Mining Unstructured Data

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Outline

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What is unstructured data?

- Information which is not organised following a pre-defined model
- This data may be from:
  - Human language (text/speech): collections of well written documents (articles, books, legal notes,...), collections of non-standard textual documents (sms, tweets, opinions, webpages, health records, chats, speech transcripts...)
  - Audio: space exploration recordings, ...
  - Image/video: digital photos (face images,...) or videos (military tracking, athmospheric movements, ...)

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  This course focuses on **data from human language**, as it is the type most frequently used for unstructured data mining

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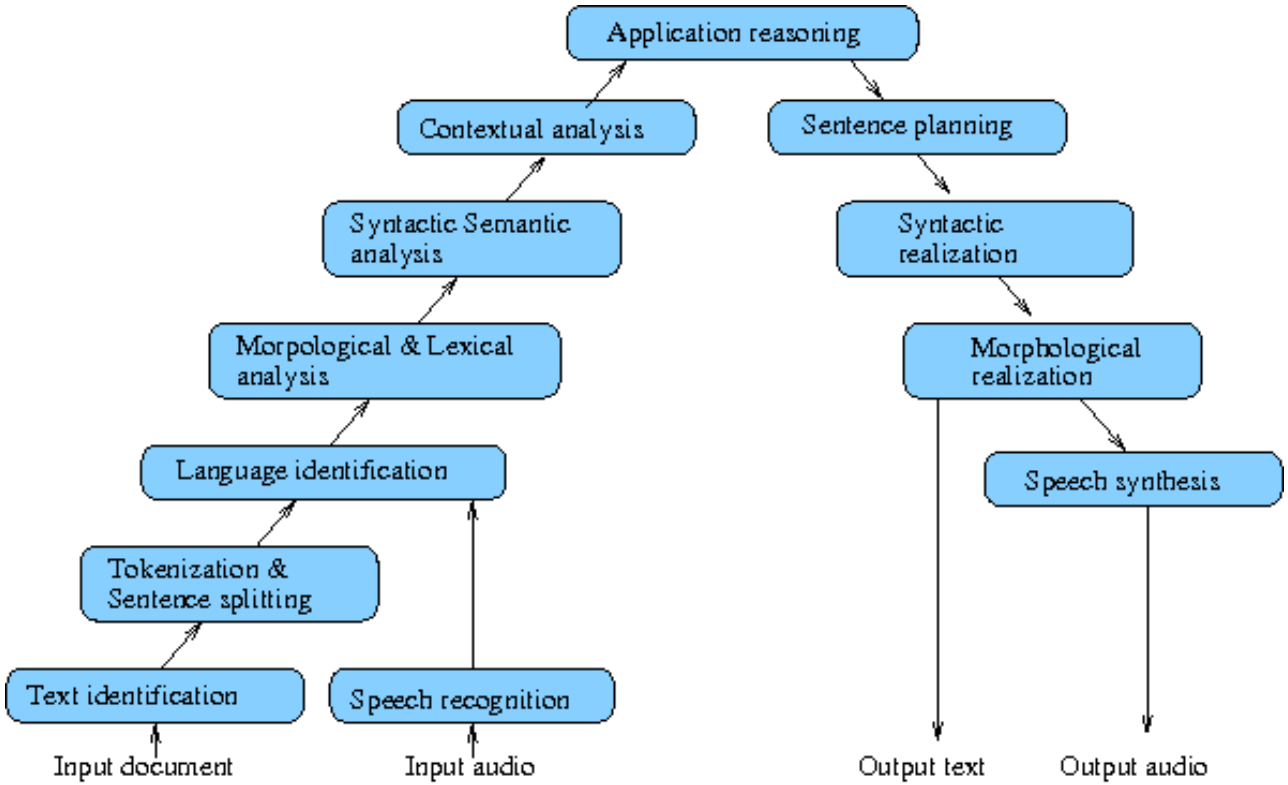
Definitions

The general strategy follows the standard subareas of linguistics:

- Phonetics: sounds of human speech.
  E.g., *infrequent* → `/ɪn'frikwənt/`
- Morphology: structural formation and categorisation of words.
  E.g., *in-frequent-ly*, *'the' is Determiner*.
- Syntax: structural relations between words in sentences.
  E.g., *a determiner is followed by a common noun*.
- Semantics: meenings of words and their composition via syntax.
  E.g., *the president of USA is Donald Trump* → `president(USA, Donald_Trump)`
- Pragmatics: meaning in the context.
  E.g., **He** *is very well known in* **his country** [sarcasm]

General architecture



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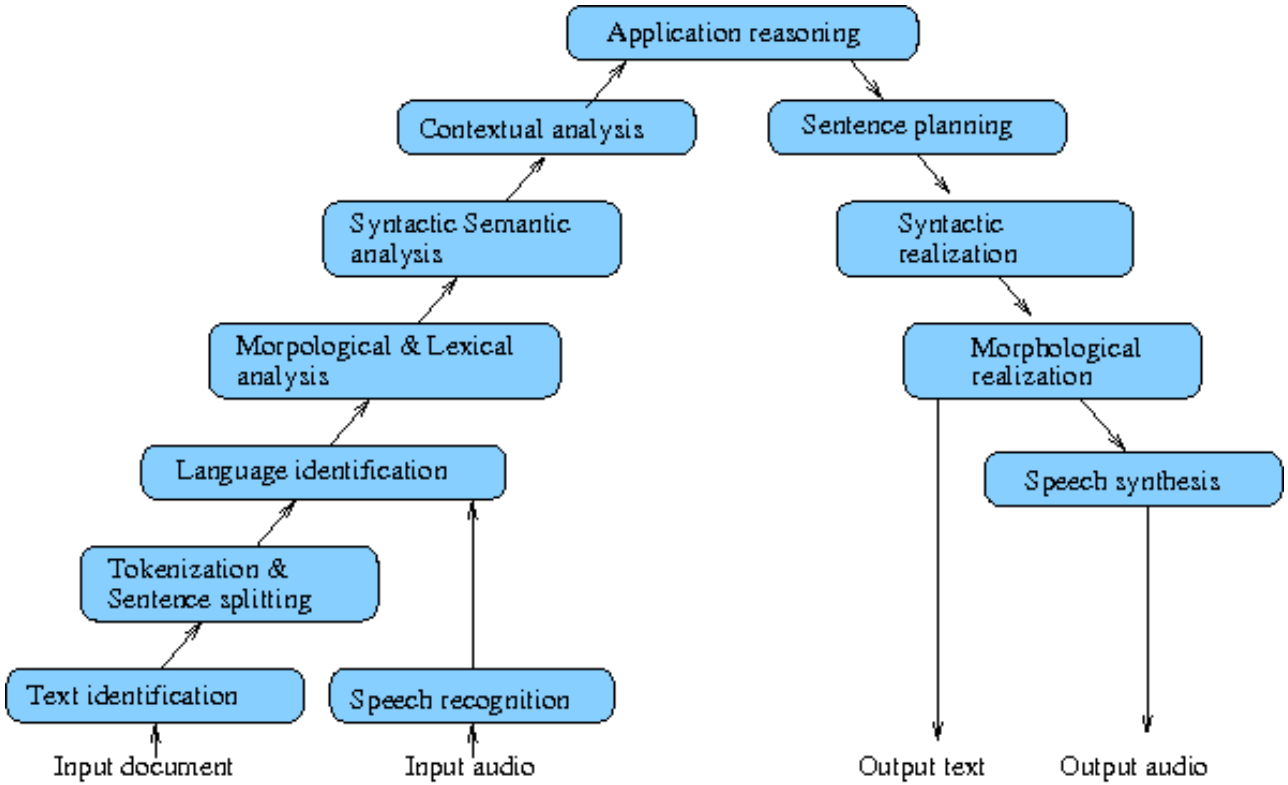

- Branches: NL Understanding and NL Generation.
- Approaches: Knowledge-based *vs.* Statistical-based.
- Shallow methods (lexical overlap, pattern matching) *vs.* Deep methods (semantic analysis, logical inference)

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Problems

- World-knowledge
  - Representing world-knowledge is mandatory for understanding NL (AI-completeness)
    e.g., Yago - facts, OpenCyc - common sense
- Multilinguality
  - Different languages require different models and resources
  - Use of words from other languages
    `Estoy a full!` (non-standard Spanish text)
- Evaluation
  - Correctness/suitability of a translation/summary
- Variability
  - Different sentences refer to one meaning
    `Where can I get a map?`
    `I need a map`
    `need map` (non-standard text)
- Ambiguity
  - One sentence refers to different meanings
    `Esther said about Alice: ''I made her duck''`

Ambiguity

E.g., Esther said about Alice: ''I made her duck''

- I cooked waterfowl for her
- I cooked the waterfowl she owned
- I created the duck she owns
- I caused her to quickly lower her head or body
- I turned her into waterfowl

Word	Ambiguity	Alternatives
make	semantic	cook or create
her	syntactic	possessive or dative pronoun
	pragmatic	Esther or Alice
duck	synt-sem	noun or verb

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Examples of applications

- Document clustering
- Document classification (e.g. anti-spamming, email routing, sentiment polarity, language identification)
- Information Retrieval
- Text correction
- Plagiarism detection
- Information Extraction
- Automatic Summarization
- Question Answering
- Machine Translation
- Dialog Systems

...

Information Retrieval (IR)

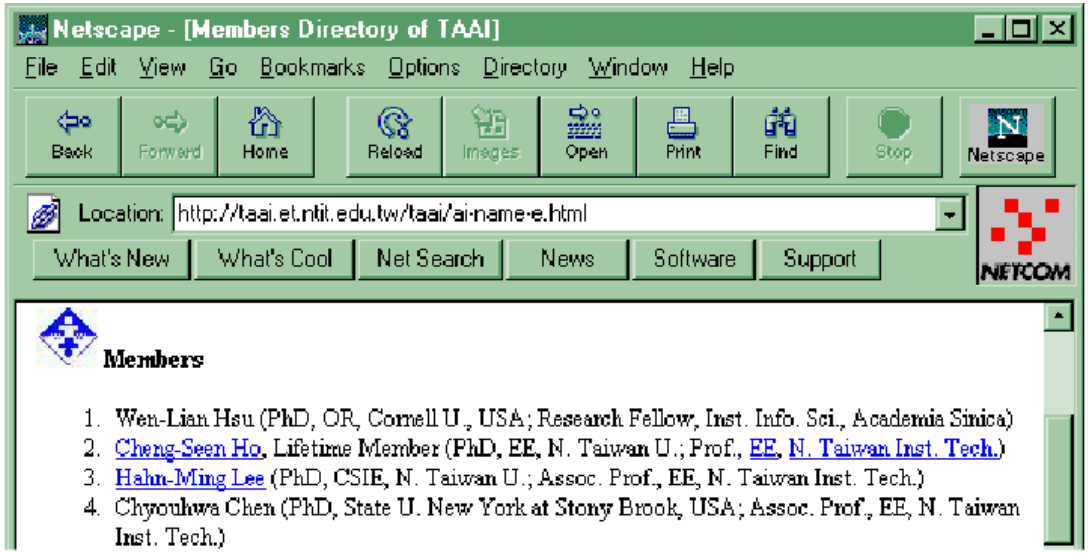
- E.g.: Searchers (Google, Yahoo, ...)
- Given a corpus, $D = \{D_i\}$, and a user query (list of words), Q , provide $\hat{D} \subset D$ that better match Q.
- $sim(v(Q), v(D_i))$, where $v(X)$ represents X in a vector space
- What vector space seems better?
  - words? $Q =$"window", $D_i =$"...he closed the windows..."
  - lemmas? $Q =$"window", $D_i =$"...he closed Windows..."
  - compounds? $Q =$"Energie", $D_i =$"...Sonnenenergie..."
  - ...
  - In-depth NLP seems not productive

Information Extraction (IE)

- E.g.: Enriching DBs or KBs with new content. Document collection indexing. Sentiment analysis.
- Extract the **relevant information** contained in text (entities, properties, relationships and events).
- Main subtasks:
  - Named Entity Recognition and Classification (NERC)
  - Slot Filling
  - Relationship Extraction
  - Event Extraction
- Depending on the specific task, more in-depth NLP is required (syntax, semantics, pragmatics, world-knowledge), as well as ML techniques.

Information Extraction (IE)

- Example 1: Member Name, Degree, School and Affiliation from WEB pages.



Name	Degree	Affiliation	School
Wen-Lan Hsu	PhD, OR, Cornell U., USA	Research Fellow	Inst. Info. Sci. Academia Sinica
Chen-Seen Hu	PhD, EE, N. Taiwan U.	Prof.	EE, N. Taiwan Inst. Tech
Hahn-Ming Lee	PhD, CSIE, N. Taiwan U.	Prof.	EE,N. Taiwan Inst. Tech
...			

Information Extraction (IE)

- Example 2: incidents from free text (type of incident, perpetrator, target, date, location, effects, instrument).

```
At 5pm on  Thursday , a  white Fiat van  veered off the road and into a
crowd outside the Plaça de Catalunya metro station in Barcelona.   The  van
continued down  Las Ramblas  for more than 500 metres while  crashing  into
 pedestrians .   13 people have been killed .   100 people were injured  and
 15 are in serious condition .  Las Ramblas attacker  Younes Abouyaaqoub
 was  killed in Subirats.
```

Information Extraction (IE)

- Example 2: incidents from free text (type of incident, perpetrator, target, date, location, effects, instrument).

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type of incident = crash

location = Las Ramblas (Barcelona)

date = 17/8/2017

perpetrator = Younes Abouyaaqoub

target = pedestrians

instrument = white Fiat van

effects = 13 people killed, 100 people injured, 15 people in serious condition

Automatic Summarization

- E.g.: Generate biographies, minutes of a meeting, abstracts or extracts of written documents
- Given a document or a corpus, generate an extract or an abstract consisting of the most relevant content.
- Abstractive methods:
  - Generate new text from the conceptual representation of the important information contained in the input text.
  - Require language understanding and generation
- Extractive methods:
  - Select the most important sentences in the input text and produce a summary.
  - The set of sentences should maximize overall importance and coherency and minimize the redundancy.
- How are *importance* and *redundancy* computed?
- Semantics and ML techniques help

Question Answering (QA)

- E.g.: Questions answered by intelligent cars and rooms.
- Given a corpus, $D = \{D_i\}$, and a question, Q, extract the exact answer for Q from D.
  - Factoid QA: answers are exact facts

    E.g.: `Who was the president of the USA in 1987?`
  - Non-factoid QA: a definition, an explanation of how or why, a biography summary, ...

    E.g.: `Tell me what has been said so far in the meeting`
- Main subtasks:
  - Document indexing
  - Question processing (question type, question focus)
  - Answer extraction
- more in-depth NLP is required as well as ML techniques. Information extraction and Automatic Summarization help.

Machine Translation (MT)

- E.g.: Translation of written documents, help in human-human communication by mobile, online translation of broadcast news.

- Classical MT (Rule-based MT or Statistical-based MT):
  - Breaks input sentence into either words or phrases
  - Maps words to words or phrases to phrases using short context for taking decisions
- Neural MT:
  - Translates sentence to sentence
  - Uses the broader context of words and phrases at each step

- In general, the results are not comparable to human translation

Machine Translation (MT)

Examples of drawbacks: (with Google Translate)

- Working sentence by sentence: lack of context

  ES: Ana no aprobó el examen. Su amigo sí.
  EN: Ana did not pass the exam. **Your** friend **yes**.
  ok: Ana did not pass the exam. Her friend did.

- Lack of world-knowledge: Named entities

  ES: Disfrutar es el mejor nuevo restaurante de Europa
  EN: **Enjoy** is the best new restaurant in Europe
  ok: Disfrutar is the best new restaurant in Europe

- Restricted domains: terminology

  ES: El níscalo se cría bajo pinos
  EN: **The níscalo** grows under pines
  ok: Red pine mushroom grows under pines

  ES: Los níscalos se crían bajo pinos
  EN: **The chanterelles are raised** under pines
  ok: Red pine mushrooms grow under pines

Dialog Systems

- E.g.: chatbots, dialog-driven QA in smart cars and rooms, health-care assistance
- Help users to achieve specific goals by means of natural language interaction
- Main subtasks:
  - Interpreting user intervention
  - Determining the next system's action considering the user intention (answer a question, ask for more info, suggest alternatives, ...)
  - Generating system's intervention
- High complexity: Natural language understanding and generation is required

Outline

Schedule and Evaluation procedure

You can find the schedule at Racó, or directly here.

- Final exam: all the content, exam period
- Lab sessions:
  - Groups of 2 students (mandatory)
  - Deliverables for 5 tasks
- Final mark = 50% Exam + 50% Lab deliverables