《语义计算与知识检索》研究生课程

词汇语义计算（三）

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内容

- 词义消歧(WSD)
- 词汇语义应用

词义消歧(WSD)

词义消歧(WSD)概述

定义

- 词义消歧(Word Sense Disambiguation)：为一个词语从预先设定的词义项集中选择一个词义
  - 词义项集来自与词典或知识库
  - 基于知识的方法 & 监督学习的方法

- 词义区分(Word Sense Discrimination)：在没有预定义的词义项集的情况下，将一个词语的使用划分为不同意义项
  - 无监督方法

WSD问题定义

- 许多词语具有多个词义 (homonymy / polysemy)

  – Ex: “chair” – furniture or person
  – Ex: “child” – young person or human offspring

- 确定在特定句子中一个词语采用哪个词义

- 说明:
  - 通常一个词语的不同词义紧密相关

Ex: Bank: -financial institute
-building of the financial institute

  - 有时候几个词义能够在一个上下文中同时被激发(co-activation)

Ex: *“This could bring competition to the trade”*
competition: - the act of competing
- the people who are competing

词义表示

- 词在给定上下文中的意义
- 词义表示
  - 根据词典

    chair = a seat for one person, with a support for the back; "he put his coat over the back of the chair and sat down"

    chair = the position of professor; "he was awarded an endowed chair in economics"
  - 根据在另一语言中的翻译

    chair = chaise (法语)

    chair = directeur (法语)
  - 根据词出现的上下文(discrimination)

    “Sit on a chair”　“Take a seat on this chair”

    “The chair of the Math Department”　“The chair of the meeting”
  - 向量表示 (词义嵌入)

    每个词对应多个向量表示，而非传统的一个向量表示

计算机 vs. 人

- 一词多义-很多词具有多个意义

- 计算机程序没有消岐的基础，即使对于人来说很容易
  - 计算机无先验知识
  - 大脑的工作机理？

- 歧义在人们的日常交流中并不是问题，除非在极端情况下
  - “阿隆索因车祸不幸去世”

对于计算机的歧义

- The fisherman jumped off the bank and into the water. (河岸)
- The bank down the street was robbed! (银行)
- Back in the day, we had an entire bank of computers devoted to this problem. (排)
- The bank in that road is entirely too steep and is really dangerous. (斜坡)
- The plane took a bank to the left, and then headed off towards the mountains. (倾斜飞行，倾斜转弯)

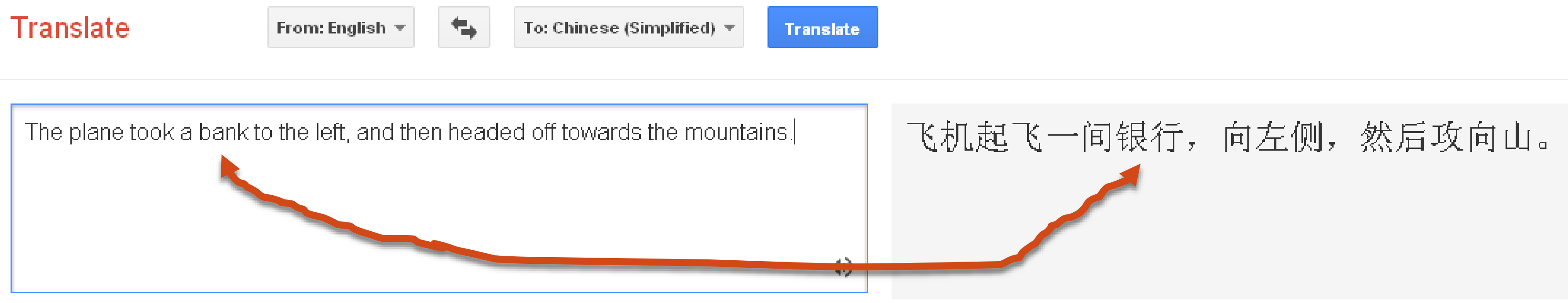
WSD历史

- 认为是影响机器翻译的一个问题 (Weaver, 1949)
  - 一个词只有知道其特定意义才能被翻译
- 1970s - 1980s
  - 基于规则的系统
  - 依赖于人工构造的知识资源
- 1990s
  - 基于语料的方法
  - 依赖于标注好词义的文本
- 2000s
  - 混合方法
  - 利用Web数据和资源

实际应用

- 机器翻译(Machine Translation)
  - Translate “bank” from English to Chinese
    - Is it a “银行” or a “河堤”？
- 信息检索(Information Retrieval)
  - Find all Web Pages about “cricket” (蟋蟀/板球)
    - The sport or the insect?
- 智能问答(Question Answering)
  - What is George Miller’s position on gun control?
    - The psychologist or US congressman?
- 知识获取(Knowledge Acquisition)
  - Add to KB: Herb Bergson is the mayor of Duluth.
    - Minnesota or Georgia?

WSD任重而道远


Translate
From: English
To: Chinese (Simplified)
Translate
The plane took a bank to the left, and then headed off towards the mountains.
飞机起飞一间银行，向左侧，然后攻向山。


Translate
From: English
To: Chinese (Simplified)
Translate
The bank in that road is entirely too steep and is really dangerous.
银行在这条道路是完全太陡，实在是危险的。

词义消岐两类任务

- All Words Word Sense Disambiguation
  - 对文本中的所有词进行词义消岐
  - "He put his suit over the back of the chair"
- Targeted Word Sense Disambiguation
  - 对一个目标词进行词义消岐

    "Take a seat on this chair"

    "The chair of the Math Department"

词义消歧方法

- 基于知识的消歧
  - 使用外部词典、知识库资源
  - 使用篇章属性
- 有监督的消歧
  - 基于标注的训练数据
- 无监督的消歧
  - 基于未标注数据
    - 不使用词典、知识库资源
    - 不使用标注数据

WSD评价

- 评价准则
  - Precision
  - Recall
- 基于标准数据集
  - SEMCOR corpus, SENSEVAL corpus, …
- 评估的困难性
  - 词义的性质对结果有影响
    - 粗粒度 vs. 细粒度词义区分

词义消歧(WSD)之基于知识的方法

方法概述

- Knowledge-based WSD =依赖于从词典知识库或原文本中得到的知识
- 资源
  - 使用
    - 机器可读词典
    - 原文本
  - 不使用
    - 人工标注的语料
- 可处理所有开放词语

机器可读词典(MRD)

- 近些年许多词典机器可读(MRD)
  - Oxford English Dictionary
  - Collins
  - Longman Dictionary of Ordinary Contemporary English (LDOCE)
- 辞典 (Thesauruses) – 添加了同义词信息
  - Roget Thesaurus
- 语义网络(Semantic Network) – 添加了更多的语义关系
  - WordNet
  - BabelNet

MRD

- 对于每一个词语，MRD提供如下信息:
  - 词义列表
  - 词义的定义
  - 典型使用样例

WordNet definitions/examples for the noun *plant*

1. buildings for carrying on industrial labor; "they built a large plant to manufacture automobiles“
2. a living organism lacking the power of locomotion
3. something planted secretly for discovery by another; "the police used a plant to trick the thieves"; "he claimed that the evidence against him was a plant"
4. an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience

MRD

- 词义之间的同义关系

WordNet synsets for the noun "plant"
  1. plant, works, industrial plant
  2. plant, flora, plant life

- Hypernymy/hyponymy (IS-A), meronymy/holonymy (PART-OF), antonymy, entailment, etc.

WordNet related concepts for the meaning "plant life"
{plant, flora, plant life}
hypernym: {organism, being}
hypomym: {house plant}, {fungus}, …
meronym: {plant tissue}, {plant part}
holonym: {Plantae, kingdom Plantae, plant kingdom}

Lesk算法

- 通过定义重叠(definition overlap)识别上下文中的词义(Michael Lesk 1986)
  1. 从MRD中获取待消歧词语的所有词义定义
  2. 确定所有词义组合的词义定义重叠程度
  3. 选择具有最高重叠度的词义组合

Example: disambiguate PINE CONE

- PINE
  1. kinds of evergreen tree with needle-shaped leaves /松树
  2. waste away through sorrow or illness /憔悴
- CONE
  1. solid body which narrows to a point /圆锥体
  2. something of this shape whether solid or hollow /圆锥形物
  3. fruit of certain evergreen trees /松果

Pine#1 ∩ Cone#1 = 0
Pine#2 ∩ Cone#1 = 0
Pine#1 ∩ Cone#2 = 1
Pine#2 ∩ Cone#2 = 0
Pine#1 ∩ Cone#3 = 2
Pine#2 ∩ Cone#3 = 0

利用Lesk算法对多个词(>2)进行词义消岐?

- *I saw a man who is 98 years old and can still walk and tell jokes*
  - nine open class words: *see(26), man(11), year(4), old(8), can(5), still(4), walk(10), tell(8), joke(3)*
- **43,929,600种词义组合! 如何找到最优的词义组合？**
- **模拟退火(Simulated annealing) [Cowie et al. 1992]**
  - **定义一个函数E = 1/(1+R), R: 词义组合的冗余度(基于词出现的次数).**
  - **找到最优的词义组合，最小化E**

1. 初始，每个词选择其最频繁(常用)词义，计算E

2. 每次迭代中，随机选择一个词将其词义替换为另一个词义，计算E'

如果ΔE=(E'-E)<0, 那么保留新词义，然后进行新的随机替换

如果ΔE=(E'-E)>=0, 那么以一定的概率(P=exp(-ΔE/T), T为常数, 初始为1，每1000次后变为0.9T)保留新词义

3. 当词义组合不再变化，停止迭代

简化的Lesk算法

- 原始Lesk算法: 评估上下文中所有词语词义的重叠程度
  - 同时识别上下文中所有词语的准确词义
- 简化Lesk算法: 评估一个词的词义与当前上下文的重叠程度
  - 每次识别一个词的准确词义
- 搜索空间显著减小

简化的Lesk算法

- 算法步骤:
  1. 从MRD中获取待消歧词语的所有词义定义
  2. 确定每个词义与当前上下文之间的重叠度
  3. 选择具有最高重叠度的词义

Example: disambiguate PINE in

"Pine cones hanging in a tree"

- PINE

  1. kinds of evergreen tree with needle-shaped leaves

  2. waste away through sorrow or illness

Pine#1 ∩ Sentence = 1
Pine#2 ∩ Sentence = 0

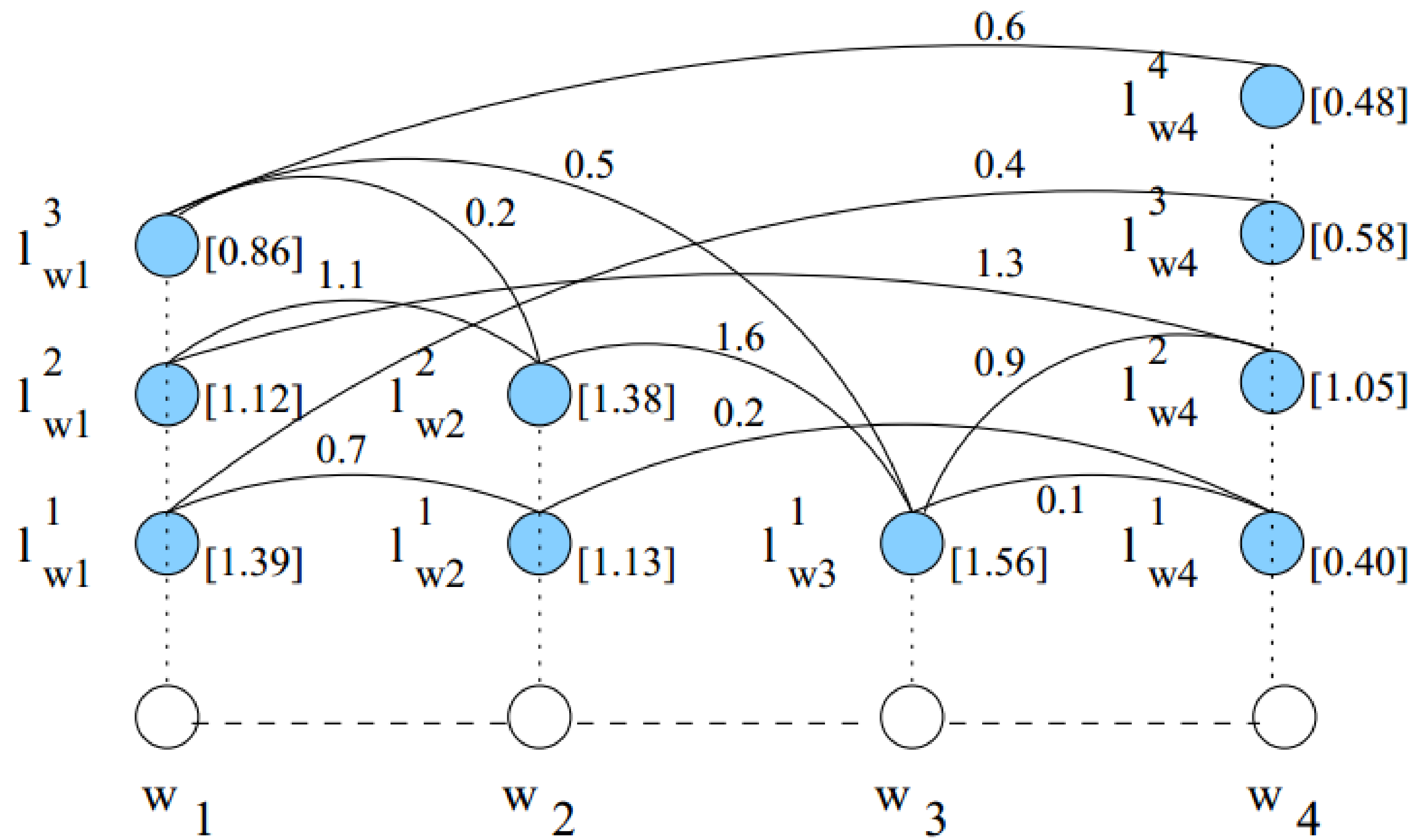
基于图排序的方法

- [Mihalcea 2005]
- 同时对所有词同时进行消岐，考虑词义之间的关联关系
- 步骤
  - 词义图的构建
    - 词的每个词义作为一个节点，词义之间的关联关系作为边(权重)
  - 基于图的排序
    - 基于Pagerank算法，一个节点的权值由跟它相连的其他节点所决定

$$P(V_a) = (1-d) + d * \sum_{V_b \in In(V_a)} \frac{P(V_b)}{|Out(V_b)|}$$

  - 词义标记选择
    - 对每个词选择权值最大的词义

基于图排序的方法



0.6
0.5
0.4
0.2
1.1
1.3
1.6
0.9
0.2
0.7
0.1
[0.48]
[0.58]
[0.86]
[1.12]
[1.38]
[1.05]
[1.39]
[1.13]
[1.56]
[0.40]
w 1
w 2
w 3
w 4

基于每个篇章段落一种意义

- 在一个篇章段落中，一个词的所有出现都倾向于表达同一个意义

E.g. The ambiguous word **PLANT** occurs 10 times in a discourse

all instances of "plant" carry the same meaning

基于每个词语搭配一种意义

- 词语搭配(collocation)：经常共同出现，强相关的词对
- 一个词在同样的搭配使用中倾向于表达同样的意义
  - 相邻搭配中更加明显
  - 词语距离增大则减弱

The ambiguous word **PLANT** preserves its meaning in all its occurrences within the collocation **"industrial plant"**, regardless of the context where this collocation occurs

词义消歧(WSD)之基于有监督学习的方法

方法概述

- 有监督的WSD: 从人工标注词义的文本上学习到分类器

- 将WSD问题看作一个分类问题
  - 基于目标词的上下文为目标词从给定词义选项中选择最准确的词义

标注词义的文本

Bonnie and Clyde are two really famous criminals, I think they were **bank/1** robbers
My **bank/1** charges too much for an overdraft.
I went to the **bank/1** to deposit my check and get a new ATM card.
The University of Minnesota has an East and a West **Bank/2** campus right on the Mississippi River.
My grandfather planted his pole in the **bank/2** and got a great big catfish!
The **bank/2** is pretty muddy, I can’t walk there.

词义的词袋模型表示 (基于在上下文窗口中词的共现)

FINANCIAL_BANK_BAG: a an and are ATM Bonnie card charges check Clyde criminals deposit famous for get I much My new overdraft really robbers the they think to too two went were
RIVER_BANK_BAG: a an and big campus cant catfish East got grandfather great has his I in is Minnesota Mississippi muddy My of on planted pole pretty right River The the there University walk West

简单的有监督WSD方法

给定包含“bank”的句子S；
对于S中每个词W_i：
如果W_i 属于FINANCIAL_BANK_BAG，那么
Sense_1 = Sense_1 + 1;
如果W_i 属于RIVER_BANK_BAG 那么
Sense_2 = Sense_2 + 1;

如果Sense_1 > Sense_2 ，那么选择词义“Financial”
否则如果 Sense_2 > Sense_1，那么选择词义 “River”
否则，打印 “Can’t Decide”；

有监督方法框架

- 训练数据获取: 构建训练数据，每个目标词人工从预定义词义集合中标注词义
- 特征选择: 选择特征集合，表示上下文
- 训练集特征向量构建: 将标注词义的训练样例转换为特征向量
- 分类器学习: 使用一种机器学习算法学习一个分类器
- 测试集特征向量构建：将单独的测试样例转换成特征向量
  - 正确的词义标签已知，但不使用
- 分类器测试: 使用分类器为测试样例赋予词义标签

从文本到特征向量

- My/pronoun grandfather/noun used/verb to/prep fish/verb along/adv the/det **banks/SHORE** of/prep the/det Mississippi/noun River/noun. (S1)
- The/det **bank/FINANCE** issued/verb a/det check/noun for/prep the/det amount/noun of/prep interest/noun. (S2)

	P-2	P-1	P+1	P+2	fish	check	river	interest	SENSE TAG
S1	adv	det	prep	det	Y	N	Y	N	SHORE
S2		det	verb	det	N	Y	N	Y	FINANCE

有监督学习算法

- 机器学习领域提供了很多这样的算法，许多算法都在WSD上取得好结果
  - Support Vector Machines
  - Nearest Neighbor Classifiers
  - Decision Trees
  - Decision Lists
  - Naïve Bayesian Classifiers
  - Perceptrons
  - Neural Networks
  - Graphical Models
  - Log Linear Models

使用单分类器的有监督WSD

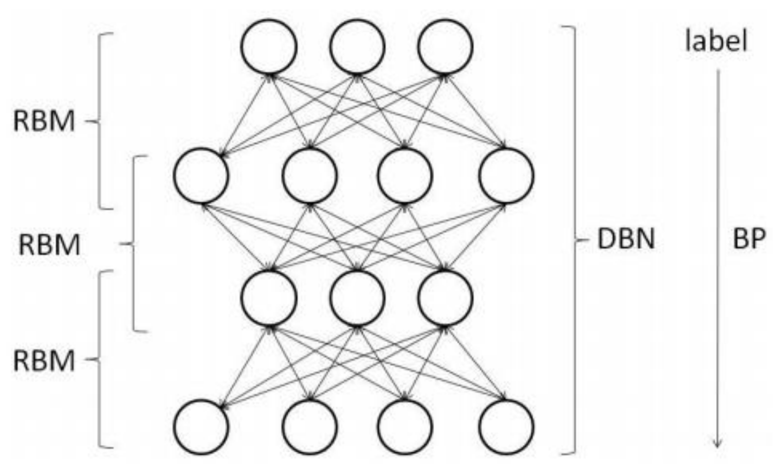
- 大多数有监督机器学习能够有效进行WSD
- 不同的方法一般在所采用的特征上有所区别
- 有效的特征包括:
  - Co-occurrences or keywords
  - Collocations
  - Part of speech
  - Predicate-argument relations
    - Verb-object, subject-verb
  - …

分类器集成(Ensemble)

- 将不同性质的分类器集成起来通常能够提高总体效果
  - 不同的学习算法
  - 不同角度/视角的特征表示
  - 对训练集的不同采样(sampling)
- Bagging, Stacking, Boosting, …
- 怎样融合分类器结果?
  - Simple Majority Voting
  - Averaging of probabilities across multiple classifier output
- 许多WSD系统都采用了集成方法

是否可以用深度学习技术？

- 当然
  - 已有人使用深度信念网络(DBN)进行WSD



Wiriyathammabhum P, Kijsirikul B, Takamura H, et al. Applying Deep Belief Networks to Word Sense Disambiguation[J]. arXiv preprint arXiv:1207.0396, 2012.

词义消歧(WSD)之基于半监督学习的方法

方法概述

- **有监督(Supervised)**WSD = 从足量标注数据中学习词义分类器

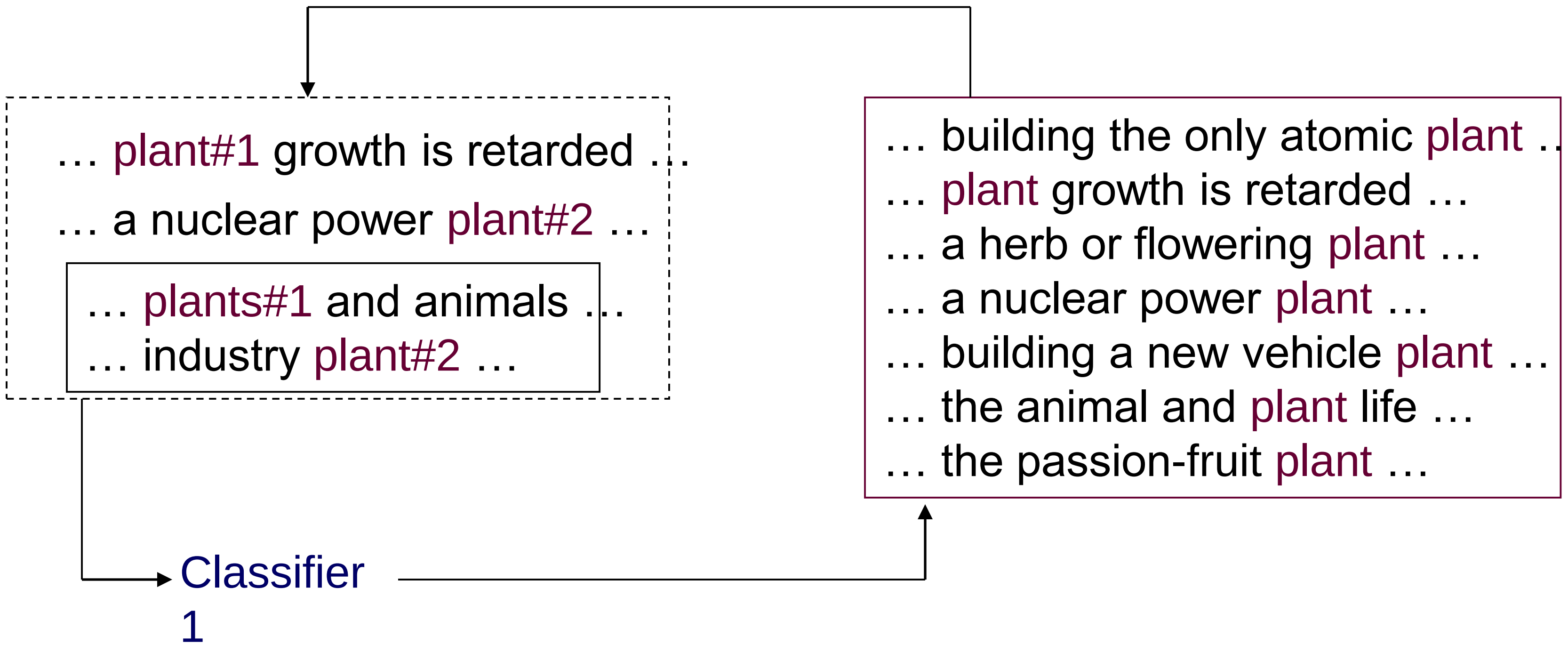
- **半监督(Semi-supervised)**WSD = 从少量标注数据与大量未标注数据中学习词义分类器

自举方法(Bootstrapping)

- 基于少量训练数据构建词义分类器
  - 扩展分类器的适用性
- 自举方法
  - Co-training
  - Self-training

自举方法的部件

- 输入
  - 少量标注数据
  - 大量未标注数据
  - 基本的分类器
- 输出
  - 比基本分类器具有更好效果的分类器


… plant#1 growth is retarded …
… a nuclear power plant#2 …
… plants#1 and animals …
… industry plant#2 …
… building the only atomic plant …
… plant growth is retarded …
… a herb or flowering plant …
… a nuclear power plant …
… building a new vehicle plant …
… the animal and plant life …
… the passion-fruit plant …
Classifier 1

通用自举过程

- 已标注的训练集L
- 未标注集合U
- 基本分类器C

- 1. 创建一个样例池U'
  - 从U中随机选择P个样例
- 2. 循环I次：
  - 基于L训练C，并用C标注U'
  - 从U ' 中选择G个最可信的样例添加到L
    - 保持L中的分布
  - 从U中选择样例重填U'
    - 保持U'的大小为P

通用自举过程

- 已标注的训练集L
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  - 从U ' 中选择G个最可信的样例添加到L
    - 保持L中的分布
  - 从U中选择样例重填U'
    - 保持U'的大小为P

Pool Size

Iteration Number

Growth Size

主要不足：最优参数值的选择比较困难

Self-training

- 单个分类器
- 基于自己的输出重新训练
- Self-training for NLP
  - Part of speech tagging
  - Co-reference resolution
  - Sentiment analysis

协同学习(Co-training)

- 两个分类器
  - 两种相互独立的视角
  - [独立性要求可放宽]
- Co-training in NLP
  - Statistical parsing
  - Co-reference resolution
  - Part of speech tagging
  - Sentiment analysis
  - …

协同学习(Co-training)

- 已标注的训练集L, 每个样例两种视角表示
- 未标注集合U，每个样例两种视角表示
- 基本分类器C

- 1. 创建一个样例池U'
  - 从U中随机选择P个样例
- 2. 循环I次：
  - 基于L和视角一训练C_1，并用C_1标注U '，从U '中选择G个最可信的样例；
  - 基于L和视角二训练C_2，并用C_2标注U '，从U '中选择G个最可信的样例；
  - 将选择的样例添加到L中；
  - 从U中选择样例重填U'
    - 保持U'的大小为P

词义消歧(WSD)之基于无监督学习的方法

方法概述

- 无监督的词义区分(Word Sense Discrimination):基于上下文相似性将词进行聚类
- 假设
  - 具有相似意义的词倾向于出现在相似的上下文中
- 仅使用原文本中的信息，不使用外部知识库或人工标注
- 没有词义列表/目录的知识，因此聚类没有词义标签

方法概述

- 资源:
  - 大量的原始语料
- Word Sense Discrimination看作是发现那些出现在相似上下文中的目标词，并将它们聚集成一个类簇的问题
  - 需要计算上下文的相似程度
  - 对于词义类簇并不赋词义标签

聚类方法

- **特征选择**

  E.g. (Pedersen and Bruce, 1997) explore discrimination with a small number (approx 30) of features near target word.

  - **Morphological form of target word (1)**
  - **Part of Speech two words to left and right of target word (4)**
  - **Co-occurrences (3) most frequent content words in context**
  - **Unrestricted collocations (19) most frequent words located one position to left or right of target, OR**
  - **Content collocations (19) most frequent content words located one position to left or right of target**
- **相似度计算**
- **聚类算法**
  - **层次式聚类，EM算法、基于图切割的聚类等**

分析

- 无监督方法不能发现与通过有监督学习得到的相同的词义类簇
- 基于已有词义类别/标签对无监督学习结果进行评价过于苛刻.
  - 可考虑人工评价

利用隐含语义分析

- Adapted by (Schütze, 1998) to word sense discrimination
- 数据表示为词语共现矩阵(co-occurrence matrix)
- 对共现矩阵进行SVD(Singular Value Decomposition)分解降维
  - 重要的维度跟语义概念关联
- 目标词汇的特征表示为其上下文中所有词汇特征向量的平均值（二阶表示）
- 通过余弦测度计算特征向量的相似度，然后进行聚类

分析

- 基于直接/一阶(first order)特征的聚类方法需要大量数据来获取有效特征
- 二阶表示(Second order representations)可以很好地利用少量数据获得丰富的非稀疏的上下文表示
- http://senseclusters.sourceforge.net 包括了SVD的完整无监督词义区分的系统

词义标注数据

- Senseval/Semeval评测数据
  - http://www.senseval.org
- Data for lexical sample
  - English (with respect to Hector, WordNet, Wordsmyth)
  - Basque, Catalan, Chinese, Czech, Romanian, Spanish, etc.
  - Data produced within Open Mind Word Expert project http://teach-computers.org
- Data for all words
  - English, Italian, Czech (Senseval-2 and Senseval-3)
  - SemCor (200,000 running words) http://www.cs.unt.edu/~rada/downloads.html
- Pointers to additional data available from
  - http://www.senseval.org/data.html

WSD Software – Lexical Sample

- Duluth Senseval-2 systems
  - Lexical decision tree systems that participated in Senseval-2 and 3
  - http://www.d.umn.edu/~tpederse/senseval2.html
- SyntaLex
  - Enhance Duluth Senseval-2 with syntactic features, participated in Senseval-3
  - http://www.d.umn.edu/~tpederse/syntalex.html
- WSDShell
  - Shell for running Weka experiments with wide range of options
  - http://www.d.umn.edu/~tpederse/wsdshell.html
- SenseTools
  - For easy implementation of supervised WSD, used by the above 3 systems
  - Transforms Senseval-formatted data into the files required by Weka
  - http://www.d.umn.edu/~tpederse/sensetools.html
- SenseRelate::TargetWord
  - Identifies the sense of a word based on the semantic relation with its neighbors
  - http://search.cpan.org/dist/WordNet-SenseRelate-TargetWord
  - Uses WordNet::Similarity – measures of similarity based on WordNet
    - http://search.cpan.org/dist/WordNet-Similarity

WSD Software – All Words

- **SenseLearner**
  - **A minimally supervised approach for all open class words**
  - **Extension of a system participating in Senseval-3**
  - **http://lit.csci.unt.edu/~senselearner**
- **SenseRelate::AllWords**
  - **Identifies the sense of a word based on the semantic relation with its neighbors**
  - **http://search.cpan.org/dist/WordNet-SenseRelate-AllWords**

WSD Software – Unsupervised

- Clustering by Committee
  - http://www.cs.ualberta.ca/~lindek/demos/wordcluster.htm
- InfoMap
  - Represent the meanings of words in vector space
  - http://infomap-nlp.sourceforge.net
- SenseClusters
  - Finds clusters of words that occur in similar context
  - http://senseclusters.sourceforge.net

互联网与WSD

- 互联网已成为NLP的一个重要数据来源，包括WSD
- 通过搜索能找到目标词汇的大量实例
- 搜索引擎能够选择与验证词语搭配(collocations)及其他的关联(association).
  - “strong tea” : 13,000 hits
  - “powerful tea” : 428 hits
  - “sparkling tea” : 376 hits

互联网与WSD

- 维基百科提供了大量的词义列表/目录，包含新词.

Jordan (disambiguation)

From Wikipedia, the free encyclopedia

Jordan is a country in the Middle East.

Jordan or **Jordán** may also refer to:

Geographical

Middle East

- The Jordan River
- Jordan, Tehran, Iran, an avenue and a surrounding district

United States

See also: Jordan Township (disambiguation)

- Jordan, Indiana (disambiguation), several places
- Jordan, Iowa
- Jordan, Minnesota, a city in Scott County
- Jordan, Minneapolis, a neighborhood of Minneapolis, Minnesota
- Jordan, Montana
- Jordan, New York
- Jordan, North Carolina
- Jordan, Oregon
- Jordan, Wisconsin, a town
- Jordan, Portage County, Wisconsin, an unincorporated community

Elsewhere

- Germán Jordán Province, Bolivia
- Jordan, Guimaras, Philippines
- Jordan, Hong Kong
- Jordan (Neumark), Poland
- Jordán Pond, pond in Tábor, Czech Republic
- Jordan River, New Zealand
- Jordan, Ontario, Canada
- Jordanhill, Glasgow, UK

Music

- "Jordan", a hymn tune by composer William Billings
- "Jordan" a 1998 song from Megaherz's *Kopfschuss*
- "Jordan" (song), a Buckethead song
- "Jordan", a 2006 song from Bellowhead's *Burlesque*
- "Jordan, Minnesota", a 1986 song from Big Black's *Atomizer*

Mathematics

- Gauss–Jordan elimination, version of Gaussian elimination
- Jordan algebra, a non-associative algebra over a field
- Jordan curve theorem in topology
- Jordan decomposition (disambiguation), several measures
- Jordan measure or Jordan content, an early form of measure
- Jordan normal form or Jordan canonical form of a matrix
- Jordan's lemma in complex analysis
- Jordan's theorem (multiply transitive groups)
- Jordan–Schönflies theorem in geometric topology
- Jordan–Hölder theorem in group theory
- Jordan's theorem in economics

People

- Jordan (name), list of people with this surname or given name

People adopting name Jordan

- Jordan (Katie Price), English former glamour model
- Jordan (Pamela Rooke), model and actress related to the punk movement

Other

- Jordan almonds, a type of candy
- Jordan Grand Prix, which competed in Formula 1 from 1991-2005
- Jordan Motor Company, an automobile manufacturer of the 1920s
- Jordan College (disambiguation), several colleges both real and fictional
- Jordan, archaic slang for a chamber pot

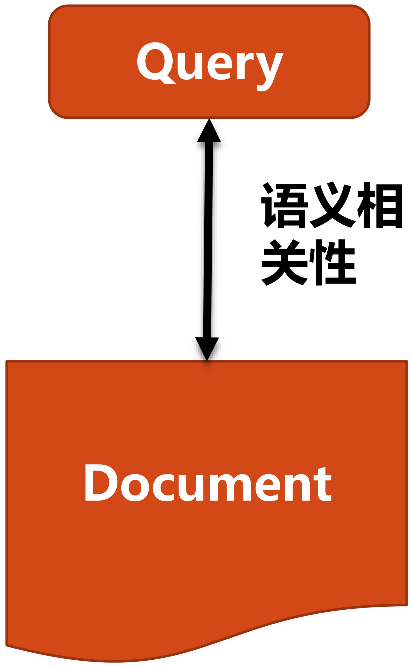
互联网与WSD

但是，互联网存在如下不足：

- 互联网上存在大量的垃圾内容，需要过滤
- 搜索引擎返回的结果页面数只是估计值，并且不断在变化
- 搜索引擎可能关闭API，阻止访问
- 访问互联网获取数据通常比较慢

词汇语义在信息检索中的应用

信息检索



Vocabulary Gap

Semantic Gap

信息检索

- 查询与文档的相似/相关性
  - 查询表示
  - 文档表示
    - 词袋模型(Bag of words)
  - 相关性计算
    - Vector space model: Cosine
    - Probabilistic model: Okapi BM25
    - Language model: KL divergence

查询重构与扩展

- 查询词通常很短，带有歧义
  - Cat: animal/Unix command
  - 在查询中加入更多的词进行消歧、改进
- 相关反馈(Relevance feedback)
  - 利用初始查询检索
  - 展示检索结果
    - 让用户标注相关性/非相关性
  - 扩展查询使之接近相关文档，远离非相关文档

$$\vec{q}_{i+1} = \vec{q}_i + \frac{\beta}{R}\sum_{j=1}^{R}\vec{r}_j - \frac{\gamma}{NR}\sum_{k=1}^{S}\vec{s}_k$$

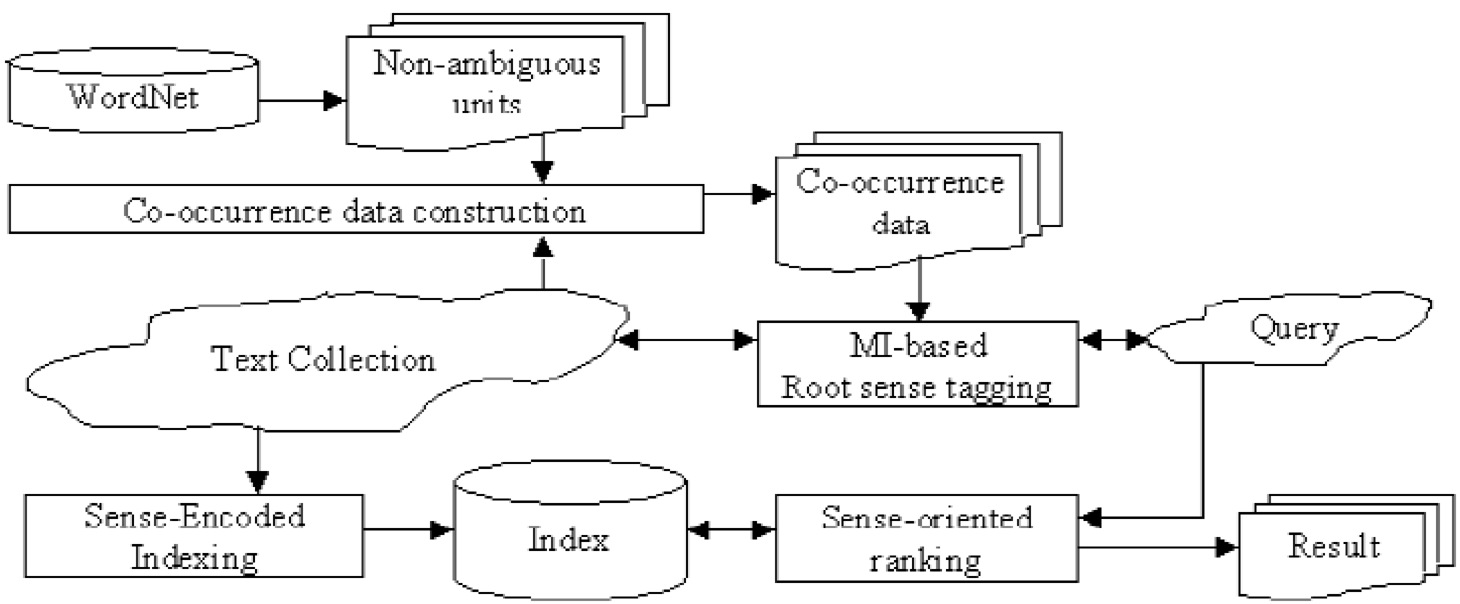
- 伪相关反馈(Pseudo-Relevance feedback)

词义与信息检索

- 动机
  - Homonymy = Bank (financial, river)
  - Polysemy = Bat ((the club used in playing cricket), (a small racket with a long handle used for playing squash))
  - Synonymy = doctor, doc, physician, MD, medico (a licensed medical practitioner)
- 上述语言现象如何影响信息检索性能？
  - Homonymy and Polysemy: 降低检索准确率
  - Synonymy: 降低检索召回率

基于词义进行索引与检索

- **对查询词进行词义消歧；**
- **对文档中词语进行词义消歧；**
- **基于词义进行相关度匹配；**
- **"Word sense disambiguation in information retrieval revisited" in SIGIR03**
- **"Information Retrieval Using Word Senses: Root Sense Tagging Approach " In SIGIR04.**



基于词义关系的查询扩展

- 基于WordNet进行查询扩展 (通常在WSD之后)
  - Synonyms, definition words, hyponyms, etc.
  - “car” => “car automobile auto motorcar vehicle”
- 从结果文档中进行伪相关反馈
  - 基于词义从Top ranked documents中选择扩展词
  - “An effective approach to document retrieval via utilizing WordNet and recognizing phrases” in SIGIR04

基于词语相似度的相关度计算

- 查询与文档中词语相似度值能够对相关文档和不相关文档进行区分，e.g. the sum of SR scores, the average SR score, etc.
  - "A study on the semantic relatedness of query and document terms in information retrieval", in EMNLP09.
- 基于词语相似度值进行查询扩展
- 将词语相似度值集成到查询-文档相关度计算中
- "Semantic similarity methods in WordNet and their application to information retrieval on the Web" in WIDM05

$$Sim(q,d) = \frac{\sum_i \sum_j q_i d_j \mathrm{sim}(i,j)}{\sum_i \sum_j q_i d_j},$$

问题

- 词汇语义能否有效改善现实中的信息检索？
  - 实验室环境下结果有好有坏
    - 如果扩展到真实Web检索…
  - WSD自身的效果影响？
  - 对不同用户查询采用同一种查询扩展方法的合理性？
  - 性能问题?

其他应用

- 文本分类
- 文本聚类
  - WordNet, WSD, Word Similarity…
  - Wikipedia

阅读材料

- “Automatic sense disambiguation using machine readable dictionaries: How to tell a pine cone from an ice cream cone. “ by Lesk, M. SIGDOC1986.
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- “Information retrieval using word senses: root sense tagging approach” by S.-B. Kim et al. SIGIR04.
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- “A study on the semantic relatedness of query and document terms in information retrieval” by C. Müller and I. Gurevych. EMNLP09.
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- “Unsupervised large-vocabulary word sense disambiguation with graph-based algorithms for sequence data labeling” by Rada Mihalcea, EMNLP05.
- “SensEmbed: learning sense embeddings for word and relational similarity.“ by Iacobacci, Ignacio, Mohammad Taher Pilehvar, and Roberto Navigli. Proceedings of ACL. 2015.

- **Some slides were borrowed or adapted from related slides written by Ted Pedersen, Rada Mihalcea, etc. Thank them for sharing their slides.**