Relation Extraction from Texts and Computational Integration of Words and Networks

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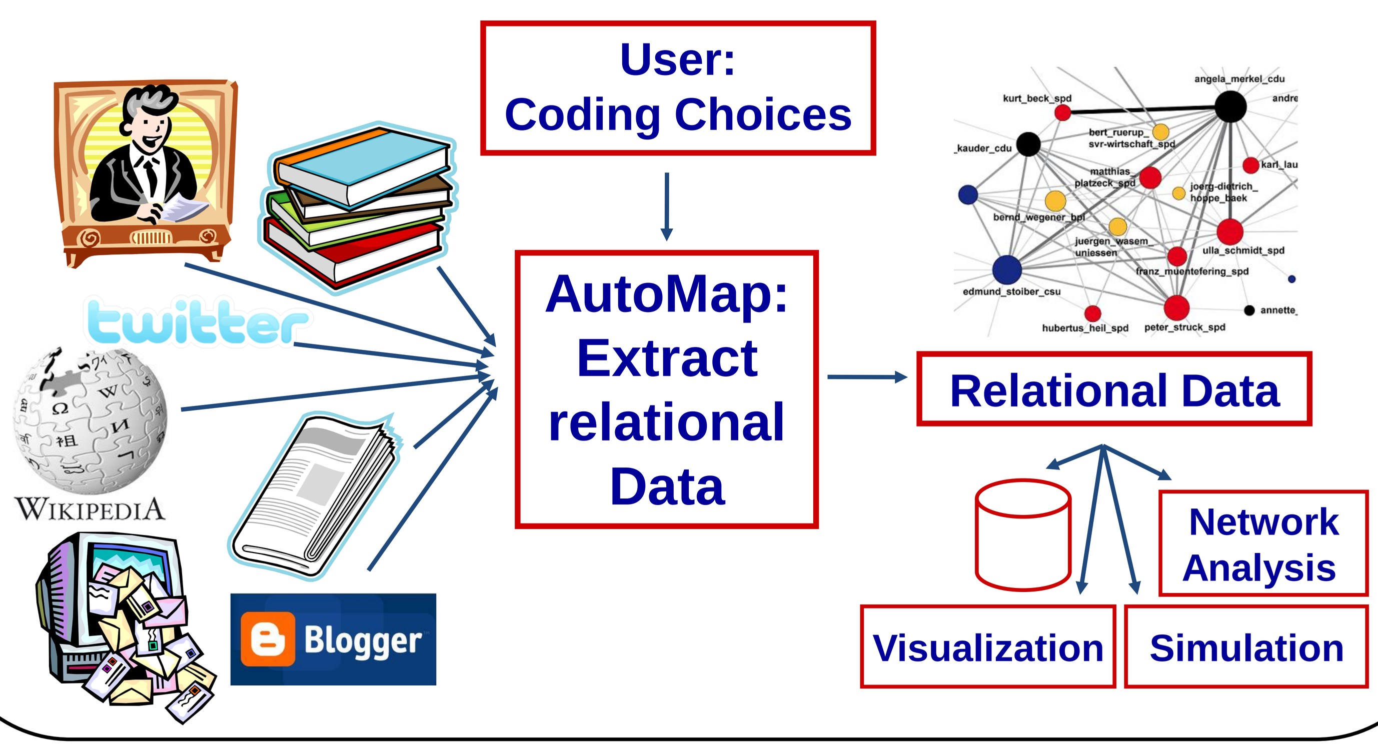
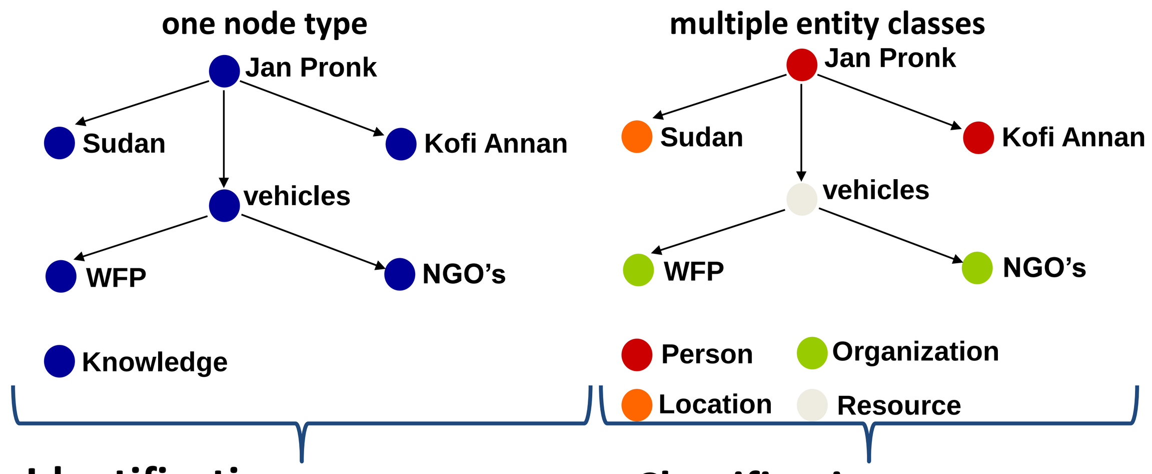


Illustrative Toy Example:

"Jan Pronk, the Special Representative of Secretary-General Kofi Annan to Sudan, today called for the immediate return of the vehicles to World Food Programme (WFP) and NGOs." (from UN News Service, New York, 12-28-2004):

proximity-based extraction of relational data :

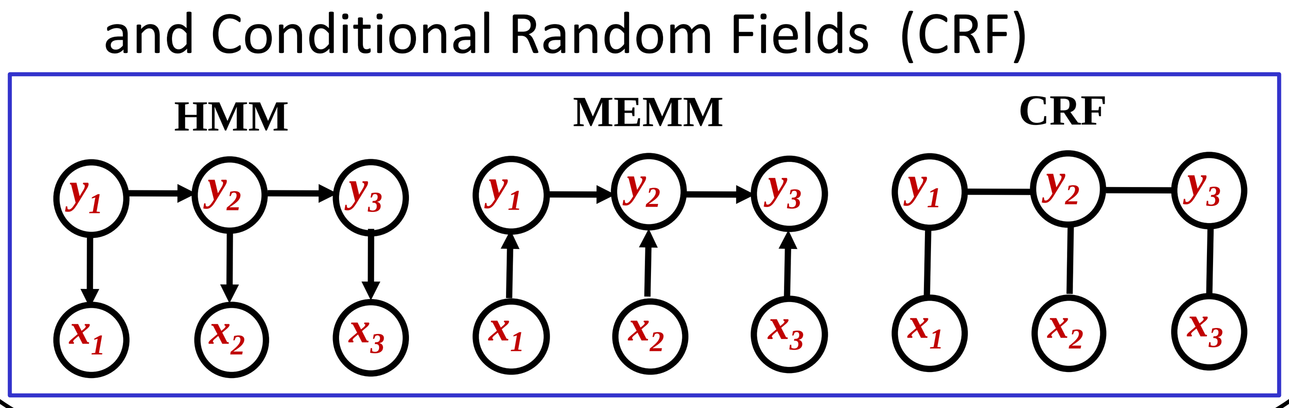


Identification: For relational data with at least one node type: **Locate/ identify** relevant nodes (may be multi-word units)

Classification: For ontologically coded networks: **Classify** relevant nodes according to an ontology or taxonomy

Development of Computational Solutions

- Utilize techniques from Machine Learning and Artificial Intelligence
- Deploy and develop supervised and semi-supervised **sequential stochastic learning techniques** in order to train classifiers and build models that generalize to new data
- Construct a classifier *h* that for every sequence of ***(x, y)*** (joint probability) (where *x* = words per sequence and *y* = corresponding category) or ***(x|y)*** (conditional probability) predicts a sequence ***y = h (x)*** for any sequence of *x*, incl. new and unseen data
- We work with Generative (aka discriminative) models: *P(x,y),* such as Hidden Markov Model (HMM), and Conditional models: *P(y|x)*, such as Maximum Entropy Markov Models (MEMM) and Conditional Random Fields (CRF)



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Natural Language Processing and Relational Extraction Routines in AutoMap

- **Stemming**: Convert words into their morphemes.
- **Reduction and Normalization**:
  - Negative filters such as delete lists and removal of symbols
  - Positive filters such as spelling correction and assigning synonyms to unique key concept
- **Part of Speech Tagging**: Assign a single best word class to every word.
- **Anaphora Resolution**: Convert personal pronouns into entity or entities that a pronoun refer to.
- **Feature Identification:** Automatically find the most important terms in a dataset.
- **Named Entity Extraction**: Identify relevant types of information that are referred to by a name, such as people, organizations, and locations.
- **Ontological Text Coding**: Identify and classify instances of pre- or user-defined node classes, such as Named Entities, resources, tasks, and time.
- Identification of and reasoning about **node and edge attributes**, such as demographic data, beliefs, and types of relationships.
- **Email Data Analysis**: Extract and combine different types of networks, such as social networks and knowledge networks, from emails.
- **Entropy Assessment**: Determine the variability of a text or text set with respect to its vocabulary.
- Classical **Content Analysis**.
- Read and write data and processing material from and to a default or user-specified **database**.

Example: Conditional Random Fields for Entity Extraction

- Identify and classify words that represent instances of entity classes of models or ontologies that **deviate** from classical set of Named Entities.
- Crucial step for coding texts as social-technical networks according to domain-specific ontologies and for advanced modeling of complex and dynamic real-world organizations or networks.
- Model relationship among y_i and y_{i-1} as Markov Random Field conditioned on *x*
- Conditional distribution of entity sequence *y* given observation sequence *x* computed as normalized product of potential functions M_i:

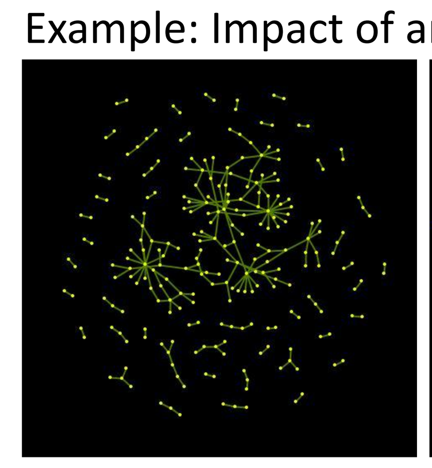
$$M_i(y_{i-1}, y \mid x) = \left(\exp\left(\sum_\alpha \lambda_\alpha f_\alpha(y_{i-1}, y_i, x) + \sum_\beta \mu_\beta g_\beta(y_i, x)\right)\right)$$

$$p_\theta(y \mid x) = \frac{\prod_{i=1}^{n+1} M_i(y_{i-1}, y_i \mid x)}{\prod_{i=1}^{n+1} M_i(x)_{start,stop}}$$

- Conditional probability of label sequence *P(y|x)*, where both *x* and *y* are arbitrarily long vectors (consider arbitrarily large bag of features (> 10,000))and any property of *x*, such as long-distance information)

Evaluation

- Rigorous assessment of the impact of information and relation extraction techniques on relational data and respective interpretations of socio-technical networks
- Example: Impact of anaphora and coreference resolution:



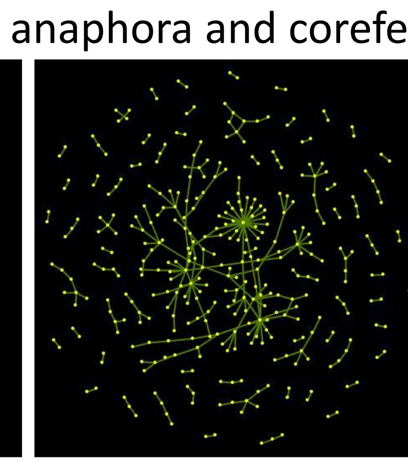


Table: Impact of AR, CR on edge level

Routine	measurement	newswire	newspaper	broadcast
raw	unique nodes	4715	4884	3743
	total node weight	5774	5916	4536
AR	unique nodes	4599	4682	3659
	node weight reduction rate	2.5%	4.1%	2.2%
CR	unique nodes	3324	3213	2835
	node weight reduction rate	29.5%	34.2%	24.3%
AR+CR	unique nodes	3050	2894	2596
	node weight reduction rate	35.3%	40.7%	30.6%
	node weight reduction rate from AR to AR+CR	5.8%	6.5%	6.4%

Visualization of relations in broadcast data of the ACE2 corpus (NIST, LDC): raw data (left image) and after applying anaphora and coreference resolution (right image), showing links with strength > 1, isolates are hidden

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