ECIR tutorial part 1 and 2
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Information Extracting and Linking in a Retrieval Context

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Overview of the tutorial

- 1. Introduction and motivation**
- 2. Information extraction and linking techniques**

Coffee break

3. Probabilistic models for information retrieval
4. Models for entity ranking

PART 1

Introduction and Motivation

Motivation

- In the fields of natural language processing, computer vision and audio processing, we develop techniques for content recognition, often called **information extraction**
- In the field of data mining, **linking equivalent or related content** is a hot topic
- The results are often of **probabilistic** nature
- How can we use these results of these developments in a (probabilistic) **information retrieval model**?

Information extraction

“Information extraction is the identification, and consequent or concurrent classification and structuring into semantic classes, of specific information found in unstructured data sources, such as natural language text, providing additional aids to access and interpret the unstructured data by information systems.”

[Moens 2006]

Information extraction from text

- Tested in ARPA's Tipster Text Program and in the past **Message Understanding Conferences (MUC)**, **Automatic Content Extraction (ACE)**, current **Text Analysis Conference (TAC)** (National Institute of Standards and Technology, NIST) and **Computational Natural Language Learning (CoNLL)**

Information extraction from text

- **Named entity recognition** (e.g., person names, locations, organizations, ...)
- **Opinion extraction** (e.g., positive, negative feelings expressed, ...)
- **Event extraction:**
 - Topics of an event and the entities involved
 - Extraction of details of an event:
 - e.g., type of event, time, location, number of victims, ...

Information extraction from text

- Extraction of information on Web page:
 - e.g., e-mail, date of availability of a product, ...
- Extraction of scientific data from publications:
 - e.g., localization of a gene, treatment of a disease, function of a gene, ...
- **AND NOT ONLY TEXT !!!**

Birthday party

Happyness

Cake

Candles

Latent semantic topic models

- = a class of unsupervised (or semi-supervised) models in which the semantic properties of words and documents are expressed in terms of topics
 - models are also called **aspect models**
- Latent Semantic Indexing:
 - the semantic information can be derived from a word-document matrix

[Deerweester et al. 1990]

- ↑ – But, LSI is unable to capture multiple senses of a word
- **Probabilistic topic models**

Probabilistic topic model

- = **Generative model** for documents: probabilistic model by which documents can be generated
 - document = probability distribution over topics
 - topic = probability distribution over words
 - To make a new document, one chooses a distribution over topics, for each topic one draws words according to a certain distribution:
 - select a document d_j with probability $P(d_j)$
 - pick a **latent class** z_k with probability $P(z_k | d_j)$
 - generate a word w_i with probability $P(w_i | z_k)$
- [Steyers & Griffiths 2007]

=> Popular model for document representation

Linking

- Links between content that is connected
 - Might be **equivalence** links
 - Or just reference links to related information
 - And many other types ...
- Often focused on persons: e.g., **Web People Search** competition

In one document

- **Noun phrase coreference resolution:**

Pakzad is one of several Afghan women's rights **advocates** who are in the U.S. Capitol this week to address a move the Obama administration is considering: reaching out to Taliban moderates in an effort to bring peace to Afghanistan.

She took part in a hearing on Capitol Hill -- sponsored by Sens. Mary Landrieu, D-Louisiana, and Richard Lugar, R-Indiana -- titled "Women Shaping Afghanistan'...

[CNN, World News, 11-3-2009]

Across documents

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What is Machine Learning, and where is it headed?

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Biography

Dr. Tom Mitchell is a Research Fellow at IDS, having previously been a member of the Benfield UCL Hazard Research Centre. He specialises in climate change adaptation and disaster risk reduction. His interests include pro-poor climate and disaster governance and he co-ordinates the children in a changing climate programme.

Across documents

...Woodward's source in the Plame scandal

... senior administration official ...

... Richard Armitage ...

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In this March 7, 2009 file photo, Secretary of State Hillary Rodham Clinton, accompanied by Turkish talk show hosts Pinar Kur, left, Mujde Ar, second left, and Cigdem Anad, second right, is seen during the taping of a talk show for the Turkish news channel NTV in Ankara, Turkey. Turkey has become so pivotal to U.S. goals in Iraq, Afghanistan and the Middle East that Barack Obama included it on his first overseas tour as president. But relations between the countries could be at risk unless Obama is willing to break a campaign promise. (AP Photo/Osman Orsal, Pool)

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Applications in IR

- Information extraction and linking: has received during decades a large interest because of its potential for information access, mining, summarization, ...
- In IR context: interest is boosted
 - Already popular:
 - **People/expert search**
 - **Opinion search**
 - **Event search**
 - Other types of search follow: **Concept search**

People and expert search

- Finding people ca. 5% of all Web queries
- Finding experts on a certain topic useful in business, educational and other settings

Opinion search

- E.g., monitoring and analyzing social media such as blogs and discussion forums => online business intelligence, intelligence informatics, ...

Event search

- Very traditional IE
- Tasks:
 - Named entity recognition
 - Noun phrase coreference resolution
 - Entity relation recognition
 - Event recognition (who, what, where, when)

Nastia Liukin wins women's gymnastics all-around gold

Adjust font size: + -

Nastia Liukin of the United States edged her compatriot Shawn Johnson to win the women's all-around after a breathtaking Olympic gymnastics competition on Friday.

Finishing one-two on the podium, the American duo let the hosts' gold rush in the gymnastics pause after China wrapped up all the first three titles (men's team, women's team, men's all-round) in the National Indoor Stadium.

Liukin collected 63.325 points, after flawless exercises on each of the four apparatus with a good combination of difficulty and quality, beating Johnson by 0.600. The bronze medal went to Yang Yilin of China in 62.650.

Coming out in her first Olympic Games, the 18-year-old Liukin struck the most coveted gold medal which she had waited for years.

She was an unlucky runner-up in the 2005 world championship in Melbourne, beaten by Chellsie Memmel by 0.001 points in her debut to the international arena, and the title also eluded her in the following two championships.

WHO?

WHEN?

WHAT?

WHERE?

Concept search

- Especially popular in multimedia search:
 - Low level features (e.g. of image frames in video) are described with conceptual terms
 - Concepts are often defined with terms from an ontology
 - Or, repeating patterns in the data can be considered as “concept”
- Less developed in text search, except for specific domains such as the legal field

- How do we successfully extract and link information?
- How do we integrate the results in a (probabilistic) retrieval model?

PART 2

Information Extraction and Linking Techniques

Overview

- Information extraction from text:
 - Named entity recognition
 - Opinion extraction
 - Event extraction
- Topic modeling (text, images, ...)
- Linking of content
 - One document
 - Across documents
 - Across media

Information extraction

- Most successful techniques:
 - **Machine learning** techniques that train from training set annotated
 - Training and test examples are usually represented as a vector of features
- From text: linguistic properties, further called **feature functions f** , that can be exploited:
 - Lexical features
 - Morpho-syntactic features
 - Semantic features
 - Discourse features

Named entity recognition

- Named entity recognition recognizes and classifies named expressions in text (such as person, company, location or protein names):

Example:

John Smith works for **IBM**.

Person

Company

Named entity recognition

- Two problems: **Segmentation** + **Classification**
- **Constituent based processing:**
 - Constituents are first identified (constituency parser or phrase chunker)
 - Constituents are classified
- **Use of BIO format:**
 - B= Begin, I = Inside, O = Outside labels per class
 - Words or tokens are classified

Here illustrated for NER, but similar approach for other extraction tasks (e.g., relation extraction)

Table 4.1. Typical features in a named entity recognition task of the candidate entity name i that occur in the context window of l words.

FEATURE	VALUE TYPE	VALUE
Short type	Boolean	True if i matches the short type j ; False otherwise.
POS	Nominal	Part-of-speech tag of the syntactic head of i .
Context word	Boolean or real value between 0 and 1; Or nominal.	True if the context word j occurs in the context of i ; False otherwise; If a real value is used, it indicates the weight of the context word j . Alternatively, the context word feature can be represented as one feature with nominal values.
POS left	Nominal	POS tag of a word that occurs to the left of i .
POS right	Nominal	POS tag of a word that occurs to the right of i .
Morphological prefixes/suffixes	Nominal	Prefix or suffix of i .

Classification

Maria Sharapova wrote an article in the **New York Times**

x_1

x_2

x_3

x_4

y_1

y_2

y_3

y_4

- Adhering to **maximum entropy principle** because of incomplete training data, e.g., maximum entropy classifier, conditional random field
- **Context dependent classification:**
 - Content cannot exist without other content, or has a large chance to occur with it, e.g., conditional random field

Logistic regression

- We predict a ratio of two probabilities as the log odds (or logit) function:

$$\text{logit}(p(x)) = \ln\left(\frac{p(x)}{1 - p(x)}\right)$$

- **Logistic regression**: model of regression in which we use a linear function to estimate the logit of the probability
- Linear function given k feature functions f and a weight vector w :

$$\sum_k w_i \times f_i = w \cdot f$$

Logistic function

$$\ln\left(\frac{p(y = \text{true}|x)}{1 - p(y = \text{true}|x)}\right) = w \cdot f$$

Maps values
from $-\infty$ to $+\infty$
to a probability

$$\frac{p(y = \text{true}|x)}{1 - p(y = \text{true}|x)} = e^{w \cdot f} = \exp(w \cdot f)$$

$$p(y = \text{true}|x) + p(y = \text{true}|x)e^{w \cdot f} = e^{w \cdot f}$$

$$p(y = \text{true}|x) = \frac{e^{w \cdot f}}{1 + e^{w \cdot f}}$$

$$p(y = \text{false}|x) = \frac{1}{1 + e^{w \cdot f}}$$

$$p(y = \text{true}|x) = \frac{1}{1 + e^{-w \cdot f}}$$

$$p(y = \text{false}|x) = \frac{e^{-w \cdot f}}{1 + e^{-w \cdot f}}$$

Logistic regression classification

New example can be labeled true if:

$$p(y = \text{true}|x) > p(y = \text{false}|x)$$

$$\frac{p(y = \text{true}|x)}{p(y = \text{false}|x)} > 1$$

$$\frac{p(y = \text{true}|x)}{1 - p(y = \text{true}|x)} > 1$$

$$e^{w \cdot f} > 1$$

$$w \cdot f = \sum_k w_k f_k > 0$$

Logistic regression training

- Learning a logistic regression function can be seen as learning a hyperplane which separates points in space that are in the positive class from points that are not in the class
- Training is learning the weights so that the probability of the observed values y is the highest: through convex optimization:
 - Several methods: quasi-Newton methods, gradient ascent, conjugate gradient and various iterative scaling algorithms

Maximum entropy modeling

- Maxent deals with a larger number of classes: **multinomial logistic regression**
- Let there be C different classes: $y_1, y_2, \dots, y_C$
- We estimate the probability that y is a particular class c given k **feature functions f** as:

$$p(y|x) = \frac{1}{Z} \exp \sum_k w_i f_i$$
$$p(y|x) = \frac{\exp \sum_k w_i f_i(y, x)}{\sum_{y' \in C} \exp \sum_k w_i f_i(y', x)}$$

- [Berger et al. CL 1996] showed that the exponential model for multinomial logistic regression when trained according to the maximum likelihood criterion, also finds the **maximum entropy distribution** subject to the constraints from the feature functions

Conditional random fields

- Let X be a random variable over data to be labeled and Y a random variable over corresponding labels
- All components Y_j of Y are assumed to range over a finite label alphabet Σ
- A conditional random field is viewed as an undirected graphical model or Markov random field, conditioned on X
- We define $G = (V, E)$ to be an **undirected graph** such that there is a node $v \in V$ corresponding to each of the random variables representing an element Y_v of Y
- If each random variable Y_v obeys the Markov property with respect to G , then the model (Y, X) is a conditional random field

Conditional random fields

- In theory the structure of graph G may be arbitrary, however, when modeling sequences, the simplest and most common graph structure encountered is that in which the nodes corresponding to elements of Y form a simple first-order Markov chain (linear-chain CRF)
- Note: in the following $\mathbf{x}$ refers to an observation sequence and not to a feature vector and y to a labeling sequence

Conditional random fields

- Named entity recognition:
 - Sequence of observations: $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_T)$
 - Sequence of semantic labels: $y = (y_1, \dots, y_T)$
 - Sequence forms first order Markov chain
- A novel observation sequence $\mathbf{x}$ is labeled with y , so that the conditional probability $p(y|\mathbf{x})$ is maximized:

$$p(y|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^k \sum_{j=1}^T w_i f_i(y_{j-1}, y_j, \mathbf{x}, j)\right)$$

- Trained with dynamic programming techniques that are similar to the Baum-Welch algorithm

[Lafferty et al. ICML 2001]

F1 scores on the CoNLL Dataset						
Approach	LOC	ORG	MISC	PER	ALL	Relative Error reduction
Bunescu and Mooney (2004) (Relational Markov Networks)						
Only Local Templates	-	-	-	-	80.09	11.1%
Global and Local Templates	-	-	-	-	82.30	
Finkel et al. (2005)(Gibbs Sampling)						
Local+Viterbi	88.16	80.83	78.51	90.36	85.51	9.3%
Non Local+Gibbs	88.51	81.72	80.43	92.29	86.86	
Our Approach with the 2-stage CRF						
Baseline CRF	88.09	80.88	78.26	89.76	85.29	12.6%
+ Document token-majority features	89.17	80.15	78.73	91.60	86.50	
+ Document entity-majority features	89.50	81.98	79.38	91.74	86.75	
+ Document superentity-majority features	89.52	82.27	79.76	92.71	87.15	
+ Corpus token-majority features	89.48	82.36	79.59	92.65	87.13	
+ Corpus entity-majority features	89.72	82.40	79.71	92.65	87.23	13.3%
+ Corpus superentity-majority features						
(All features)	89.80	82.39	79.76	92.57	87.24	

Named entity recognition: 2-stage approach: 1) CRF with local features; 2) local information and output of first CRF as features. Comparison against competitive approaches. Baseline results are shown on the first line of each approach.

[Krishnan & Manning 2006]

Opinion extraction

- Web documents: forum for:
 - Exchange of opinions
 - Dissemination of propaganda
- => extracting opinions or sentiments is of interest for businesses, governments, ...

Opinion extraction

- Learning emotion patterns in **blog** texts:
 - Positive, negative and neutral feeling
- Problems:
 - Large variety of expressions (noisy texts !!!) and relatively few annotated examples
 - Emotion is attributed to an entity
 - How to reduce annotation?
 - Language/domain portability

— *The movie really seems to be spilling the beans on a lot of stuff we didnt think we hand if this is their warm up, what is going to get us frothing in December*

— + *de grote merken mogen er dan patserig uitzien en massa's pk hebben maarals de bomen wat dicht bij elkaar staan en de paadjes steil enbochtig,dan verkies ik mijn Jimny .*

+ *L'é tro bel cet voitur Voici tt ce ki me pasione ds ma petite vi!!!é tt mé pote é pll dotre truk!!!Avou de Dcouverir*

Opinion extraction

- Solutions tested:
 - Feature selection or extraction
 - Single classifier versus a cascaded classifier versus bagged classifiers
 - Active learning

[Abassi et al. TOIS 2008]

[Boiy & Moens IR 2009]

Table IV. English and Arabic Feature Sets

Category	Feature Group	English	Arabic	Examples
Syntactic	POS N-grams	varies	-	frequency of part-of-speech tags (e.g., NP_VB)
	Word Roots	-	varies	frequency of roots (e.g., slm, ktb)
	Word N-grams	varies	varies	word n-grams (e.g. senior editor, editor in chief)
	Punctuation	8	12	occurrence of punctuation marks (e.g., !;,:.?)
Stylistic	Letter N-Grams	26	36	frequency of letters (e.g., a, b, c)
	Char. N-grams	varies	varies	character n-grams (e.g., abo, out, ut, ab)
	Word Lexical	8	8	total words, % char. per word
	Char. Lexical	8	8	total char., % char. per message
	Word Length	20	20	frequency distribution of 1-20 letter words
	Vocab. Richness	8	8	richness (e.g., hapax legomena, Yule's K)
	Special Char.	20	21	occurrence of special char. (e.g., @#\$%^&*+)
	Digit N-Grams	varies	varies	frequency of digits (e.g., 100, 17, 5)
	Structural	14	14	has greeting, has url, requoted content, etc.
	Function Words	250	200	frequency of function words (e.g., of, for, to)

[Abassi et al. TOIS 2008]

Opinion extraction

- Many studies use machine learning techniques that train from classified examples:
 - Support vector machines and naive Bayes classifiers are very popular
 - Link analysis techniques
 - Active learning to select examples to annotate
- Augmented with linguistic rules of a language

Figure 1: Instantiation of the cascade model used in our experiments.

[Boiy & Moens IR 2009]

Event extraction

- Event = happening at a certain place at a certain time
 - Involves named entities
 - Involves topics
 - Can be expressed in sentence
 - Can be expressed in discourse
- => Named entities combined with topic models

Probabilistic Latent Semantic Analysis (pLSA)

[Hofmann 1999]

M = number of documents

N = number of words

Topic 1

Topic 2

waitress
\$ food
Menu
...

park
Tree
...

Probabilistic Latent Semantic Analysis

- Translating the document or text generation process into a joint probability model:

$$P(d_j, w_i) = P(d_j)P(w_i|d_j)$$

$$\text{where } P(w_i|d_j) = \sum_{k=1}^K P(w_i|z_k)P(z_k|d_j)$$

K = number of topics (a priori defined)

Training:

$$\text{maximizing } L = \prod_{j=1}^M \prod_{i=1}^N P(d_j, w_i)^{n(d_j, w_i)} = \sum_{j=1}^M \sum_{i=1}^N n(d_j, w_i) \log P(d_j, w_i)$$

where $n(d_j, w_i)$ = frequency of w_i in d_j , N = number of words in the vocabulary

(e.g. trained with EM algorithm)

PROBABILISTIC GENERATIVE PROCESS

STATISTICAL INFERENCE

Figure 2. Illustration of the generative process and the problem of statistical inference underlying topic models

[Steyvers & Griffiths 2007]

Latent Dirichlet Allocation

(1)

(2)

[Blei et al. JMLR 2003]

Latent Dirichlet Allocation

- pLSA:
 - learns $P(z_k|d_j)$ only for those documents on which it is trained except for some limited folding in
 - number of hidden variables to learn grows linearly with the growth of the number of documents
- **Latent Dirichlet Allocation** (LDA) treats topic mixture weights as a K -parameter hidden random variable θ
- **Training**
 - Key inferential problem: computing the distribution of the hidden variables θ and z given a document, i.e., $p(\theta, z | \mathbf{w}, \alpha, \beta)$: intractable for exact inference (model 1)
 - α : Dirichlet prior, can be interpreted as a prior observation count for the number of times a topic is sampled in a document, before having observed any actual words from that document

Latent Dirichlet Allocation

- Model 2 = simple modification of the original graphical model 1: the chain $\alpha \rightarrow \theta \rightarrow z$ is replaced by $\gamma \rightarrow \theta$ and $\phi \rightarrow z$
- Compute approximation of model 1 by model 2 for which the KL divergence $\text{KL}[p(\theta, z | \gamma, \phi), q(\theta, z | \mathbf{w}, \alpha, \beta)]$ is minimal
- Iterative updating of γ and ϕ for each document and recalculation of corpus-level variables α and β by means of EM algorithm
- Inference for new document:
 - Given α and β : we determine γ (topic distribution) and ϕ (word distribution) with a variational inference algorithm

Concept recognition

- Concept recognition in text, images, ... :
 - When examples annotated with concepts are available:
 - Training of classifier: super vector machine, maximum entropy model, ...
 - Unsupervised: extensions of probabilistic topic models

Expert recognition

- Experts = persons named with strong correlation to certain topics
- Expert recognition requires:
 - Named entity recognition
 - Topic detection

Linking of content

- Here restricted to linking of person mentions:
 - **In one document**: anaphora resolution and noun phrase coreference resolution includes mention clustering and disambiguation
 - **Across documents**: noun phrase coreference resolution includes mention clustering and disambiguation
 - **Across media**: alignment of names and faces

Table 4.2. Typical features in a single-document noun phrase coreference resolution task of the syntactic heads, i and j , of two candidate coreferent noun phrases in text T where $i < j$ in terms of word position in T .

FEATURE	VALUE TYPE	VALUE
Number agreement	Boolean	True if i and j agree in number; False otherwise.
Gender agreement	Boolean	True if i and j agree in gender; False otherwise.
Alias	Boolean	True if i is an alias of j or vice versa; False otherwise.
Weak alias	Boolean	True if i is a substring of j or vice versa; False otherwise.
POS match	Boolean	True if the POS tag of i and j match; False otherwise.
Pronoun i	Boolean	True if i is a pronoun; False otherwise.
Pronoun j	Boolean	True if j is a pronoun; False otherwise.
Appositive	Boolean	True if j is the appositive of i ; False otherwise.
Definiteness	Boolean	True if j is preceded by the article “the” or a demonstrative pronoun; False otherwise.
Grammatical role	Boolean	True if the grammatical role of i and j match; False otherwise.
Proper names	Boolean	True if i and j are both proper names; False otherwise.
Named entity class	Boolean	True if i and j have the same semantic class (e.g., person, company, location); False otherwise.
Discourse distance	Integer ≥ 0	Number of sentences or words that i and j are apart.

Pairwise coreference classifier

- $\mathbf{m}$ is a set of mentions (m_i) (e.g., noun phrases) in the document
- $\mathbf{x}$ is the set of pairs of noun phrases: $x_{ij} = \{m_i, m_j\}$
- $\mathbf{y}$ is the set of variables representing each pairwise coreference decision y_{ij} involving mentions m_i and m_j
- Binary random variable $y_{ij} = 1$ if m_i and m_j are coreferent
- Let $F = \{x_{ij}, y_{ij}\}$ be a set of feature functions over x_{ij} (e.g., Boolean)
- $p(y_{ij}|x_{ij})$: computed with a classification model

Pairwise coreference classifier

- Maximum entropy model (i.e., (multinomial) logistic regression):

$$p(y_{ij}|x_{ij}) = \frac{1}{Z} \exp\left(\sum_k w_k f_k(x_{ij}, y_{ij})\right), \quad 0 < w_k < \infty$$

$f_l(x_{ij}, y_{ij})$ = one of the k binary-valued feature functions

w_l = real-valued weight parameter estimated from the training data

Z = normalizing constant

Constructing the clusters

Figure 1: An example noun coreference graph in which vertices are noun phrases and edge weights are proportional to the probability that the two nouns are coreferent. Partitioning such a graph into disjoint clusters corresponds to performing coreference resolution on the noun phrases.

Constructing the clusters

- Goal: partition graph into clusters with high intra-cluster edge weights and low inter-cluster edge weights:
 - Based on strength (or probability) of detected relations
 - Possibly augmented with heuristic constraints of forbidden merge of mentions
- Often greedy clustering: each noun phrase m_i is assigned to the same cluster as the closest preceding noun phrase m_j for which $p(y_{ij}|x_{ij}) > \delta$ (threshold) (e.g., $\delta = 0.5$)

Constructing the clusters

- How to incorporate information over sets of noun phrases? Some alternatives:
 - Best clustering: intractable problem
 - At least incorporate transitivity constraints

Enforcing transitivity with ILP

- After computing the pairwise classification decisions:
 - Use **integer linear programming** to enforce transitivity constraints:

$$\max \sum_{x_{ij}} \log p(y_{ij}|x_{ij}) \cdot y_{ij} - \log(1 - p(y_{ij}|x_{ij})) \cdot (1 - y_{ij})$$

- $p(y_{ij}|x_{ij})$: computed with a classification model (see above)

[Finkel & Manning ACL-HLT 2008]

Enforcing transitivity with ILP

- Add binary constraints on each of the variables: $y_{ij} \in \{0,1\}$
- Add constraints over each triplet of mentions to enforce transitivity: $(1-y_{ij}) + (1-y_{jk}) \geq (1-y_{ik})$
 - ensures that whenever $y_{ij} = y_{jk} = 1$ also $y_{ik} = 1$
- Use ILP tool to solve the ILP optimization problem
- Solution for short text because of computational complexity of ILP

Linking of entities across documents

- 2 problems:
 - **Homonymy** = names have the same writing, but refer to different entities:
 - E.g., persons disambiguation on the Web, cf. Web People Search Task (WePs)
 - **Synonymy** = names are written differently, but refer to the same entity (cf. within document noun phrase coreference resolution, but “one sense per discourse” heuristic not applicable):
 - E.g., people hide their identity in different names or names might have different writing forms

Linking of entities across documents

- In both cases the context is important:
 - Context determines whether two mentions refer to the same entity or to different ones
 - Context:
 - Surrounding words
 - Other entities mentioned in close vicinity
 - Other linked information

Homonymy

- Most simple problem: given a name only disambiguation
- Approaches:
 - Feature vector represents potential coreference relationship
 - Usually supervised:
 - Training of classifier
 - Clustering of the candidate coreference relationships possibly via graph partitioning

Table 4.3. Typical features in a cross-document noun phrase coreference resolution task of the syntactic heads, i and j , of two candidate coreferent noun phrases where i and j occur in different documents.

FEATURE	TYPE	VALUE
Context word	Boolean or real value between 0 and 1	True if the context word x occurs in the context of i and j ; False otherwise; If a real value is used, it indicates the weight of the context word; Proper names, time and location expressions in the context might receive a high weight.
Named entity class	Boolean	True if i and j have the same semantic class (e.g., person, company, location); False otherwise.
Web-related information	Boolean	True if URL or email address x occurs in the context of i and j ; False otherwise.
Semantic role	Boolean	True if the semantic role of i matches the semantic role of j ; False otherwise.

Synonymy

- Given a name, find synonyms AND also disambiguation
- String edit distances might not be sufficient
- Graph based approaches: link based similarity measures between nodes (exploiting similarity of neighbors), e.g.,
 - Co-citation
 - SimRank, Connected-Triple, PageSim
 - Variety of random-walk methods

[Getoor & Diehl ACM SIGKDD Explorations 2005]
[Liben-Nowell & Kleinberg JASIST 2007]

Alignment across media

- Novel area of research, currently mainly focusing on aligning names and faces
- Helps in automatically annotating images, video, ...

Alignment of names and faces

- Given image-text pairs: align faces (f) and names (n)
- Constraints:
 - Within image/text resolution of a face/name => same name and face occur once in each image/text
 - One name can only be aligned with one face, but faces can be aligned with “null” name and names with “null” face

...French President 1. Nicolas Sarkozy and girlfriend 2. Carla Bruni on a trip in Egypt...

Preprocessing

- **Images:**
 - **face detection**
 - **clustering of similar faces** (within and) across images (based on face descriptors)
 - computation of the **namedness** of the faces
- **Texts:**
 - **named entity (person) recognition:** maximum entropy classifier augmented with gazetteers
 - **clustering of similar names** within and across texts: **noun phrase coreference resolution**
 - computation of the **picturedness** of the names

[Moens JNLE 2006] [Deschacht & Moens ACL 2007]

Cardinal from Cologne Joachim Meisner cries during a meeting with Pope Benedict XVI at the centre for dialog and prayer in Oswiecim, Poland May 28, 2006.

```
<?xml version="1.0" encoding="UTF-8"?><output><si="0">Cardinal from Cologne <ENAMEX ID="0" TYPE="PERSON">Joachim Meisner</ENAMEX> cries during a meeting with Pope <ENAMEX ID="1" TYPE="PERSON">Benedict</ENAMEX> XVI at the centre for dialog and prayer in <ENAMEX ID="2" TYPE="LOCATION">Oswiecim</ENAMEX>, <ENAMEX ID="3" TYPE="LOCATION">Poland</ENAMEX> May 28, 2006.</si>
```

[Yahoo! News]

Picturedness of name:
Joachim Meisner: 0.75
Benedict: 0.33

[Yahoo! News]

U.S. President George W. Bush (2nd R) speaks to the press following a meeting with the Interagency Team on Iraq at Camp David in Maryland, June 12, 2006. Pictured with Bush are (L-R) Vice President Dick Cheney, Defense Secretary Donald Rumsfeld and Secretary of State Condoleezza Rice.

Namedness of face: is proportional with size of detected face and confidence of detection

Likelihood of image-text pair x_i and the alignment a_j :

$$L_{x_i, a_j}^{(n \rightarrow f)} = \prod_{\alpha} P(f_{\sigma(\alpha)} | n_{\alpha})$$

$$L_{x_i, a_j}^{(f \rightarrow n)} = \prod_{\beta} P(n_{\sigma(\beta)} | f_{\beta})$$

$$L_{x_i, a_j}^{(n^* \rightarrow f)} = \prod_{\alpha, \sigma(\alpha) \neq NULL} (P(pictured_{\alpha} | t_{x_i}) P(f_{\sigma(\alpha)} | n_{\alpha})) \prod_{\alpha, \sigma(\alpha) = NULL} ((1 - P(pictured_{\alpha} | t_{x_i})) P(f_{\sigma(\alpha)} | n_{\alpha}))$$

...

Initialization

- Different methods for initial parameter estimation:
 - Based on one document/story: e.g., use of picturedness or namedness value
 - Use of face/name clusters combined with co-occurrence information of names and faces

e.g., estimating
 $P(f|n)$

...

Optimization

- Use of the EM algorithm to maximize the log-likelihood of all image-text pairs S :

$$\sum_{x_i \in S} \sum_{a_j \in C_i} \delta_{i,j} \log(L(x_i, a_j))$$

where C_i = set of all possible alignments for image-text pair x_i ; $\delta_{i,j}$ = strength of the alignment a_j for image-text pair x_i

- “Faces in the wild” dataset: 11820 stories or image-text pairs with 5637 unique person faces and 8878 unique person names.
- Best alignment results: 72.33% F_1 measure

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