Information extraction

8. Consolidation

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Announcements

• Results assignment 7 online
The ideas behind this code:

1. For sentences that have S-P-O format:
   - Take the subject by dependency of "nsubj" or "nsubjpass" that have "head" as "verb".
   - Use the token.head as the verb
   - Put the remaining words on the object

2. Passive sentences are identified by the structure of '-object- verb -agent--subject-': (line 78-105)
   i.e. Annualized interest rates on certain investments as reported by the Federal Reserve Board
   - object : Annualized interest rates on certain investments
   - verb : reported
   - agent : by
   - subject: the Federal Reserve Board

3. For sentences that have "verb" conjunction: (line 107-109)
   i.e. Large cross-border deals numbered 51 and totaled $17.1 billion in the second quarter, the firm added.
   - subject of "toteded" is taken from the subject of conjunction "verb", in this case "numbered"

4. For sentences that have subject and verb at last: (line 111-119)
   i.e. Large cross-border deals numbered 51 and totaled $17.1 billion in the second quarter, the firm added.
   - Find the whole family of "verb's child". In this case, "numbered" is the child of "added",
   - so we extract anything that connected to "numbered".
   - The similar case also used to extract the subject (line 120-122).

5. What does "find_full_subj(word)" do? (line 149-160)
   This function give all the family of the given word and returning the ordered words by the index.
   This is used in finding "complete subject" and "complete object" in 4th case.

Interesting findings:

1. By only changing the "object" of baseline to the whole sentence after the "verb"
   can give us 0.69 F1 score with: 0.92 precision and 0.54 recall
   i.e. Large cross-border deals numbered 51 and totaled $17.1 billion in the second quarter, the firm added.
   - subject : deals
   - predicate : numbered
   - object : 51 and totaled $17.1 billion in the second quarter, the firm added.
Outline

1. Motivation

2. Consolidation
   - MaxSAT
   - Probabilistic Soft Logic
   - Google Knowledge Vault

3. Pattern Learning
   - Association rule mining
   - Matrix completion
   - Knowledge graph embeddings
Consolidation: Context

• **Ambiguity** at all stages of the pipeline
  - Entity recognition, coreference, entity disambiguation, relation extraction, ...
  → All extractions are only probabilistically correct

• **Solution: Redundancy**
  - Extract from large corpora like web
  - Try to spot information multiple times
    - Multiple sentences, documents, patterns
    - Unlike e.g. a redundancy-free WP biography in isolation

• **Solution or curse?**
  - Redundancy enables competitive and contradictory information
Contradictory information

- 30x R(a, b)
- 25x R(a, c)
- 17x S(d, e)
- 17x S(e, f)
- 3x S(f, d)

- Contradictory?
  - R = place of birth
  - S = childOf

→ Contradictions surface only with world knowledge
→ Expert input or constraint/pattern mining needed
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MaxSAT for IE

“Hermione is married to Ron”

IE faces at least 3 problems:
- Understand patterns  (“X is married to Y” = killed(X,Y)?)
- Disambiguate entities (“Ron” = Ronald Reagan?)
- Resolve inconsistencies (Reagan married to 2 women?)
MaxSAT for IE

“Hermione is married to Ron”

- Disambiguation avoids inconsistency
- Pattern helps disambiguation
- Consistency helps finding patterns

=> Solve all 3 problems together!
Idea: Solve all problems together

“Hermione is married to Ron”

\[ A \land B \Rightarrow C \]

Find best conclusion

\textit{hasSpouse}(Hermione, RonWeasley)
Refresh: Atoms and KBs

An positive literal holds ("is true") in a KB, if it appears in the KB.
A negative literal \( \neg A \) holds in a KB if \( A \) does not hold.
A conjunction \( A \land B \land \ldots \land Z \) holds in a KB, if all of its elements hold.

\[ \text{likes(Hermione, Ron)} \]
\[ \neg \text{envies(Ron, Harry)} \]
\[ \neg \text{envies(Ron, Harry)} \land \text{likes(Harry, Hermione)} \]
\[ \text{envies(Harry, Ron)} \land \text{likes(Hermione, Ron)} \land \text{likes(Harry, Elvis)} \]
Refresh: Implications

An positive literal holds ("is true") in a KB, if it appears in the KB.
A negative literal \( \neg A \) holds in a KB if \( A \) does not hold.
A conjunction \( A \land B \land \cdots \land Z \) holds in a KB, if all of its elements hold.
An implication \( \overline{B} \Rightarrow H \) holds in a KB if \( \overline{B} \) does not hold or \( H \) holds.

\[
\begin{align*}
\text{likes(Hermione, Ron)} & \Rightarrow \text{likes(Harry, Ron)} \\
\text{likes(Harry, Ron)} & \Rightarrow \text{hasSpouse(Harry, Hermione)} \\
\neg \text{likes(Hermione, Harry)} & \Rightarrow \text{envies(Harry, Ron)} \\
\neg \text{likes(Hermione, Harry)} & \Rightarrow \text{hasSpouse(Harry, Ron)} \\
\text{likes(Hermione, Ron)} & \land \neg \text{envies(Harry, Ron)} \Rightarrow \text{ffe(Harry, Ron)}
\end{align*}
\]
Def: Rules, Disjunctions, Clauses

An implication (also: rule) \( B_1 \land ... \land B_n \Rightarrow H \)

is equivalent to a disjunction \( \neg B_1 \lor ... \lor \neg B_n \lor H \)

which we also write as a clause \( \{ \neg B_1, ..., \neg B_n, H \} \).

\[
\text{likes}(Hermione, Ron) \Rightarrow \text{likes}(Harry, Ron)
\]

is equivalent to

\[\neg \text{likes}(Hermione, Ron) \lor \text{likes}(Harry, Ron)\]

is equivalent to

\[\{ \neg \text{likes}(Hermione, Ron), \text{likes}(Harry, Ron) \}\]

“at least one of these has to hold”
Refresh: Universally quantified formula

A universally quantified formula holds in a KB, if all of its instantiations hold.

\[ \text{hasSpouse}(x, y) \]

\[ \text{hasSpouse}(x, y) \Rightarrow \text{hasSpouse}(y, x) \]

\[ \text{hasSpouse}(\text{Elvis}, y) \Rightarrow \text{hasSpouse}(y, \text{Elvis}) \]

\[ \text{hasSpouse}(\text{Ron}, y) \Rightarrow \text{hasSpouse}(y, \text{Ron}) \]
Def: Weighted Rule

A weighted rule is a rule with an associated real-valued weight.

\[ \text{hasSpouse}(Elvis, Priscilla) \Rightarrow \text{hasSpouse}(Priscilla, Elvis) \] [3.14]

A weighted rule can also be seen as a weighted disjunction...

\[ \neg \text{hasSpouse}(Elvis, Priscilla) \lor \text{hasSpouse}(Priscilla, Elvis) \] [3.14]

...or a weighted clause.

\[ \{ \neg \text{hasSpouse}(Elvis, Priscilla), \text{hasSpouse}(Priscilla, Elvis) \} \] [3.14]
Def: Weight of a KB

Given a set of atoms (= possible world, KB) and a set of instantiated rules with weights, the weight of the KB is the sum of the weights of all rules that hold in the KB.

\[ \text{hasSpouse}(Elvis, Priscilla) \Rightarrow \text{hasSpouse}(Priscilla, Elvis) [3] \]

\[ \text{hasSpouse}(cat, dog) \Rightarrow \text{hasSpouse}(dog, cat) [2] \]

KB1

\[ \text{hasSpouse} \]

Weight: 2

KB2

\[ \text{hasSpouse} \]

Weight: 5
Def: Weighted MAX SAT

Given a set of instantiated rules with weights, weighted MAX SAT is the problem of finding the KB with the highest weight. If there are several, find the one with the least number of atoms.

\[
is(Ron,immature) \ [10] \\
is(Ron,immature) \land type(H.,sorceress) \Rightarrow likes(H.,Ron) \ [3] \\
type(Hermione,sorceress) \ [4]
\]

Best world:

\[
is(Ron,immature) \\
type(Hermione,sorceress) \\
likes(Hermione,Ron)
\]

weight: 17
Def: Exhaustive search

Exhaustive search is an algorithm for the Weighted MAX SAT problem that tries out all possible worlds with the atoms that appear in the rules in order to find the possible world with the maximal weight.

\[ is(Ron, \text{immature}) \] [10]

\[ is(Ron, \text{immature}) \land type(H., \text{sorceress}) \Rightarrow likes(H., Ron) \] [3]

\[ type(Hermione, \text{sorceress}) \] [4]

Atoms:

\[ is(Ron, \text{immature}), type(H., \text{sorceress}), likes(H. Ron) \]

Exhaustive search is a correct and complete algorithm for the Weighted Max Sat problem. However, it has to analyze \(2^n\) possible worlds, where \(n\) is the number of atoms.

\( \{is(Ron, \text{immature}), type (H., \text{sorceress})\} \): weight 14, etc.
Task: Weighted MAX SAT

Find the KB with the highest weight:

\[ is(Hermione,smart) \] [1]

\[ is(Hermione,smart) \land is(Harry,smart) \Rightarrow likes(Hermione,Harry) \] [3]

\[ likes(Hermione,Ron) \Rightarrow \neg likes(Hermione,Harry) \] [100]

\[ is(Harry,smart) \] [10]

\[ likes(Hermione,Ron) \] [20]
Solving Weighted MAX SAT

To always find the optimal solution, one has to do an exhaustive search. Since SAT is NP-complete, so is MAX SAT and Weighted MAX SAT.

To find an approximate solution, possible strategies are:
• do an exhaustive search if there are few atoms
• try out several random KBs
• apply unit propagation wherever possible
• give preference to rules/unit clauses with higher weights
• remove atoms that appear only negative, add atoms to the KB that appear only positive.
Back to our problem

"Hermione is married to Ron"

\[ A \land B \Rightarrow C \]

transform everything to logical formulas

Find best conclusion

\[ \text{hasSpouse}(\text{Hermione}, \text{RonWeasley}) \]
Consistency

Consistency constraints can be expressed by rules:

\[
has\text{Spouse}(X,Y) \land different(Y,Z) \Rightarrow \neg has\text{Spouse}(X,Z) \ [10]
\]

\[
has\text{Spouse}(X,Y) \Rightarrow type(X,\text{person}) \ [20]
\]

\[
\ldots
\]

Rules and weights can be designed manually. Such rules will guide our information extraction process.
A KB can be expressed as rules

Every fact from the KB can be expressed as a weighted rule:

\[ \text{type}(\text{Hermione}, \text{Person}) \] $[100]$

$\uparrow$

High weight

This corresponds to the rule

\[ \Rightarrow \text{type}(\text{Hermione}, \text{Person}) \] $[100]$
Expressing the corpus as rules

D42: Hermione married Ron.

\text{occurs}(\text{Hermione} @ D42, \text{“married”}, \text{Ron} @ D42)

Does not talk about Ronald Reagan or Ron Weasley, but about the word “Ron” in document D42.

\text{Ron} @ D42 is a “word in context” (wic).
Expressing the corpus as rules

D42: Hermione married Ron.

occurs(Hermione@D42, “married”, Ron@D42)

The word “Ron” in document D42 can mean different entities (from KB):

\[ \text{means}(\text{Ron}@D42, \text{RonaldReagan}) \]

\[ \text{means}(\text{Ron}@D42, \text{RonWeasley}) \]

But only one entity in practice:

\[ \text{means}(X,Y) \land \text{different}(Y,Z) \Rightarrow \neg \text{means}(X,Z) \]
Weights for corpus rules

\[\text{occurs}(\text{Hermione@D42, "married", Ron@D42})[3]\]

\[\text{means}(\text{Ron@D42, RonaldReagan})\]

\[\text{means}(\text{Ron@D42, RonWeasley})\]

\[\text{means}(X,Y) \land \text{different}(Y,Z) \Rightarrow \neg \text{means}(X,Z)\]
Weights for corpus rules

occurs(Hermione@D42, "married", Ron@D42)[3]

From disambiguation by context/prior

means(Ron@D42, RonaldReagan)[5]

means(Ron@D42, RonWeasley)[7]

means(X,Y) ∧ different(Y,Z) ⇒ ¬ means(X,Z)
Weights for corpus rules

\textit{occurs}(\textit{Hermione@D42, “married”, Ron@D42})[3]

\textit{means}(\textit{Ron@D42, RonaldReagan})[5]

\textit{means}(\textit{Ron@D42, RonWeasley})[7]

“Hard” rule with very high weight

\textit{means}(X,Y) \land \textit{different}(Y,Z) \Rightarrow \neg \textit{means}(X,Z) [100]
Weights for corpus rules

\( \text{occurs}(\text{Hermione@D42, } \text{“married”}, \text{Ron@D42})[3] \)

\( \text{means}(\text{Ron@D42, RonaldReagan}) \)

\( \text{means}(\text{Ron@D42, RonWeasley}) \)

\( \text{means}(X,Y) \land \text{different}(Y,Z) \Rightarrow \neg \text{means}(X,Z) [100] \)

Let us ignore the weights for a moment.
Deducing patterns

hasSpouse(Reagan, Davis)

occurs(R@1, "married", D@1)

means(R@1, Reagan)

means(D@1, Davis)

occurs(X, P, Y)

∧ means(X, X’)

∧ means(Y, Y’)

∧ R(X’, Y’)

⇒ isPatternFor(P, R)

isPatternFor("married", hasSpouse)
Applying patterns

“X married Y”
is pattern for
\( \text{hasSpouse}(X,Y) \)

\( + \)

Elvis married Priscilla.

\( \Rightarrow \)
\( \text{hasSpouse}(\text{Elvis},\text{Priscilla}) \)

\( \text{isPatternFor}(“\text{married”}, \text{hasSpouse}) \)

\( \text{occurs}(E@1, “\text{married”}, P@1) \)

\( \text{means}(E@1, \text{Elvis}) \)

\( \text{means}(P@1, \text{Priscilla}) \)

\( \text{occurs}(X,P,Y) \)

\( \land \text{means}(X,X’), \land \text{means}(Y,Y’) \)

\( \land \text{isPatternFor}(P,R) \)

\( \Rightarrow R(X’,Y’) \)
Task: Pattern deduction by rules

Pattern deduction:

\[ \text{occurs}(X,P,Y) \]
\[ \land \text{means}(X,X') \]
\[ \land \text{means}(Y,Y') \]
\[ \land R(X',Y') \]
\[ \Rightarrow \text{isPatternFor}(P,R) \]

Pattern application:

\[ \text{occurs}(X,P,Y) \]
\[ \land \text{means}(X,X') \]
\[ \land \text{means}(Y,Y') \]
\[ \land \text{isPatternFor}(P,R) \]
\[ \Rightarrow R(X',Y') \]

1: \text{occurs}(P@1, "adores", E@1)
2: \text{means}(E@1, Elvis)
3: \text{means}(P@1, Priscilla)
4: hasSpouse(Priscilla, Elvis)
5: \text{occurs}(M@1, "adores", E@1)
6: \text{means}(M@1, Madonna)

All rules have weight 1.

Compute facts that will be in the best world.
Life is not easy

• words are ambiguous
  “Ron”
• corpora may err
  “Madonna is married to Elvis”
• contradictions may occur
  Reagan was married twice.

=> we will compute the most plausible world
Finding the most plausible world

“Hermione married Ron”

occurs(H@1, “married”, R@1)[1]

isPatternFor(“married”, spouse)[1]

means(H@1, Hermione)[5]

means(R@1, RonWeasley)[2]

means(R@1, Reagan)[3]

means(X, Y) ∧ Y ≠ Z ⇒ ¬ means(X, Z)[10]

spouse(X, Y) ∧ Y ≠ Z ⇒ ¬ spouse(Z, X)[6]

+ Symmetry of marriage

+ Pattern Application Rule [10]

+ Facts from the KB [100]

World1:

World2:
Finding the most plausible world

“Hermione married Ron”

occurs(H@1, “married”, R@1)[1]

isPatternFor(“married”, spouse)[1]

means(H@1, Hermione)[5]

means(R@1, RonWeasley)[2]

means(R@1, Reagan)[3]

means(X, Y) ∧ Y ≠ Z ⇒ ¬ means(X, Z)[10]

spouse(X, Y) ∧ Y ≠ Z ⇒ ¬ spouse(Z, X)[6]

+ Symmetry of marriage

+ Pattern Application Rule [10]

+ Facts from the KB [100]

World1:

spouse

loses 2

wins 3

loses 6

World2:

spouse

loses 3

wins 6

wins 2
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   • MaxSAT
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Probabilistic Soft Logic

• MaxSAT computes THE most likely world
• Probability of individual statements to be true?
  → Via sum of probability of all worlds in which they are true

→ Markov logic networks/Probabilistic soft logic
  ▪ Efficient approximations via Gibbs sampling
    ▪ Compute random worlds
    ▪ Update individual variables based on priors and state of other variables
    ▪ Repeat updating until convergence
    ▪ Sum up probabilities from samples with positive variable value

→ Prominent system: DeepDive
Google Knowledge Vault

• Four text-based extractors
  • Text, HTML (DOM) trees, tables, manual RDF annotations
• Two predictive models
  • ~Random walk-based, supervised matrix completion using MLP
→ 6 features per triple
→ Supervised classification
  • linear regression/boosted decision stumps

• Ignores interaction between tuples

• Prototypical for many IE systems
  • E.g., Aristo TupleKB, Quasimodo
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Finding the most plausible world

“Hermione married Ron”

\[
\begin{align*}
\text{occurs} & (H@1, \text{“married”}, R@1)[1] \\
\text{isPatternFor} & (\text{“married”, spouse})[1] \\
\text{means} & (H@1, \text{Hermione})[5] \\
\text{means} & (R@1, \text{RonWeasley})[2] \\
\text{means} & (R@1, \text{Reagan})[3] \\
\text{means} & (X, Y \land Y \neq Z \Rightarrow \neg \text{means}(X, Z))[10] \\
\text{spouse} & (X, Y \land Y \neq Z \Rightarrow \neg \text{spouse}(Z, X))[6] \\
\text{+ Pattern Application Rule} & [10]
\end{align*}
\]
"Whenever someone has a child, this is also the child of the spouse."

Diagram:

- **hasChild**
- **marriedTo**
- **citizenOf**
- **presidentOf**
Association rule mining

\[
\text{hasChild}(x, y) \\
\land \text{marriedTo}(x, z) \\
\Rightarrow \text{hasChild}(z, y)
\]

(rules don’t have to be always correct)
Rule Mining for Completion

\[ \text{hasChild}(x,y) \land \text{marriedTo}(x,z) \implies \text{hasChild}(z,y) \]
Rule Mining for Correction

\[ \text{hasChild}(x, y) \land \text{marriedTo}(x, z) \Rightarrow \text{hasChild}(z, y) \]
Rule Mining for Insights

\[ \text{hasChild}(x,y) \land \text{marriedTo}(x,z) \Rightarrow \text{hasChild}(z,y) \]

... in 4% of the cases

\[ \text{in}(x, \text{Europe}) \land \text{president}(x, y) \Rightarrow \text{male}(x) \]

\[ \text{married}(x, y) \Rightarrow \text{married}(y, x) \]

... obvious for us, but non-trivial for a computer.

Applications in

- artificial intelligence / question answering
- information extraction (as we saw)
- science
- engineering (fault finding)
- medicine
- social network mining
Running example

\[ type(x, \text{sorceress}) \land dumb(y) \Rightarrow \text{likes}(x, y) \]
Def: Safe Rule

The head of a rule is its positive literal, the other literals are the body of the rule. A rule is safe, if all variables of the head appear in the body.

Example:

- safe: \( \text{child}(x, y) \land \text{spouse}(x, z) \Rightarrow \text{child}(z, y) \)
- not safe: \( \text{smart}(x) \Rightarrow \text{loves}(y, x) \)
Def: Connected Rule & Closed Rule

Two atoms are connected if they share a variable or constant. A rule is connected if every atom is transitively connected to every other atom.

Example:
- not connected: \( dumb(y) \land smart(x) \Rightarrow rich(x) \)

A rule is closed, if every variable appears at least twice.

Example:
- closed: \( married(x, y) \land male(x) \Rightarrow married(y, x) \)
- not closed: \( married(x, y) \land likes(x, z) \Rightarrow married(y, x) \)

A variable is dangling, if it appears only once.
Query

A (conjunctive) query is a conjunction of literals

\[ \text{loves}(\text{Hermione}, x) \land \text{dumb}(x) \land \text{smart}(y) \, ? \]

An answer to a query for a given KB is a binding that makes the query true.

\{ x \rightarrow \text{Ron}, y \rightarrow \text{Harry} \}
Example

likes(x, y) ∧ gender(x, male) ?

gender(x, male) ?

likes(x, y) ∧ is(y, smart) ∧ gender(y, male) ?
Queries and Rules

A query can be written as a rule.

\[ \text{likes}(x, y) \land \text{gender}(x, \text{male}) \Rightarrow \text{answer}(x, y) \]

The body of a rule is basically a query.

\[ \text{gender}(x, \text{male}) \land \text{is}(x, \text{dumb}) \Rightarrow \text{likes}(\text{Hermione}, x) \]

query
Types of Reasoning

Deductive reasoning:
• Given $\alpha$ and $\alpha \Rightarrow \beta$
• Deduce $\beta$

\[ \text{smart}(\text{Bill}). \quad \text{smart}(x) \Rightarrow \text{rich}(x) \]
\[ \rightarrow \quad \text{rich}(\text{Bill}) \]

Abductive reasoning:
• Given $\beta$ and $\alpha \Rightarrow \beta$
• Deduce $\alpha$

\[ \text{rich}(\text{Bill}). \quad \text{smart}(x) \Rightarrow \text{rich}(x) \]
\[ \rightarrow \quad \text{smart}(\text{Bill}) \]

Inductive reasoning:
• Given $\alpha$ and $\beta$
• Deduce $\alpha \Rightarrow \beta$

\[ \text{rich}(\text{Bill}). \quad \text{smart}(\text{Bill}) \]
\[ \rightarrow \quad \text{smart}(x) \Rightarrow \text{rich}(x) \]

This is what we want to do
Example

\[ \text{type}(x, \text{sorceress}) \land \text{is}(y, \text{dumb}) \Rightarrow \text{likes}(x, y) \] ?

\[ \text{type}(x, \text{sorceress}) \land \text{is}(y, \text{childish}) \Rightarrow \text{likes}(x, y) \] ?

\[ \text{is}(x, \text{smart}) \land \text{is}(y, \text{dumb}) \Rightarrow \text{likes}(x, y) \] ?

\[ \text{type}(x, s) \land \text{is}(y, \text{dumb}) \land \text{gender}(y, \text{male}) \Rightarrow \text{likes}(x, y) \] ?
**Def: Inductive Logic Programming**

**Given**
- **background knowledge** $B$
  
  $B$ is a set of logical formulae.
  
  In most cases, $B$ is simply a set of atoms, i.e., a KB.

- **positive examples** $E^+$ and **negative examples** $E^-$
  
  $E^+$ and $E^-$ are commonly just sets of atoms, usually of the same relation, which is called the target relation.

**Inductive logic programming (ILP)** is the task of finding
- **a hypothesis** $h$

  Usually, the hypothesis is a set of rules that have the target relation in the head. Often, $h$ is a single rule.

such that we have
- **completeness**: $B \land h \models E^+$ (all positive examples are predicted)
- **correctness**: $B \land h \not\models E^-$ (no negative example is predicted)
- **minimality**: There is no shorter rule with the same properties
Example: ILP

Given

• background knowledge $B$
  
  dumb(Ron), smart(Harry), male(Ron), male(Harry)
  sorceress(Hermione)

• positive examples $E^+$ and negative examples $E^-$
  
  $E^+$: likes(Hermione, Ron)
  $E^-$: likes(Hermione, Harry)

inductive logic programming (ILP) is the task of finding

• a hypothesis $h$
  
  sorceress($x$) $\land$ dumb($y$) $\Rightarrow$ likes($x$, $y$)

such that we have

• completeness: $B \land h \models E^+$ (all positive examples are predicted)

• correctness: $B \land h \not\models E^-$ (no negative example is predicted)

• minimality: There is no shorter rule with the same properties
Language Bias

The language bias of an ILP problem is the type of hypotheses that we consider.

• rules or arbitrary formulae?
  \(\text{loves}(x, y) \lor \text{hates}(x, y)\)

• with or without negation?
  \(\neg \text{smart}(x) \Rightarrow \text{loves}(\text{Hermione}, x)\)

• with or without quantifiers?
  \(\text{smart}(x) \Rightarrow \exists y: \text{loves}(y, x)\)

• how many atoms per rule?
  \(\text{loves}(\text{Herm.}, x) \iff \text{smart}(x) \land \text{cute}(x) \land \text{rich}(x) \land ...\)

• with or without constants?
  \(\text{hates}(\text{Harry}, x) \Rightarrow \text{loves}(\text{Hermione}, x)\)

• how many rules?
Def: Properties of hypotheses

- $h$ is **complete**, if it predicts all positive examples.
- $h$ is **consistent**, if it does not predict any negative examples.

- **Complete & consistent**
  
- **Complete & inconsistent**
  
- **Incomplete & consistent**
  
- **Incomplete & inconsistent**
Overfitting

A hypothesis overfits, if it does not generalize to new positive examples.

B: dumb(Ron), smart(Harry), male(Ron), male(Harry)
   sorceress(Hermione)
E+: likes(Hermione, Ron)
E-: likes(Hermione, Harry)

\[ x = \text{Ron} \land y = \text{Herm.} \land \text{dumb}(x) \land \text{male}(x) \Rightarrow \text{likes}(x, y) \]
Overgeneralization

A hypothesis overgeneralizes, if it does not generalize to new negative examples.

B: dumb(Ron), smart(Harry), male(Ron), male(Harry), sorceress(Hermione)

E+: likes(Hermione, Ron)
E-: likes(Hermione, Harry)

\[ y \neq Harry \Rightarrow \text{likes}(x, y) \]
Def: Support

The **support** of a hypothesis is the number of predicted positive examples.

\[ \text{support} = 4 \]
Task: Support

The support of a hypothesis is the number of predicted positive examples.

\[ B = \{ \text{person(Ron), person(Harry), person(Hermione)} \} \]
\[ E^+ = \{ \text{likes(Hermione, Ron), likes(Harry, Hermione), likes(Hermione, Harry)} \} \]
\[ E^- = \{ \text{likes(Hermione, Hermione)} \} \]

\[ \text{person}(x) \Rightarrow \text{likes(Hermione, } x) \]
Def: Confidence

The confidence of a hypothesis is the ratio of predicted positive examples, out of all predicted examples.

\[
\text{confidence} = \frac{4}{6}
\]
Task: Confidence

The confidence of a hypothesis is the ratio of predicted positive examples, out of all predicted examples.

\[ B = \{ \text{male(Ron), male(Harry)} \} \]
\[ E^+ = \{ \text{likes(Hermione, Ron), likes(Harry, Hermione)} \} \]
\[ E^- = \{ \text{likes(Hermione, Harry)} \} \]

\[ \text{male}(x) \Rightarrow \text{likes}(\text{Hermione}, x) \]
Confidence / Support trade-off

Usually, confidence and support are in a trade-off.

- high confidence
- low support
  => conservative hypothesis

- high support
- low confidence
  => general hypothesis
Confidence in a KB

KBs usually do not store negative information:

\[ B = \{ \text{gender(Harry, male), gender(Ron, male)} \} \]
\[ E^+ = \{ \text{likes(Hermione, Ron), likes(Harry, Hermione)} \} \]
\[ E^- = \{ \} \]

\[ \text{gender}(x, \text{male}) \Rightarrow \text{likes}(\text{Hermione}, x) \]
Def: Closed World Assumption

The Closed World Assumption (CWA) assumes that all atoms that are not in the KB are wrong (i.e., negative examples).
Confidence with CWA

\[ B = \{ \text{gender}(Harry, \text{male}), \text{gender}(Ron, \text{male}) \} \]
\[ E^+ = \{ \text{likes}(Hermione, Ron), \text{likes}(Harry, Hermione) \} \]
\[ E^- = \{ \text{likes}(Hermione, Hermione), \text{likes}(Ron, Hermione), \text{likes}(Ron, Ron), \ldots \} \]
Task: Confidence with CWA

\[ B = \{ \text{gender}(\text{Harry, male}), \text{gender}(\text{Ron, male}) \} \]
\[ E^+ = \{ \text{likes}(\text{Hermione, Ron}), \text{likes}(\text{Harry, Hermione}) \} \]
\[ E^- = \{ \text{likes}(\text{Hermione, Hermione}), \text{likes}(\text{Ron, Hermione}), \text{likes}(\text{Ron, Ron}), \ldots \} \]

\[ \text{male}(x) \Rightarrow \text{likes}(x, \text{Hermione}) \]
Problem with the CWA

We have a great rule that makes great predictions, but since these predictions were not yet known, they act as counter-examples!

\[
B = \{ \text{gender}(Harry, \text{male}), \text{gender}(Ron, \text{male}) \}
\]
\[
E^+ = \{ \text{likes}(Hermione, Ron), \text{likes}(Harry, Hermione) \}
\]
\[
E^- = \{ \text{likes}(Hermione, Hermione), \text{likes}(Ron, Hermione), \text{likes}(Ron, Ron), \ldots \}
\]

\[
\text{male}(x) \Rightarrow \text{likes}(x, Hermione)
\]
\[
\text{likes}(Harry, Hermione) \quad \text{confidence} = 50\%
\]
\[
\text{likes}(Ron, Hermione)
\]
Def: Open World Assumption

The Open World Assumption (OWA) assumes that not all absent atoms are wrong (i.e., not all are neg. examples).
Problem with the OWA

The Open World Assumption (OWA) assumes that not all absent atoms are wrong (i.e., not all are neg. examples).

\[ E^- = \{ \} \]

\[ \text{gender}(x, \text{male}) \Rightarrow \text{is}(x, \text{smart})? \]

The OWA does not yield counter-examples!
Def: Partial Completeness Assumption

The partial completeness assumption assumes that if the KB contains \( r(x, y) \) then it contains all correct \( r(x, y') \).
Task: Partial Completeness Assumption

The partial completeness assumption assumes that if the KB contains $r(x, y)$ then it contains all correct $r(x, y')$.

Is Harry dumb?
Does Hermione like herself?
Is Hermione male? female? none? both?
Does Ron like Hermione?
Confidence with the PCA

\[ \text{gender}(x, \text{male}) \Rightarrow \text{likes}(x, \text{Hermione}) \]
Task: Confidence with the PCA

\[ \text{gender}(x, \text{male}) \Rightarrow \text{likes}(\text{Hermione}, x) \]
Computing the PCA confidence

Let's compute the PCA confidence for

\[ p(x, y) \Rightarrow r(x, y) \]

i.e., the ratio of predictions that are true out of the predictions that are true or supposed to be false.
Computing the PCA confidence

Let's compute the PCA confidence for

\[ p(x, y) \Rightarrow r(x, y) \]

Predictions that are true:

\[ \# (x, y): \ p(x, y) \in KB \ \land \ r(x, y) \in KB \]

Predictions that are supposed to be false:

\[ \# (x, y): \ (p(x, y) \in KB) \ \land \ (\exists y': r(x, y') \in KB) \ \land \ (r(x, y) \notin KB) \]

\[ \uparrow \ \ \ \ \ \ \ \uparrow \]

KB knows r about x \ but not the one that we predict

Predictions that are true + supposed to be false:

\[ \# (x, y): \ p(x, y) \in KB \ \land \ \exists y': r(x, y') \in KB \]
Computing the PCA confidence

The PCA confidence for

\[ p(x, y) \Rightarrow r(x, y) \]

is

\[
\# (x, y): \ p(x, y) \in KB \ \land \ r(x, y) \in KB
\]

\[
\# (x, y): \ p(x, y) \in KB \ \land \ \exists y': r(x, y') \in KB
\]

The numerator is just the support of the rule.
Computing the PCA confidence

The PCA confidence for

$$\beta \Rightarrow r(x, y)$$

is

$$\frac{\text{support}(\beta \Rightarrow r(x, y))}{\# (x, y): p(x, y) \in KB \land \exists y': r(x, y') \in KB}$$
Top-down ILP

Top-down ILP starts with one all-embracing hypothesis and specializes it until no negative examples are covered.
Specialization operator
A specialization operator is a function that takes a rule, and returns a set of more special rules. Some specialization operators for binary atoms are:

\[ \Rightarrow \text{hasChild}(x, y) \]

- Add dangling atom: Adds a connected atom that has a fresh variable.
  \[ \text{married}(x, z) \Rightarrow \text{hasChild}(x, y) \]

- Add instantiated atom: Adds a connected atom that has a constant.
  \[ \text{likes}(x, \text{cheese}) \Rightarrow \text{hasChild}(x, y) \]

- Add closing atom: Adds an atom that is connected in both arguments.
  \[ \text{hasFather}(y, x) \Rightarrow \text{hasChild}(x, y) \]
Example: Specialization operators

\[ \Rightarrow \text{hasChild}(x, y) \]

- add dangling atom
  \[ \text{married}(x, z) \Rightarrow \text{hasChild}(x, y) \]

- add closing atom
  \[ \text{hasChild}(z, y) \land \text{married}(x, z) \Rightarrow \text{hasChild}(x, y) \]

- add instantiated atom
  \[ \text{rel}(z, \text{catholic}) \land \text{hasChild}(z, y) \land \text{married}(x, z) \Rightarrow \text{hasChild}(x, y) \]
Example: Add dangling atom

\[ \text{add dangling atom} \quad \Rightarrow \text{hasChild}(x, y) \]

All combinations of a connected variable \((x, y)\) with a fresh variable \((z)\).

married\((x, z)\) \(\Rightarrow\) hasChild\((x, y)\)
married\((z, x)\) \(\Rightarrow\) hasChild\((x, y)\)
married\((z, y)\) \(\Rightarrow\) hasChild\((x, y)\)
married\((y, z)\) \(\Rightarrow\) hasChild\((x, y)\)

With all relations

loves\((x, z)\) \(\Rightarrow\) hasChild\((x, y)\)
loves\((z, x)\) \(\Rightarrow\) hasChild\((x, y)\)
loves\((z, y)\) \(\Rightarrow\) hasChild\((x, y)\)
loves\((y, z)\) \(\Rightarrow\) hasChild\((x, y)\)
Pruning

Pruning a rule means abandoning it together with all specializations. Examples for pruning strategies are:

• Prune rules that are too long

\[
rel(z, \text{catholic}) \land hasChild(z, y) \land married(x, z) \Rightarrow hasChild(x, y)
\]
Pruning a rule means abandoning it together with all specializations. Examples for pruning strategies are:

- Prune rules that are too long
  \[ rel(z, \text{catholic}) \land \text{hasChild}(z, y) \land \text{married}(x, z) \Rightarrow \text{hasChild}(x, y) \]

- Prune rules that have too small support
  \[ \text{type}(x, \text{pope}) \land \text{married}(x, y) \Rightarrow \text{hasChild}(x, z) \]

Support decreases monotonically with specialization!
Other pruning strategies

• Prune rules that are redundant

\[ \text{married}(x, z) \land \text{married}(x, z) \Rightarrow \text{hasChild}(x, y) \]

\[ \times \]

• Prune rules that have an equivalent elsewhere

\[ \text{married}(x, y) \land \text{hasChild}(x, y) \Rightarrow \text{hasChild}(z, y) \]

\[ \times \]

\[ \text{hasChild}(z, y) \land \text{married}(z, y) \Rightarrow \text{hasChild}(x, y) \]

\[ \times \]

• Prune specializations of rules with perfect confidence

\[ \text{married}(x, y) \Rightarrow \text{married}(y, x) \]

100% confidence, do not specialize further, because confidence will stay and support will decrease.
AMIE for Rule Mining

AMIE is the following top-down rule mining algorithm:

- start with the queue of rules for each relation:
  \[ Q := [ \Rightarrow r_1(x_1, y_1), \ldots ] \]

- while \( Q \) is not empty
  - \( h := Q.\text{dequeue()} \)
  - if \( h \) is a good rule, output \( h \)
  - for each specialization \( h' \) of \( h \)
    - if \( h' \) is not pruned, \( Q.\text{enqueue}(h') \)

Prune:
- rules \( > 3 \) atoms
- rules with support \( < \) threshold
- ...

\( \text{support} > \text{threshold} \)
\( \text{PCA conf} > \text{threshold} \)
Example: AMIE

gender(x, male) ⇒ likes(Herm, x)

support: 2
confidence: 100%
⇒ output this rule

Rule cannot get better ⇒ stop
Summary

- ILP is the task of finding hypotheses that cover examples
- ILP can be performed top-down by specialization (AMIE)
- ... or bottom-up by generalization (GOLEM)
- The Open World Assumption allows that data that is not in the KB can still be true.
Outline

1. Motivation

2. Consolidation
   • MaxSAT
   • Probabilistic Soft Logic
   • Google Knowledge Vault

3. Pattern Learning
   • Association rule mining
   • Matrix completion
   • Knowledge graph embeddings
Matrix completion for IE

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Classical problem in recommender systems
- PCA, Matrix factorization, ...

See e.g., Riedel et al., “Universal schema”
Knowledge graph embeddings

from [Mikolov 2013]
Knowledge graph embeddings (2)

• For word embeddings a by-product
• Idea: Train embeddings to intentionally exhibit such features:

“Translation intuition”
For a triple \((h, l, t)\): \(\overrightarrow{h} + \overrightarrow{l} \approx \overrightarrow{t}\).

Plethora of ML works: TransE, TransH, TransG, TransR, …
References

• Core papers:
  • Suchanek et al., SOFIE — a self-organizing framework for IE, WWW 2009
  • Galarraga et al., AMIE: Association rule mining under incomplete evidence, WWW 2013

• Further reading
  • Dong, Xin, et al. "Knowledge vault: A web-scale approach to probabilistic knowledge fusion." KDD 2014
  • Wu et al., Incremental Knowledge Base Construction Using DeepDive, VLDB 2015
  • Riedel et al. "Relation extraction with matrix factorization and universal schemas." NAACL. 2013.

• Slides
  • Adopted from Fabian Suchanek, Laura Dietz, Andrew McCallum
Assignment 8

• Find patterns in Game of Thrones

• Data: Subset of infobox relations from https://gameofthrones.fandom.com (provided)

• Task:
  • Evaluate rules of the form $P(_,_), R(_,_) \rightarrow S(_,_,)$
    • 3 specific variable patterns
  • For each form, find top 10 rules in terms of support

• Bonus
  • All rules with two atoms in body (safe + connected)
  • Rules w/ constants
  • Other scores, e.g., PCA confidence
Take home

• IE typically operates in settings of uncertainty and noise
  • Redundancy is solution and challenge at same time

• Consolidation frameworks translate background knowledge, logical constraints, extraction candidates into logical/probabilistic frameworks
  • Then optimize for global coherence
  • Usually require some constraints
  • MaxSAT as example approach

• Pattern discovery in extractions is useful for completion and consolidation
  • Association rule mining as sample approach