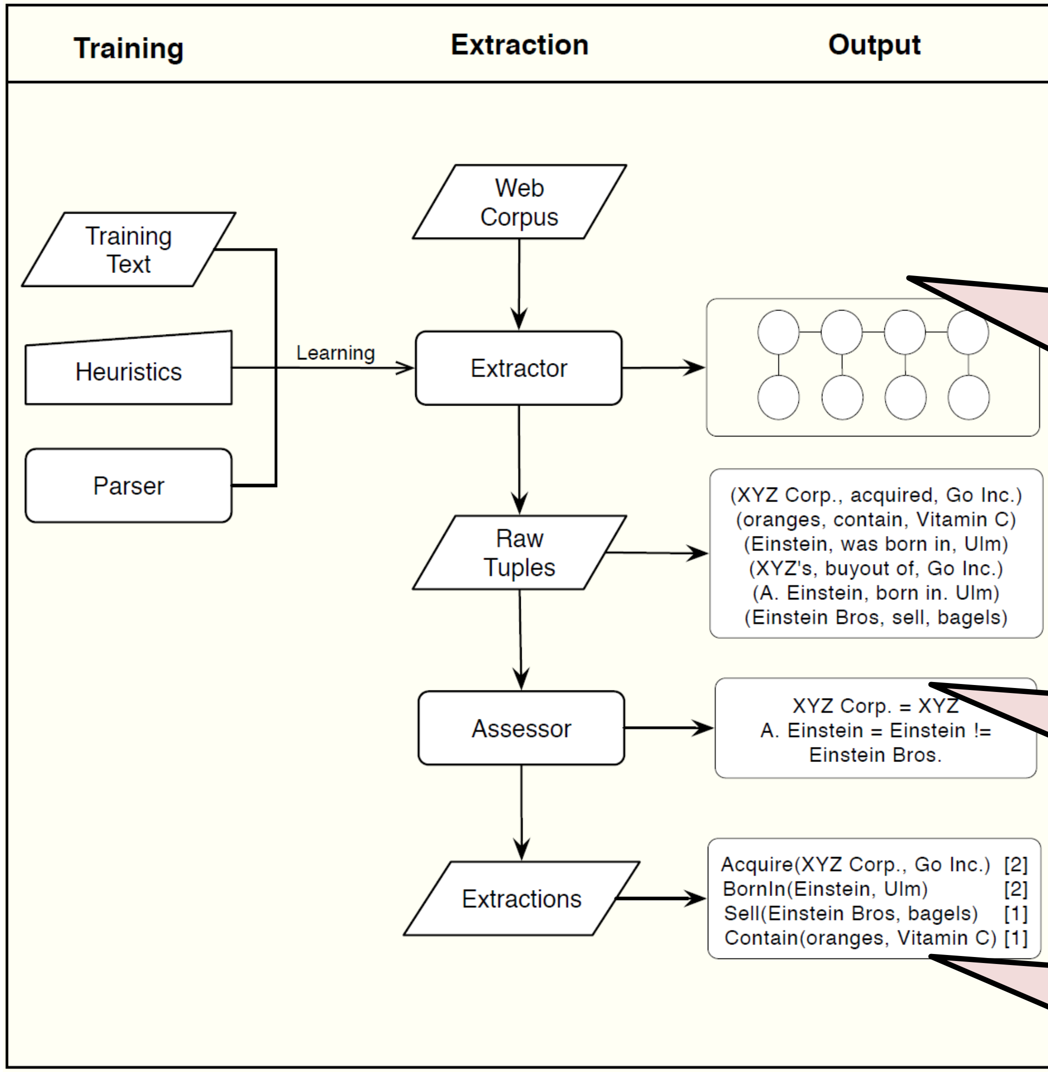
"Tim Berners-Lee is credited with having invented the WWW"

- **Which words denote the relation?**
- Mechanism: learn via linear CRF



TextRunner Architecture

Distant supervision ➔ **180,000** training examples



Unlexicalized model of relations

Count tuples; identify synonyms

Index in Lucene; relational queries

Two Types of Extraction Errors

"Al Gore invented the Internet."

Invented(Al Gore, Internet)

Sound extraction of incorrect fact.

"The cost of the war against Iraq has risen above 500 billion dollars"

above(Iraq, 500 billion dollars)

Unsound extraction.

How to Filter Unsound Extractions?

Leverage redundancy:

- More **distinct** clues → more confidence
- Higher **proportion** of clues → confidence
  - proportion = clues/mentions

Caveat: count over **independent** sentences!

Combinatorial Model (Downey, IJCAI ’05, AIJ ‘10)

If an extraction *x* appears *k* times in a set of *n distinct* sentences matching a clue, what is the probability that *x* ∈ *class C*?

$$P(x \in C \mid x \text{ appears } k \text{ times in } n \text{ draws}) = \frac{\sum_{r \in num(C)} \left(\frac{r}{s}\right)^k \left(1 - \frac{r}{s}\right)^{n-k}}{\sum_{r' \in num(C \cup E)} \left(\frac{r'}{s}\right)^k \left(1 - \frac{r'}{s}\right)^{n-k}}$$

15x more accurate than previous work.

Key Ideas in TextRunner

- Open IE on the Web is possible!
- Identified tractable subset of English
- Used “macro reading” to filter errors

Error Analysis of TextRunner Relations

Incoherent relations: 13% of the time

Sentence	Incoherent Relation
The guide *contains* dead links and *omits* sites.	contains omits
The Mark 14 *was central* to the *torpedo* scandal of the fleet.	was central torpedo
They *recalled* that Nungesser *began* his career as a precinct leader.	recalled began

Uninformative relations: 7% of the time

is	is an album by, is the author of, is a city in
has	has a population of, has a Ph.D. in, has a cameo in
made	made a deal with, made a promise to
took	took place in, took control over, took advantage of
gave	gave birth to, gave a talk at, gave new meaning to
got	got tickets to see, got a deal on, got funding from

ReVerb (Fader, EMNLP ’11; Etzioni *et al.,* IJCAI ‘11)

Identify **Re**lations from **Verbs**.

1. Find longest phrase matching a simple syntactic constraint:

$$\boxed{\begin{array}{l} \quad\quad\quad\quad V \mid V P \mid V W^* P \\ V = \text{verb particle? adv?} \\ W = (\text{noun} \mid \text{adj} \mid \text{adv} \mid \text{pron} \mid \text{det}) \\ P = (\text{prep} \mid \text{particle} \mid \text{inf. marker}) \end{array}}$$

ReVerb Refinement

Overly-specific Relation phrase: *"is offering only modest greenhouse gas reductions at"*

2. Constraint: |args(Relation)| > k

ReVerb ≈ two simple constraints!

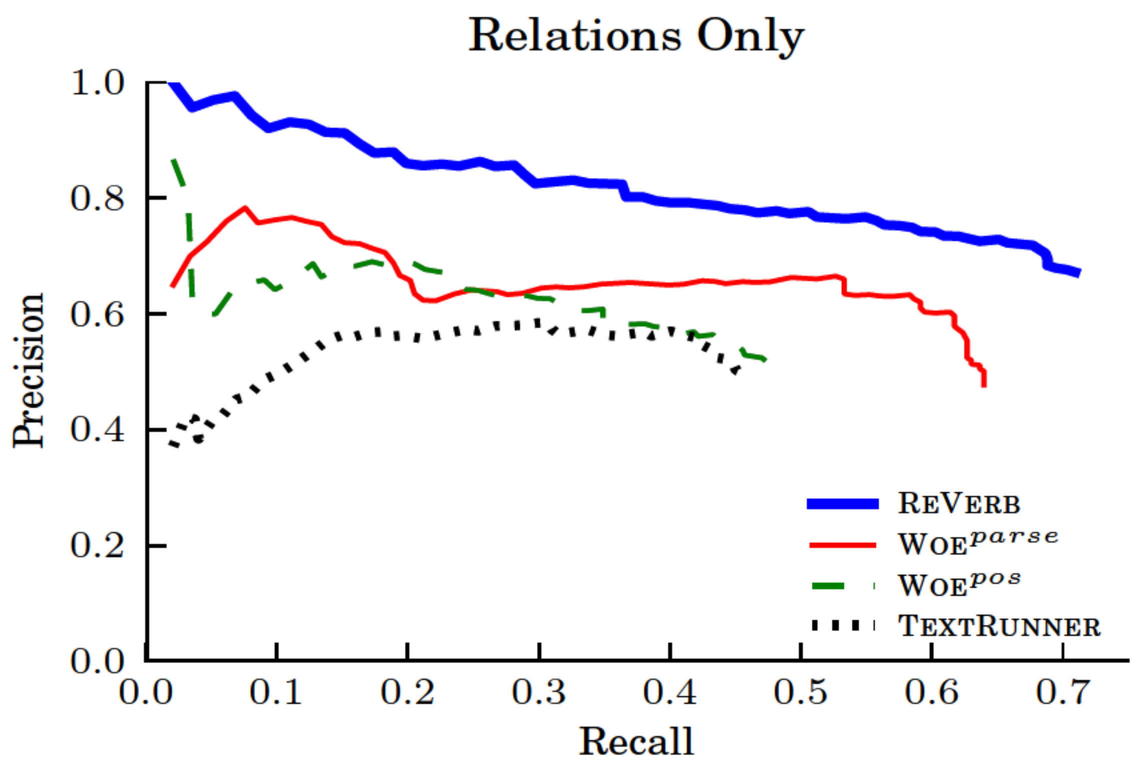
Sample of ReVerb Relations

inhibits tumor growth in	**has a PhD in**	**joined forces with**
is a person who studies	**voted in favor of**	**won an Oscar for**
has a maximum speed of	**died from complications of**	**mastered the art of**
gained fame as	**granted political asylum to**	**is the patron saint of**
was the first person to	**identified the cause of**	**wrote the book on**

Number of Relations

Yago	92
NELL	~500
DBpedia 3.2	940
PropBank	3,600
VerbNet	5,000
WikiPedia InfoBoxes, f > 10	~5,000
TextRunner	**100,000+**
ReVerb	**1,500,000+**

ReVerb versus TextRunner



Surprise: **"overlearning"**

3. Demo

- Note: open source ReVerb extractor + sample of data publically available at **reverb.cs.washington.edu**

ReVerb Search Results - Mozilla Firefox

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ReVerb Search Results

http://rv.cs.washington.edu:8080/rbart/cgi-bin/reverb/reverb_demo.pl

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ReVerb Search

ReVerb took .88 seconds.

Retrieved **363** results for Predicate containing "**kills**" and Argument 2 containing "**bacteria**"

Grouping results by predicate. Group by: argument 2 | argument 1

kills (211 results)

antibiotics (67), Antibiotics (33), Chlorine (31), *162 more...* **kills bacteria**

UV-lights (3), antibiotics (5), chlorine (4), *14 more...* **kills** most **bacteria**

UV technology (3), Cooking food (2), Iodine (2), *2 more...* **kills bacteria** and viruses

Antibiotics (5) can **kill** both beneficial and harmful **bacteria**

Antibiotics (2), Antibiotics (2) **kill** the gonorrhea **bacteria**

benzoyl peroxide (4) **kills** the acne-causing **bacteria**

Low-level disinfection (5), UV-C light (2) **kills** some viruses and **bacteria**

Antibiotics (2) **kill** chlamydia **bacteria**

home-care technique (2) **kills** deep gum disease **bacteria**

antibiotics (3) **kill** good gut **bacteria**

Chlorine (2) **kills** iron **bacteria**

powerful and effective sanitizer (2) **kills** algae and **bacteria**

antibiotics (3) **kill** ALL **bacteria**

Antibiotics (2) **kill** disease **bacteria**

Heat (2) **kills** food poisoning **bacteria**

Pasteurization (2) **kills** harmful levels of **bacteria**

benzoyl peroxide (2) **kills** the p-acnes **bacteria**

Freezing (3) **kills** all parasites and **bacteria**

ReVerb Search Results - Mozilla Firefox

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http://rv.cs.washington.edu:8080/rbart/cgi-bin/reverb/reverb_demo.pl

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Heat (2) **kills** food poisoning **bacteria**

Pasteurization (2) **kills** harmful levels of **bacteria**

benzoyl peroxide (2) **kills** the p-acnes **bacteria**

Freezing (3) **kills** all parasites and **bacteria**

Chlorination (2) **kills** many pathogenic **bacteria**

High temperatures (2) **kill** Salmonella **bacteria**

Active ingredient Triclosan (2) **kills** a broad spectrum of **bacteria** and yeasts

Razor Rinse (3) instantly **kills** harmful staph **bacteria**

Have we made progress towards Machine Reading?

III. Extractions as basis for Inference

Freebase Labs

1,000,000,000 Extractions

Identify synonyms
(Yates & Etzioni, JAIR ‘09)

1st order Horn-clause inference
(Schoenmackers ,EMNLP ‘08)

Learn argument types
(Ritter, ACL ‘10)

Transitive Inference
(Berant ACL ‘11)

Synonyms (Mars = Red Planet)

Resolver **(Yates & Etzioni, HLT '07, JAIR '09):** determines synonymy based on relations found by TextRunner

• born in(X, 1961)	born in(Y, 1961)
• citizen(X, US)	citizen(Y, US)
• Married to(X, Obama)	Married to(Y, Obama)

P(X = Y) ~ shared relations

P(R1 = R2) ~ shared argument pairs

Argument Typing

Example: P was born in Y

- P is a person
- Y is location or date

Text → Argument Types
(Ritter et. al, ACL '10)

- Previous work (Resnick, Pantel, etc.)
- Utilize generative topic models
- Topics → Terms → document

relation + args = "document"

Relations as Documents

TextRunner Extractions

born_in(Sergey Brin,Moscow)
headquartered_in(Microsoft, Redmond)

born_in(Bill Gates, Seattle)

born_in(Einstein, March)
founded_in(Google, 1998)

headquartered_in(Google, Mountain View)
born_in(Sergey Brin,1973)
founded_in(Microsoft, Albuquerque)
born_in(Einstein, Ulm)
founded_in(Microsoft, 1973)

LinkLDA

[Erosheva et. al. 2004]

X born_in Y

P(Topic1|**born_in**)=0.5

P(Topic2|**born_in**)=0.3

…

Person **born_in** **Location**

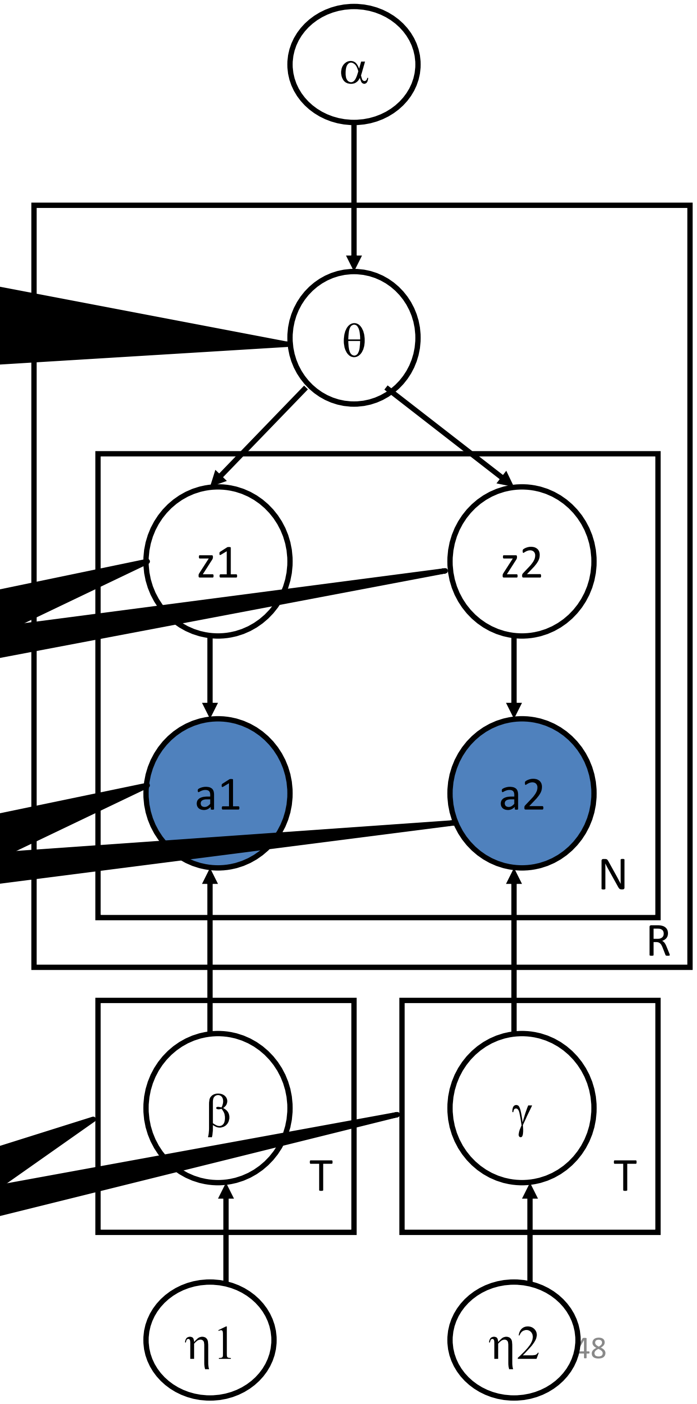
Sergey Brin **born_in** Moscow

For each relation, randomly pick a distribution over types

For each extraction, pick type for a1, a2

Then pick arguments based on types

Two separate sets of type distributions



Demo of LDA-SP (data publically available)

Argument types for relations

IV. Open IE Lessons

- Open IE is simple and highly scalable
(download at reverb.cs.washington.edu)

- Open IE is basis for “extractive interfaces”

- Open IE is basis for inference!

Conclusions/Speculations

Machine Reading = platform for NLP and AI (**VLSAI**)

Keyword Search → Question answering

Machine Reading ≠ human reading **(Remember Computer Chess!)**

	Binary Verbal Relation Phrases
85%	Satisfy Constraints
8%	Non-Contiguous Phrase Structure Coordination: X is produced and maintained by Y Multiple Args: X was founded in 1995 by Y Phrasal Verbs: X turned Y off
4%	Relation Phrase Not Between Arguments Intro. Phrases: Discovered by Y, X … Relative Clauses: … the Y that X discovered
3%	Do Not Match POS Pattern Interrupting Modifiers: X has a lot of faith in Y Infinitives: X to attack Y

Locating Arguments for Relations

ReVerb, TextRunner: arguments are the two nearest NPs.

"The cost of the war against Iraq has risen above 500 billion dollars"

(Iraq, has risen above, 500 billion dollars)

ArgLearner (Etzioni *et al.*, Ijcai '11)

- Learn independent extractors for left and right boundaries of each arg.

R2A2 = ReVerb + ArgLearner

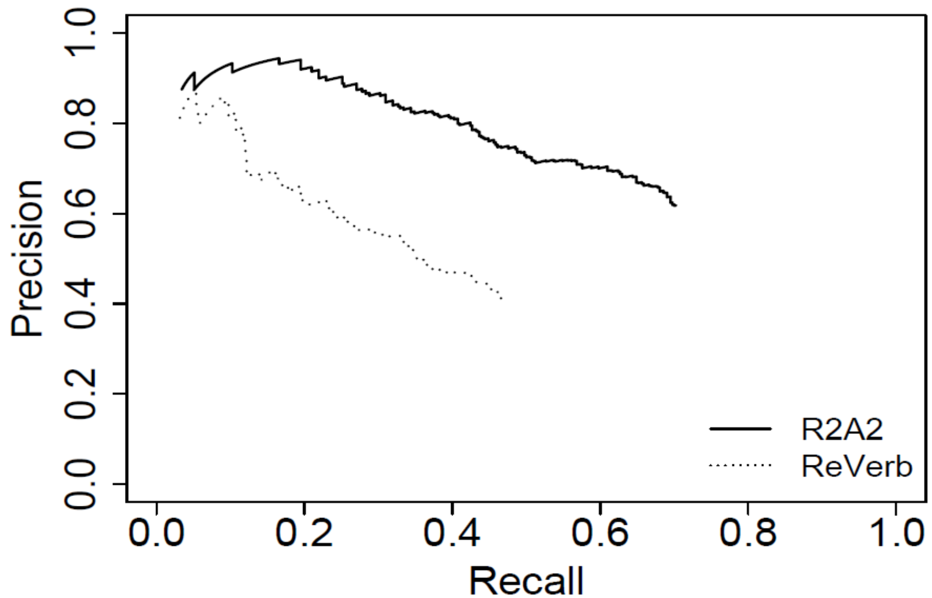


Figure 5: R2A2 has substantially higher recall and precision than REVERB.

Combinatorial Model (Yates, JAIR '09)

Theorem: *If two strings, s_i and s_j, have P_i and P_j potential properties, and they appear in extracted assertions D_i and D_j such that $|D_i| = n_i$ and $|D_j| = n_j$, and they share k extracted properties, the probability that s_i and s_j co-refer is:*

$$P(R^t_{i,j} \mid D_i, D_j, P_i, P_j) = \frac{P(k \mid n_i, n_j, P_i, P_j, S_{i,j} = \min(P_i, P_j))}{\sum_{S_{i,j}=k}^{\min(P_i,P_j)} P(k \mid n_i, n_j, P_i, P_j, S_{i,j})}$$

where:

$$P(k \mid n_i, n_j, P_i, P_j, S_{i,j}) = \frac{\binom{S_{i,j}}{k} \sum_{r,s \geq 0} \binom{S_{i,j}-k}{r+s} \binom{r+s}{r} \binom{P_i - S_{i,j}}{n_i - (k+r)} \binom{P_j - S_{i,j}}{n_j - (k+s)}}{\binom{P_i}{n_i}\binom{P_j}{n_j}}$$