FROM INFORMATION EXTRACTION TO TEXT UNDERSTANDING

Marie-Francine Moens
Language Intelligence and Information Retrieval
Human Computer Interaction
Department of Computer Science
Katholieke Universiteit Leuven, Belgium
Overview

- Information extraction from text: some history
- **MUSE**: from information extraction to text understanding
- Information extraction: current NLP components
- Implementation: a machine learning framework
- **Challenges:**
  - Lack of training data for infrequent items
  - Learning of complex interrelated structures
  - Lack of world or domain knowledge
  - Text semantics vs. planning representation
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]
Early origin of information extraction

- end 1960s and 1970s: [Schank 1972, 1975]
- Defines all natural language words in terms of elementary primitives or predicates in an attempt of capturing the semantic content of a sentence
- Conceptual dependency representation specifies semantic roles: the action of the sentence (e.g., as reflected by the verbs of the text) and the arguments (e.g., agent, object) and circumstances
- Main categories of concepts are PPs (i.e., picture producers, in other words, concrete nouns) and actions
- Representations are ordered in a script or scenario which outlines sequences of events or actions
**Script:** human (X) taking the bus to go from LOC1 to LOC3

1. X PTRANS X from LOC1 to bus stop
2. bus driver PTRANS bus from LOC2 to bus stop
3. X PTRANS X from bus stop to bus
4. X ATRANS money from X to bus driver
5. bus driver ATRANS ticket to X
6. Various subscripts handling actions possible during the ride.
7. bus driver PTRANS bus from bus stop to LOC3
8. X PTRANS X from bus to LOC3

X performs a physical transition expressed by PTRANS
X gives money to the bus driver. ATRANS is used to express a transfer of an abstract relationship, in this case the possession of money.

(3), (7), (8): mandatory

[Schank 1975]
Frame-based approaches

- [Minsky 1975]: frame-based knowledge representations
  - Frames are often triggered by the occurrence of a certain word or phrase
  - Very **partial analysis** of the input text:
    - Algorithm tries to match natural language sentences with particular frames by simply filling out the slots in accordance with the constraints placed on them
    - Often top-down (expectation-driven): guided by the expected patterns to be found in the text
    - Robust: ignoring of irrelevant information
  - **Template frames** that outline the information can be used as output
Frame-based approaches

- Patterns to be identified can be encoded as regular expressions and recognized by finite state automaton.
- Frames are often organized in a **script:**
  - Because of their strict organization, scripts have good predictive ability useful in information extraction.
- Examples of some famous information extraction applications:
  - FRUMP: Yale University
  - FASTUS: Stanford Research Institute
Finite state automaton implementation: set of cascaded, non-deterministic finite-state transducers

- Application of symbolic rules in the form of hand-crafted regular expressions
- Cascade: output of finite state transducer is input for next finite state transducer

[Hobbs et al. 1996] [Hobbs JBioInformatics 2002]
Cascade of finite state transducers

1. Recognition of compound words and named entities
2. Partial parse: recognition of verb, noun, prepositional phrases, actives, passives, gerunds
3. Recognition of complex noun groups
4. Resolution to active form, recognition of information to be extracted
5. Structure merging
Example sentence:

*Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan.*
**Company name**  | **Bridgestone Sports Co.**
--- | ---
**Verb group**  | said
**Noun group**  | Friday
**Noun group**  | it
**Verb group**  | had set up
**Noun group**  | a joint venture
**Preposition**  | in
**Location**  | Taiwan
**Preposition**  | with
**Noun group**  | a local concern
**And**  | and
**Noun group**  | a Japanese trading house
**Verb group**  | to produce
**Noun group**  | golf clubs
**Verb group**  | to be shipped
**Preposition**  | to
**Location**  | Japan
### Extraction rules:

<Company/ies> {Set-up} {Joint-Venture} {with} <Company/ies> {Produce} <Product>

<table>
<thead>
<tr>
<th>Relation: TIE-UP</th>
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<tbody>
<tr>
<td>Entities:</td>
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<tr>
<td>Bridgestone Sports Co.</td>
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<tr>
<td>a local concern</td>
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<tr>
<td>a Japanese trading house</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Activity: PRODUCTION</th>
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<tbody>
<tr>
<td>Company:</td>
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<tr>
<td>Product: golf clubs</td>
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<td>Start Date:</td>
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Symbolic techniques: results

- Successful systems, built and tested in many subject domains
  - e.g., MUC-7 (1998): subject domain of airplane crashes:
    - Performance of individual systems: largely similar
    - Certain information much easier to extract than others
- Problem:
  - Infinite variety of subject domains: very difficult to exhaustively implement the symbolic knowledge
  - Very difficult to construct a script for every conceivable situation
<table>
<thead>
<tr>
<th>Evaluation\Tasks</th>
<th>Named Entity</th>
<th>Coreference</th>
<th>Template Element</th>
<th>Template Relation</th>
<th>Scenario Template</th>
<th>Multilingual</th>
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<tbody>
<tr>
<td>MUC-3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>R &lt; 50%</td>
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<td>P &lt; 70%</td>
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<td>MUC-4</td>
<td></td>
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<td>JJV F &lt; 64%</td>
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<td>EME F &lt; 50%</td>
<td>JME F &lt; 57%</td>
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<tr>
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<td>F &lt; 97%</td>
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<td>F &lt; 57%</td>
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<td>P &lt; 72%</td>
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<td>F &lt; 94%</td>
<td>F &lt; 62%</td>
<td>F &lt; 87%</td>
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<td>F &lt; 51%</td>
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<td>MET-1</td>
<td>C F &lt; 85%</td>
<td>J F &lt; 93%</td>
<td>S F &lt; 94%</td>
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<tr>
<td>MET-2</td>
<td>C F &lt; 91%</td>
<td>J F &lt; 87%</td>
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</tbody>
</table>

Legend:  
R = Recall  
P = Precision  
F = F-Measure with Recall and Precision Weighted Equally  
E = English  
C = Chinese  
J = Japanese  
S = Spanish  
JV = Joint Venture  
ME = Microelectronics
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)
  - Computational Natural Language Learning (CoNLL)
  - SemEval competitions
Today

- **Machine reading**
  - = The automated discovery of meaningful knowledge in free text
    => form of automated understanding of the text

- Can be evaluated in the translation to another modality
  => MUSE project: *translation of text into a virtual reality*
  => translation of text to planning language
  = translation to a meaning representation
MUSE project

- **MUSE**: Machine Understanding for interactive Storytelling
- **Algorithms for translating text into virtual worlds**, 9/2012-8/2015, EU FP7-296703 (FET-open call)
The ability of a computer or other machine to perform those activities that are normally thought to require intelligence:

- Automated reading or understanding of texts written in natural language
- Understanding of images
- ...

- Beyond: story telling, game development, story generation, case based reasoning, ...
Current NLP Components
Information extraction: Where are we now?

- NLP components:
  - Named entity recognition
  - Noun phrase coreference resolution
  - Semantic role labeling
  - Event recognition
  - Temporal expression recognition
  - Temporal relation recognition
  - Spatial relation recognition
  - …

Semantic labeling
Named entity recognition

- Recognition of classes of entities (persons, locations, companies, organizations, ...)

Over the past month the **BBC** has had rare access to the **International Monetary Fund** boss **Christine Lagarde**. Now, as European leaders meet in **Brussels**, she will be at the centre of the fight to avert another financial crisis.

(BBC News 1-3-2012)
Noun phrase coreference resolution

Identify all noun phrases (mentions) that refer to the same entity

Figure 1: Coreference System

[Ng & Cardie ACL 2002]
Recognizing the basic event structure of a sentence
("who" "does what" "to whom/what" "when"
"where", ...)

fall.01

Arg1: Logical subject, patient, thing falling
Arg2: Extent, amount fallen
Arg3: Start point
Arg4: End point, end state of Arg1

Ex1: [Arg1 Sales] fell [Arg4 to $251.2 million] [Arg3 from $278.7 million].
Ex2: [Arg1 The average junk bond] fell [Arg2 by 3.7%].

(PropBank roles)
Event recognition

Events = situations that happen or occur
Events can be punctual (1-2) or last for a period of time (3-4), or describing states or circumstances in which something obtains or holds true (5)

1. Ferdinand Magellan, a Portuguese explorer, first \textbf{[event reached]} the islands in search of spices.
2. A fresh flow of lava, gas and debris \textbf{[event erupted]} there Saturday.
3. 11,024 people, including local Aeta aborigines, were \textbf{[event evacuated]} to 18 disaster relief centers.
4. “We’re \textbf{[event expecting]} a major eruption,” he said in a telephone interview early today.
5. Israel has been scrambling to buy more masks abroad, after a \textbf{[event shortage]} of several hundred thousand gas masks. (Sauri et al. 2005)
Temporal information recognition

- Recognition: identify which phrases are temporal and which are not
- Normalization: translate the temporal phrase to a standard time expression

Show me platform six five days ago at 17:20.
Temporal relation recognition

- Recognition of temporal relations between events: e.g., BEFORE, AFTER, INCLUDES, IS_INCLUDED, DURING, SIMULTANEOUS, BEGINS, ... (TimeML)

[Screenshot of example sentence with annotations: “So she [event considered] a while, and then [event climbed] up the wall and let herself [event hang] down by her hind legs from a peg, and [event pretended] to be dead. By and by a Mouse [event peeped] out and [event saw] the Cat hanging there.”] [Kolomiyets et al. ACL 2012]
Spatial relation recognition

- Recognition of:
  - **Trajector**: entity (person, object or event) whose location is described
  - **Landmark**: the reference entity in relation to which the location or the motion of the trajector is specified

- Recognition of more fine-grained spatial meanings: e.g., direction, motion

```
[ Trajector [She] ]
[ Motion-Indicator [went] ]
[ Spatial-Indicator(type=REGION/RCC8,value=TPP) [to] ]
[ Landmark(path=END) [school] ].
```

[Kordamshidi et al. TSLP 2011]
Implementation of NLP Components
Classifier approach to extracting semantics

Method:

- The text fragments (tokens, chunk, parse nodes) in training and test data are segmented.
- Special attention goes to feature engineering: use of NLP resources to extract features (e.g., part-of-speech tagging, syntactic dependencies, signaling words, etc.).
- A classifier is trained on manually annotated examples (e.g., maximum entropy) possibly integrating constraints in structured output classifiers (Markov random fields, structured support vector machines).
- The classifier is applied on previously unseen test examples.
Classifier approach to extracting semantics

- = assignment of controlled language descriptors to words or phrases in a text

Semantic classes or labels:
\[ C = \{C_1, C_2, \ldots, C_m\} \]

- Although not a necessary condition, classes are usually mutually exclusive:
  - Often seen as a single-label multi-class learning problem
  - But classes can be organized in a hierarchy, ontological structure
What are machines capable of?

1. If sufficient training examples and if the classifier is tested on texts of a same domain as the training examples

Roughly: F1-values of the recognition maximum ca. 80% (lower for noun phrase coreference resolution, temporal expression normalization and temporal relation extraction)

Room for improvement!
What are machines capable of?

- (2) The machine recognizes fragmentary pieces (e.g., names, facts) and the recognition of related fragments of text are often limited to the sentence level.

- Emerging recognition of discourse understanding: e.g. noun-phrase coreference resolution and temporal relation recognition

Human understanding of text:
inferencing, connecting content

[Wikipedia]
What are machines capable of?

- The machine only uses information resided in the texts

- Human understanding of text: humans connect to their world/domain knowledge
What are machine capable of in restricted domains?

- **Method:**
  - Use of handcrafted grammar that translates to primitives in form of prolog commands that steer a virtual world [Rochefort et al. AAAI 1997]
  - Learn alignments between words/phrases and semantics
    - Grounded language learning in form of PCFG [Börschinger et al. EMNLP 2011], [Kim & Mooney EMNLP 2012], CCG [Zettlemoyer & Collins EMNLP 2007], or logical form [Liang et al. HLT 2011]
    - Mapping from a dependency parsing tree to a planning tree [cf. Jones et al. ACL 2012]
    - Often EM like reinforcements [e.g., Chen & Mooney 2008; Goldwasser et al. 2011] or EM/Gibbs sampling trained generative models [Liang et al. ACL-IJCNLP 2009], though some interest in spectral models [Dhillon et al. EMNLP 2012]

- **Results:**
  - Some success on restricted domains
    - Robot directions, weather reports, sports descriptions
NLP in MUSE
= bringing text to life

Children’s stories and patient education guidelines render these as 3D-virtual worlds

http://www.muse-project.eu/
MUSE: What do we recognize in the texts?

- At the **sentence level**:  
  - Actions/events and their semantic roles (actor, patient, instrument ...)
  - Scope of negation, modality

- At the **discourse level**:  
  - Conditional, pre/postconditions of actions/scenario, causal (local, multicausal)
  - Coreferent noun phrases
  - Temporal relations between actions
  - (Spatial relations)
  - Intention (of actors), goals
  - Abstract attitudes, personality treats
MUSE: Beyond information extraction

- But mapping needed to PDDL knowledge representation
- Possibility of consistency feedback with setting specific knowledge
Challenges still remain
- Lack of training data for infrequent items
- Learning of complex interrelated structures
- Lack of world or domain knowledge

Additional challenge:
- Text is incomplete or not right level of detail is given to translate to planning language
Challenge 1:
Lack of training data for infrequent items
Lack of training data

- Lexical items (words) are very important: they carry an important part of the semantic meaning.
- Many, many different words in a language! Many of which are never seen in the training examples!
Leveraging unlabeled data

- Semi-supervised learning (some labeled data)
  - Self-learning: iterative retraining after labeling of data points for which the current model is most confident
  - Transductive inference: labels of the unlabeled examples are predicted according to a most likely model that explains the labeled and unlabeled examples

- Unsupervised learning (no labeled data)
  - Try to find meaningful clusters
  - Clusters can be used as features for supervised models
Figure 2: Schematic figure illustrating how unlabeled data might improve a supervised classifier. Grey dots are unlabeled data, white dots labeled data and the dotted line the classification boundary.
Leveraging unlabeled data

- The semantic classes are expressed with many different words that when used as features do not cluster.

- Even if we normalize syntactic constructions clustering is difficult.

- Many words have different meanings.
Unsupervised learning

- Learn classes of exchangeable phrases, words and syntactic constructs

- Potential of latent class models

Learn from large textual data sets!

[Blei et al. ML 2003]
Latent Words Language Model

E.g., learning of synonyms and related words from a representative corpus
[Deschacht, De Belder & Moens CSL 2012] [Kolomiyets et al. ACL 2011]

Cf. use of language modeling in information extraction:: [Deschacht, De Belder & Moens CSL 2012] [Yates et al. Comp. Ling. 2013]
Latent Words Language Model

Generative model: Bayesian network with observed (grey nodes) and hidden variables (white nodes). The hidden nodes represent the probability distribution of each word of the vocabulary being present in the specific context. In our implementation a second order Markov dependency of the hidden words left and right of the target hidden word is modeled. The model is trained with a forward-forward beam search or with Markov Chain Monte Carlo sampling.
Latent class model challenges

- Latent class models are computationally expensive
  - Essentially have to enumerate all possibilities for all latent class assignments
  - Opportunities for new optimization techniques, sampling techniques
  - Opportunities for building contextual vectors [Vulic & Moens NAACL 2013]

- In MUSE, the domain is constrained
  - So computational expense may be acceptable given potential performance improvements
Challenge 2: Learning complex interrelated structures
Complex structures and combining evidence

- Already done on a limited scale in the literature:
  - Several passes through the data (output of one pass serves as input for other)
  - Output of local extractors is combined (e.g., template filling) possibly by using additional constraints
  - Prediction of a structured output (parse tree, predicate logic, or graph) (e.g., learning of semantic parser, jointly learning the ontological classes)

- Uncertain recognition can be reinforced by other evidences:
  
  Supporting and combining evidence!
Several passes through the data

- Noun phrase coreference resolution:
  - First step: train and apply classifier with local context
  - Reinforcing pair-wise relationships through clustering

Not all pair-wise probabilities are shown

Cf. [Culotta et al. ACL 2007]
Several passes through the data

- Named entity recognition:
  - First step: train classifier with local context
  - Second step: retrain with additional features which are the output of the first classifier

Figure 1: An example of the label consistency problem. Here we would like our model to encourage entities Albert Einstein and Einstein to get the same label, so as to improve the chance that both are labeled PERSON.

[Krishnan & Manning ACL 2006]
Constrained output of local classifiers

- Template filling:
  - Local extractors and templates are filled based on enforcing constraints in a late fusion approach [Minkov & Zettlemoyer ACL 2012]
  - Possibility of integer linear programming formulation

Figure 2: The relational schema for the seminars domain.

Figure 3: A record partially populated from text.
Prediction of a structured output

- Potential of
  - Extension of dependency framework – graph based approach now used in TERENCE (PhD of Oleksandr Kolomiyets)
  - Semi-supervised dependency parsing [Mirroshandel et al. ACL 2012]
  - Tensor form frameworks [Cohen et al. ACL 2012]
  - Decomposition models [Samdani & Roth ICML 2012]
  - Communicative optimization [current PhD research of Parisa Kordjamshidi]
Learning of a semantic dependency structure: graph based mining: [Kolomiyets et al. ACL 2012]
Prediction of a structured output

[PhD of Parisa Kordjamshidi] [Kordjamshidi & Moens ROKS 2013]
Supporting and combining evidences

- Guessing labels in contexts:
  - Current work in computer vision could be inspiring

Work of Fei-Fei Li and her group at Stanford
MUSE: Learning of complex related structures

- Recognition of the **narrative structure** [cf. Mani Morgan & Claypool 2013]
  - Connected events
  - Protagonists
  - Temporal and causal relations/preconditions - postconditions
  - Character traits
  - ...
Challenge 3: Lack of world knowledge
Examples of world knowledge

- Multiple examples of world knowledge:
  - It is much more likely that a person says something than a location
  - It is much more likely that a chair is next to the table than on top of the table
  - It is much more likely that you jump in the water and then swim than vice versa
  - ...
  - Could be learned from text, video, databases (Freebase – Krishnamurthy and Mitchell 2012), etc.
Learning temporal relations between events

- VerbOcean

**VerbOcean**

...Jump Right In!

Example: **VerbOcean**'s temporal precedence chains (the "happens-before" relation) between *invent* and *manufacture* shown with edge weights

[Chklovski & Pantel EMNLP 2004]

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Learning of narrative scripts

<table>
<thead>
<tr>
<th>row</th>
<th>$s_1$</th>
<th>$s_2$</th>
<th>$s_3$</th>
<th>$s_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>♦</td>
<td>walk into restaurant ♦</td>
<td>walk to the counter ♦</td>
<td>enter restaurant ♦</td>
</tr>
<tr>
<td>2</td>
<td>♦</td>
<td>find the end of the line ♦</td>
<td>♦</td>
<td>go to counter ♦</td>
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<td>3</td>
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Figure 2: A MSA of four event sequence descriptions

[Chambers & Jurafsky ACL 2009; Regneri et al. ACL 2010; Jans et al. EACL 2012; Li et al. AAAI 2012]
World knowledge in MUSE

- World knowledge in MUSE:
  - Some very basic knowledge (e.g. physics) will always be manually encoded in the VR environment anyway
  - Automatically acquiring the world knowledge can reduce the need for hand-coding (but in MUSE we can still fall back on hand-coding world knowledge when necessary)
- Knowing when world knowledge is relevant
Challenge 4: Matching text semantics to the planning representation
A central problem is learning the correspondence between a rich world state and a stream of text referring to that state.

Information in the text can be missing or being communicated at a different level of detail than is needed in the planning language (e.g., [Branahan et al. ACL 2012]).

A key challenge for MUSE will be to match the semantics we extract from text to the semantics of the story planner.

[related to Challenges 2 and 3]
Text semantics vs. planning representation

- **Virtual camera control**: e.g., translation of an image caption of museum object to guide video exploration of the object [Reiterer et al. 2010]

- **Robot control**: e.g., translating instructions to planning language
Text (input):
A pickaxe, which is used to harvest stone, can be made from wood.

Precondition Relations:
wood $\rightarrow$ pickaxe  
 pickaxe $\rightarrow$ stone

Plan Subgoal Sequence:

Figure 2: A high-level plan showing two subgoals in a precondition relation. The corresponding sentence is shown above.

[Branavan et al. ACL 2012]: (in reinforcement learning framework)
1) extract a set of precondition/effect relations implied by the text
2) use these induced relations to determine an action sequence for completing a given task in the environment
⇒ learning of general knowledge about the domain structures Cf. [Jans et al. EACL 2012], PhD thesis of Aparna Nurani
⇒ domain structure constraints the possible actions
Text: Over several months, you will meet various professionals who are members of a multidisciplinary team (surgeon, nutrition doctor, dietician, psychiatrist or psychologist, anaesthetist, etc.) who will provide you with information and examine you. They will also request various examinations (blood tests, upper gastrointestinal endoscopy* and, if necessary, X-rays, assessments of respiratory and cardiac function, pregnancy test and an examination of the mouth and teeth).

Planning Domain Definition Language (PDDL) representation:

(:action clinical-examination
 :precondition
   (and
     (= ?l practitionersoffice)
     (at ?d ?l)
     (at ?p ?l)
     (not (examined-by ?p ?d))
   )
 :effect
   (and
     (examined-by ?p ?d)
     (blood-test-required ?p)
   )
)
Conclusions

- Semantic parsing of sentences and discourses is still different from machine understanding of text

- **MUSE = test case for machine understanding**

- Promising directions:
  - Latent class models and other unsupervised techniques will help us handle the lack of training data
  - Structured learning allows different pieces to be recognized and integrated while reinforcing each other: will be useful in mapping to knowledge representation
  - Some world knowledge might be automatically acquired from large corpora or other resources
Our MUSE team

- Steve Bethard
- Wim De Mulder
- Oleksandr Kolomiyets
- Ngoc Quynh Do Thi

Thanks!
Questions?