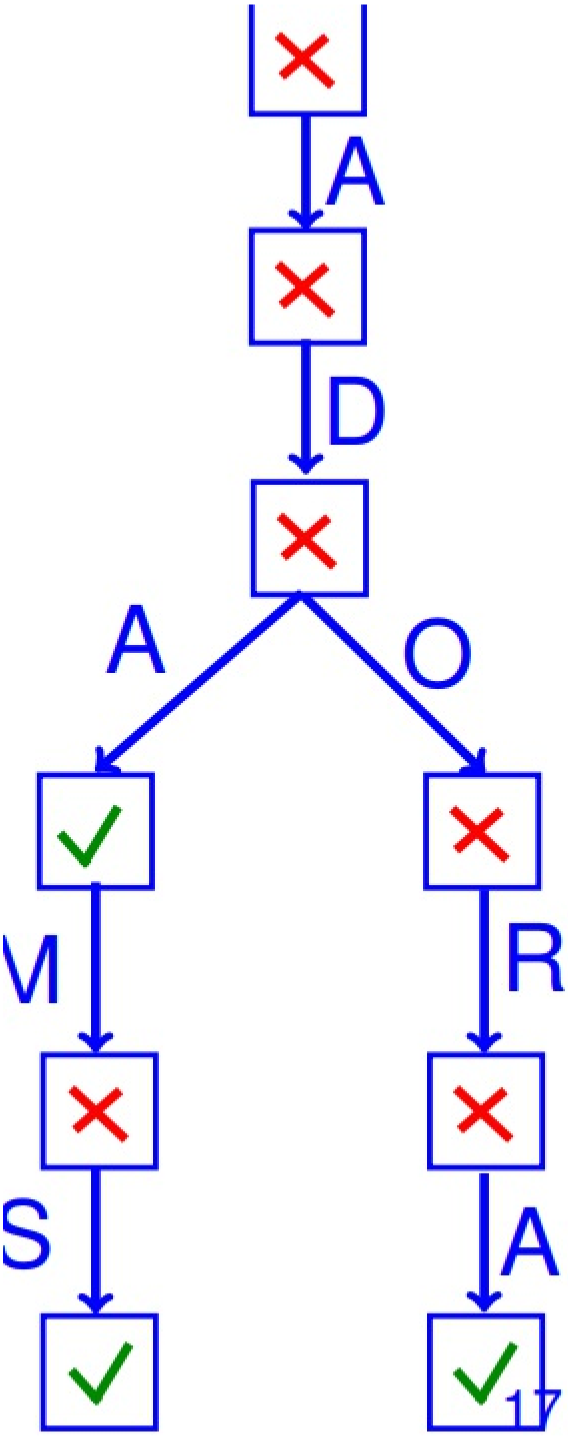
Knowledge Base Construction

Named Entity Recognition

- 命名实体是具有名称的实体
- 命名实体识别（NER）是在语料库中查找实体名称的任务。
- Dictionary 包含一组实体名称，如果实体在前面已知，则可以使用它。
- Naive Dictionary NER is slow 时间复杂度 O（textLength X dictSize X maxWordLength）
- Trie(字典树)，统计或排序大量的字符串，以空间换时间，公共前缀在相同路径上，若为true，则为一个单词。O(textLength × maxWordLength)

- 

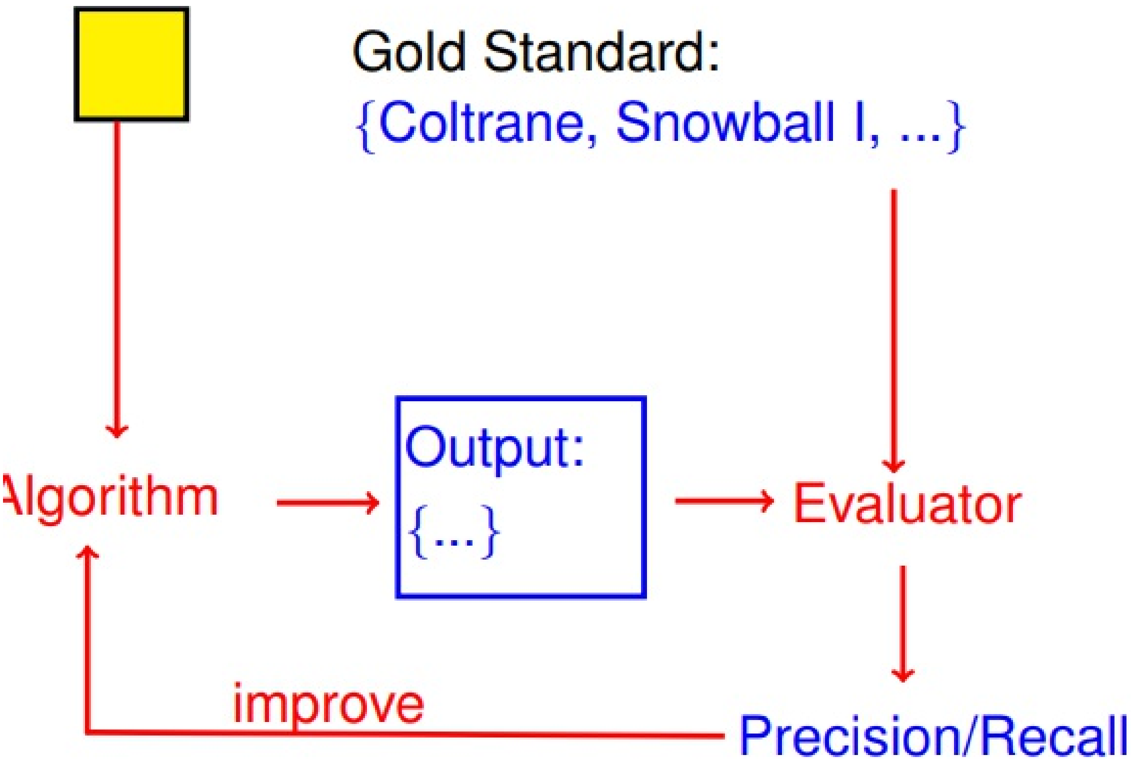
  从上图可以看出
  Adams adores Adora的判断顺序为

  ada ->true
  adams -> true
  adore -> false
  adores -> false
  adora -> true

- Dictionary NER
  - very efficient
  - have to be given upfront,have to be maintened to accommodate new names,cannot deal w ith name variants, cannot deal w ith infinite or unknow n sets of names

- Language
  - 通过正则的方式来描述，所需要的空间变少
  - 例如:
    -{,ab,abab,ababab}=>(ab)*
    -{1990,1992,1993}=>[0-9]{4}

  He found the answw er to life, => the answ er to ([a-z]+),
  the universe, and everything => the (([a-z]+) and ([a-z]+))

  - 1st group: life
  - 2nd group: universe and everything
  - 3rd group: universe
  - 4th group: everything
- Evaluation
  - prec = output ∩ standard / output
  - Recall = output ∩ standard / standard
  - F1 = 2 * pre * recall / (pre+recall)
- IE algo
  - 

- Disambiguation
  - 鉴于一个语料库中含糊不清的名字及其含义，消除歧义是确定意图的任务。
  - Usually Named Entity Recognition (NER) runs first, and the goal is to map the names to entities in a Know ledge Base (KB)
  - Stopw ord: Allw ords/{nom,adj,非组动词non-auxiliary verbs}
  - Context of a w ord
  - Context of an entity
  - Context-based disambiguation
  - Disambiguation Prior 通过匹配成功次数+1算分

- Coherence 相干性，文中的词之间可有相关联系

NERC Named Entity Recognition and Classification

- NE Recognition & Classification 对里面的单词进行分类
    - the task of (1) finding entity names in a corpus and (2) annotating each name w ith a class out of a set of given classes.
    - Not EZ
    - Window 在读取句子时，其上下文的范围。例如 [a,a,a,a,at,b,b,b,b] at为正在读取的，这里size=4
    - NERC Feature
    -

	know ,	”,	said,	Arthur,	“,	I,	really
is stopword	0	0	0	0	0	1	1
matches [A-Z][a-z]+	0	0	0	1	0	0	0
is punctuation	0	1	0	0	1	0	0

    - Stanford NERC system
    - Paris —> Xxxx
    - M2 D&K —> X# X&X
    - +33 1234 —> +## ####
    - POS
    - Part-of-Speech 词性，adj啊 vt啊 vi啊。。
    - Morphological features
    - -ish, -ist, … 某一种身份
    - Rule
    - in XXX -> location
    - XX is -> Person
    - Dr, Ms -> Person
    - **Statistical NERC corpus**
    -

Adams	lives	in	California	=: X, input
pers	oth	oth	loc	=: Y, output

    - f(X,i,y) = 1 if Xi is CapWord 并且y="location" else = 0
    - f1(X, i, y) := 1 if xi−1 is title ∧ y =“pers”
        - f1(, 1, pers) = 0
        - f1(, 2, pers) = 1
        - f1(, 1, loc) = 0
    - 上面的0，1是权值的一种，但是对于某一些feature，其权值不应该为1，所以会乘以W,而这个W要用梯度下降法去得到

X =<Dr., Dent>

$f_1(X,i,y) :=$ 1 if x_i upcased word $\wedge y$ =“loc”

$f_2(X,i,y) :=$ 1 if x_{i-1} is title $\wedge y$ =“pers”

$w_1 = 2, w_2 = 5$

Find $Y =< y_1, y_2 >$

that maximizes $\sum_i \sum_j w_j f_j(X,i,y_i)$

for every feature j

for every position i

Try all Y

$i = 1, x_i =$ Dr. $i = 2, x_i =$Dent

$w_1 \times f_1 \; w_2 \times f_2 \quad w_1 \times f_1 \; w_2 \times f_2$

$Y =< oth, loc >: 2 \times 0 + 5 \times 0 + 2 \times 1 + 5 \times 0 = 2$

- $Y =< oth, per >: 2 \times 0 + 5 \times 0 + 2 \times 0 + 5 \times 1 = 5$ winner

CRFs 条件随机场

- https://www.jianshu.com/p/55755fc649b1
- $$score(l|s) = \sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s,i,l_i,l_{i-1})$$
  - 句子s（就是我们要标注词性的句子）
  - i，用来表示句子s中第i个单词
  - l_i，表示要评分的标注序列给第i个单词标注的词性
  - l_i-1，表示要评分的标注序列给第i-1个单词标注的词性
- 对这个分数进行指数化和标准化，我们就可以得到标注序列l的概率值p(l|s)
  - $$p(l|s) = \frac{exp[score(l|s)]}{\sum_{l'} exp[score(l'|s)]} = \frac{exp[\sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s,i,l_i,l_{i-1})]}{\sum_{l'} exp[\sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s,i,l'_i,l'_{i-1})]}$$
  - 当l_i是“副词”并且第i个单词以“ly”结尾时，我们就让f1 = 1，其他情况f1为0。不难想到，f1特征函数的权重λ1应当是正的。而且λ1越大，表示我们越倾向于采用那些把以“ly”结尾的单词标注为“副词”的标注序列
- CRF 与 HMM 的比较
  - HMM的思路是用生成办法，就是说，在已知要标注的句子s的情况下，去判断生成标注序列l的概率
  - $$p(l,s) = p(l_1) \prod_i p(l_i|l_{i-1}) p(w_i|l_i)$$
  - p(l_i|l_i-1)是转移概率，比如，l_i-1是介词，l_i是名词，此时的p表示介词后面的词是名词的概率。
  - p(w_i|l_i)表示发射概率（emission probability），比如l_i是名词，w_i是单词“ball”，此时的p表示在是名词的状态下，是单词“ball”的概率。
- CRF比HMM要强大的多，它可以解决所有HMM能够解决的问题，并且还可以解决许多HMM解决不了的问题。事实上，我们可以对上面的HMM模型取对数，就变成下面这样：

- $$\log p(l,s) = \log p(l_0) + \sum_i \log p(l_i|l_{i-1}) + \sum_i \log p(w_i|l_i).$$

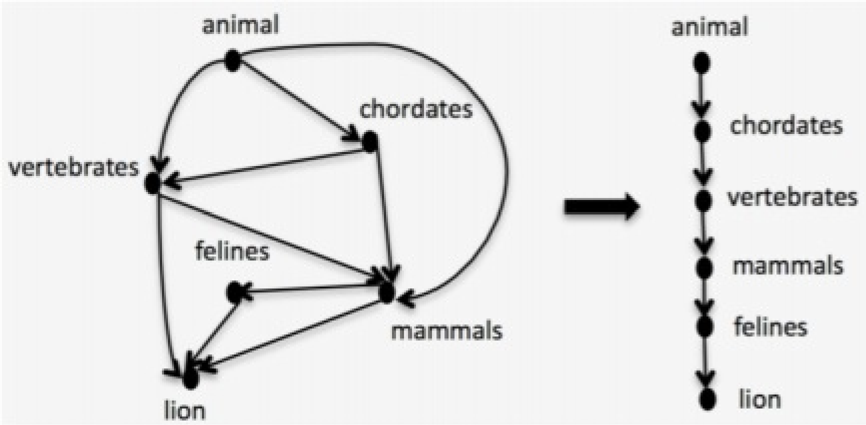
- 不难发现，如果我们把第一个HMM式子中的log形式的概率看做是第二个CRF式子中的特征函数的权重的话，我们会发现，CRF和HMM具有相同的形式
- 每一个HMM模型都等价于某个CRF

POS-Tagging

- Probabilistic POS-Tagging
  - 每个单词都有多种词性，给其匹配的概率
  - Markov Assumption 1 取决于他的邻居
  - P(N|PN, V, D) = P(N|D)
  - Markov Assumption 2 取决于他的tag
  - The probability that the 4th word is “song” depends just on the tag of that word:
  - P(song|Elvis, sings, a, PN, V, D, N) = P(song|N)
  - Homogeneity Assumption 1
  - Homogeneity Assumption 2
  - **Hidden Markov Model**
  - https://www.youtube.com/watch?v=4lB5bzJxuMw
  - Viterbi Algorithm
- Given a sentence and transition and emission probabilities, Probabilistic POS Tagging computes the sequence of tags that has maximal probability (in an HMM).
  - $$\vec{X} = \text{Elvis sings}$$
    $$P(Elvis, sings, PN, N) = 0.01$$
    $$P(Elvis, sings, V, N) = 0.01 \quad \text{winner}$$
    $$P(Elvis, sings, PN, V) = 0.1$$

Instance Extraction

- Is-A
  - is-a(X,Y), x is an instance or subclass of Y
    - 从句子中提取出这种殷果关系（such as）
  - Classical Hearst Patterns
    - Y such as X+ X+ is a set of X (I lived in suchcountries as Germany,France, and Bavaria)
    - and, including, especially
  - Taxonomy induction 分类归纳
    - Taxonomy induction is the process of creating an entire taxonomy

- 

- steps:

a. is-a extraction, as seen before
b. Removal of cycles根据从属关系去掉环
c. Classify edges as “is-a” or “non-is-a” w ith
    - frequency counts (in both directions)
    - substring inclusion
    - difference in generality (distance to the root)

- Set Expansion
    - 给其添加额外的属性，比如说
    - city:{Springfield, Seattle} => cities: {Springfield, Seattle, Washington, Chicago, …}
    - Recursive Pattern Application
    - 以递归的形式进行扩展
        a. Start w ith the seeds
        b. Find the pattern "X, Y, and Z" in the corpus. (从中找出句子，包含seeds的，已经另外一个不包含在内的)
        c. If 2 variables match know n instance names, add the match of the 3rd.
        d. Go to 2
    - Table Set Expansion

    a. Start w ith the seeds
    b. Find HTML tables w here one column contains 2 know n instance names
    c. Add all column entries to the set
    d. goto 2

    - ex:

countries: {Russia, China}

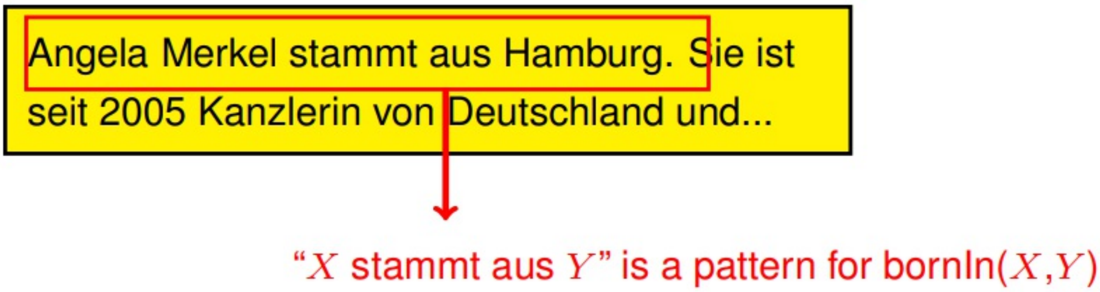
Largest Countries in the World

view as: list / slideshow / map

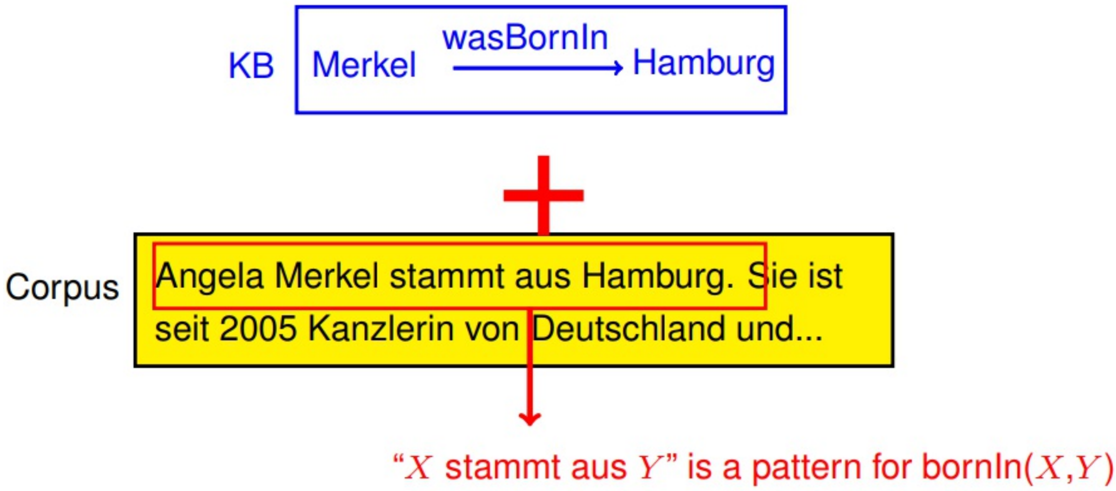
▲	Country	Total Area (sq km)
1.	Russia	17,098,242
2.	Canada	9,984,670
3.	United States	9,826,675
4.	China	9,596,961

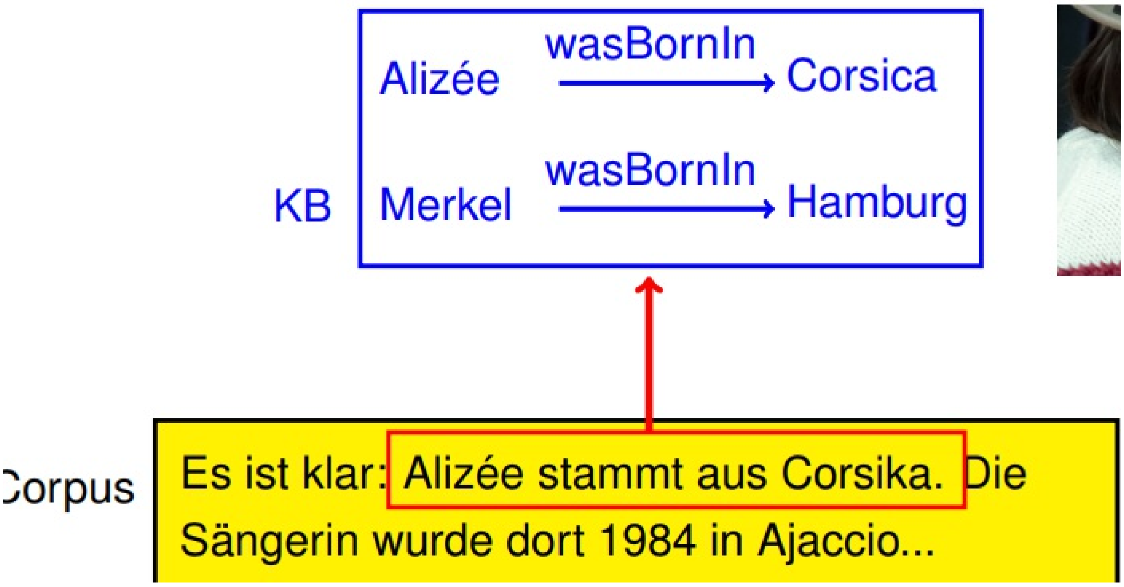
- countries: {Russia, China, Canada, United States}

Fact Extraction

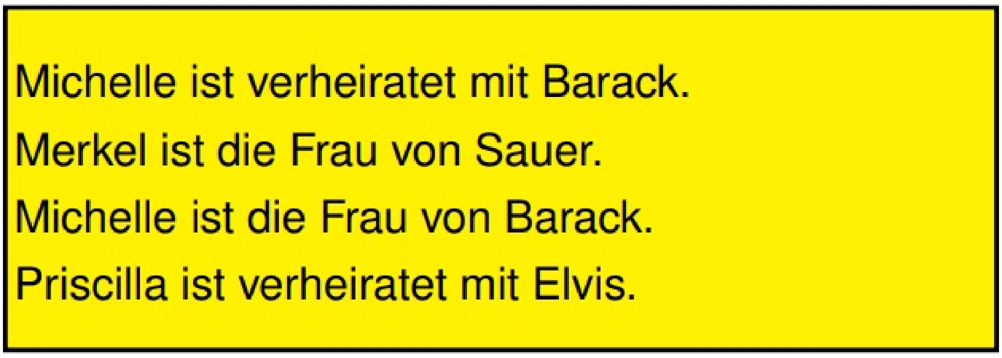
- Fact Extraction 事实抽取是从语料库中提取有关实体的事实
    - the extraction of facts about entities from a corpus.
    - patterns: X -> Y -> is the relation like born in
    - Get patterns:
        - Option 1: Manually compile patterns.
        - Option 2: Manually find the patterns in texts
        - 

        - Option 3: Pattern deduction
        - 给定一个corpus和一个知识库KB，然后通过corpus去产生一个知识库的事实

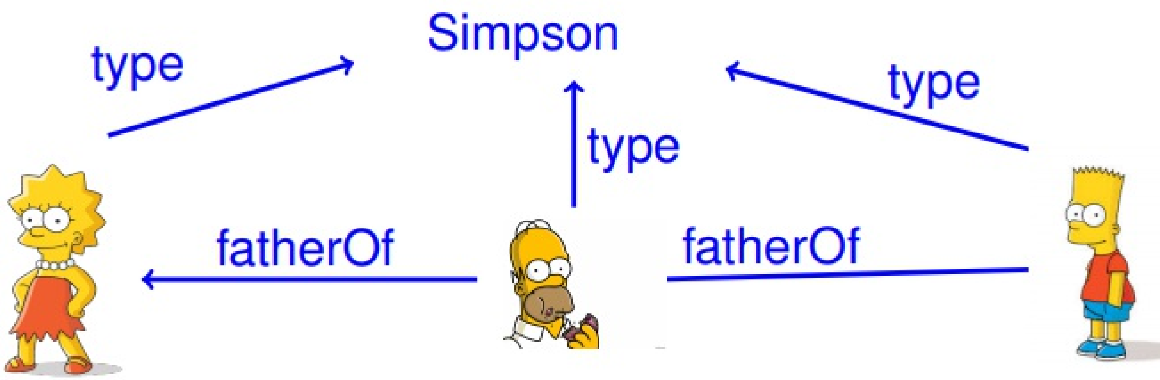
- 

- Pattern Application
- Given a corpus, and given a pattern, pattern application is the process of finding the facts produced by the pattern
- 

- Pattern iteration/DIPRE
  - Pattern iteration (also: DIPRE) is the process of repeatedly
  - applying pattern deduction
  - using the patterns to find new facts

- 

  Michelle ist verheiratet mit Barack.
  Merkel ist die Frau von Sauer.
  Michelle ist die Frau von Barack.
  Priscilla ist verheiratet mit Elvis.
  - => X ist Frau von Y is a pattern for marriedTo(X,Y)
  - => X ist verheriratet mit Y is a pattern for marriedTo(X,Y)
  - => Priscilla marriedTo Elvis
- Patterns in NELL
  - Never Ending Language Learner
  - Apple (produced) -> Maxbook

- Summary:
  `I love Simpsons such as Bart, Lisa, and Homer. Homer is the father of Bart. Homer is the father of Lisa.`
  - 

- Confidence of a pattern
  - Pattern produces mostly new facts => risky
  - Pattern produces mostly known facts => safe

Information Extraction by Reasoning

- atom
- Rules, Disjunctions, Clauses
  - likes(Hermione, Ron) ⇒ likes(Harry, Ron) = ¬likes(Hermione, Ron) ∨ likes(Harry, Ron) = {¬likes(Hermione, Ron),

likes(Harry, Ron)}

- Weighted MAX SAT
  - 找出条件使得满足最高权值
- Exhaustive search 彻底搜索使得得到MAX SAT
- Intuition of unit propagation 将重复的单元删除
- Unit propagation for clauses 根据给出的clause去删除rule和否定的rule

Markov Logic

Semantic Web in practice

- RDF
  - is a know ledge representation based on
    - entities
    - classes
    - binary relations
    - labels
- URIs
  - Namespace / Qualified Name
    - is a named set of (so-called “local”) names
    - KB1, KB2, KB3
  - URI
    - is a string that follow s the syntax
    - : [ ] [&]
    - Ex: Priscilla in elvis: http://elvis.org/kb/Priscilla
- Standard Vocabularies

  -

Decidability

- Decision problem 是一个yes or no 问题，
- Undecidable problem 他无论如何也不可能有一个正确的算法来解决
- Entscheidungsproblem 询问一个真假问题是否可以被回答
- Turing Machine -> a simplifiedmodel of an algorithm (computer program).
- FOL is Undecididable problem
- FOL is semi-decidable