Multi-lingual Meaning Representation:
trying to tame a force of nature

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The mapping between form and meaning

• What are the ways in which it is complex?
• How is it different in different languages?
Outline

Part I: Theoretical foundations and definitions
Part II: A journey through form and meaning

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Morphosyntactic strategies  
The importance of constructions | Design by linguists  
Live meetings with developers of each language |
| A classifier for definiteness | The complexity of semantic maps  
Intersecting meaning systems | Broad knowledge of linguists  
Read reference grammars |
| A classifier for causality | Morphosyntactic recruitment  
Intersecting meaning systems | Two-phase: expert, less-expert |

Part III: Opinions and advice for multi-lingual meaning representation projects
Foundation and Definitions
Foundations

• Cognitive Grammar
  • Grammatical categories like noun and subject are prototypes with radial categories.

• Construction Grammar
  • Constructions are conventionalized (grammaticalized) pairings of form and meaning.
  • Croft, *Radical Construction Grammar*,
    • universal and language-specific constructions

• Language Typology focusing on morphosyntax
  • The study of variation in human language
  • Croft, *Morphosyntax*
    • Typology and Radical Construction Grammar
Multi-lingual meaning representations for morphosyntax

• A discrete (not continuous), symbolic representation that is independent of different ways of saying the same thing.

1. The boy wants the girl to believe him.
   (w / want-01
     :ARG0 (b / boy)
     :ARG1 (b2 / believe-01
       :ARG0 (g / girl)
       :ARG1 b))

Bonial et al., LREC 2018
What is a multi-lingual meaning representation?

• A discrete (not continuous), symbolic representation that is independent of different ways of saying the same thing in any human language.

  • Otokonoko wa onnanoko ni kare o shinjite morai-tai.
  • boy TOP girl DAT him ACC believing receive-want
  • Literal: the boy wants to receive believing him from the girl.

1. The boy wants the girl to believe him.
   (w / want-01
    :ARG0 (b / boy)
    :ARG1 (b2 / believe-01
      :ARG0 (g / girl)
      :ARG1 b))
Partial meaning representations

• PropBank (argument structure)
• FrameNet (frame semantics)
• WordNet (word senses)
• Many corpus annotation schemes for meanings like modality, temporal expressions, negation, genericity, definiteness, factivity
The uses of meaning representations

• Machine translation
• Communication with robots
• Automatic Question Answering
Granularity of meaning representations

• The granularity is determined by what is typically lexicalized and grammaticalized.
  • No inferences or pragmatic meaning

• In a multi-lingual meaning representation the granularity is what *can* be lexicalized or grammaticalized in a human language.
Interlingua-based Machine Translation

• The typology of argument realization
• Morphosyntactic strategies
• The importance of constructions

• Design by linguists
• Have meetings with developers for different languages
The Vauquois Triangle
(Bernard Vauquois, 1968)
The Vauquois Triangle

Direct translation (phrasebook):

Source language sentence: I read it

Target language sentence: Je l’ai lu
The Vauquois Triangle

Transfer-based Machine Translation

Source language sentence: I read it

Source language structure:
Pronoun-1-agr1 V-pst  pronoun-2-agr2

Target language structure:
Pronoun-1-agr1 pronoun-2-agr2 AVOIR-agr1 V-pastpart

Target language sentence: Je l’ai lu
The Vauquois Triangle

Interlingua-based machine translation

I read it             Je l’ ai lu             (Watashi wa) (sore o) yonda
I it have read       I TOP that ACC read

(READ ( (agent 1sg) (patient 3sg) (tense past) )

I read it             Je l’ ai lu             (Watashi wa) (sore o) yonda
I it have read       I TOP that ACC read
KBMT 89: Carnegie Mellon University and IBM Japan

- Sergei Nirenburg, Lori Levin, Teruko Mitamura, Eric Nyberg, Donna Gates, Koichi Takeda, and many others
- English and Japanese
Morphosyntactic Strategies

• Informally: morphosyntactic strategies are different grammar for doing the same thing.

• Example of morphosyntactic strategies:
  • To express subject and object: word order, case marking, agreement.
  • To express location: case marker, preposition, postposition, or genitive plus noun.
  • To express possession: mark on head, mark on possessor
  • To express negation: affix, verb, adverb
  • And thousands more
Typology of argument realization, verb classes, and transitivity alternations in linguistics

Causative-Inchoative Class
I (subj) opened the door (obj).
The door (subj) opened.

Conative Class
I kicked the ball (obj).
I kicked at the ball (obl).

Argument Realization Divergences
I (subj) like cake (obj).
Me (oblique) gusta el pastel (subject).

Argument Realization is the mapping from syntactic relations like subject and object to semantic roles like agent and patient.

Transitivity alternations are different mappings for a verb with the same semantic roles. There are classes of verbs that undergo the same set of transitivity alternations. (B. Levin, 1993)

Verbs with similar meanings may have different argument realization in different languages. (Dorr 1993)
Following Lexical Functional Grammar, KBMT 89 separated parsing from semantic mapping.

- Morphosyntactic strategies were handled during parsing
- Argument realization was handled during semantic mapping
Interlingua-based machine translation

Parser: handles morphosyntactic strategies

Mapping Rules: handle typological differences in argument realization

Syntactic Generator: handles morphosyntactic strategies
Morphosyntactic Strategies for identifying subject and object in English and Japanese

Japanese: free word order and case marking
Neko ga inu wo mi-ta
Cat SUBJ dog OBJ see-PAST

English: word order
The cat saw the dog ≠ The dog saw the cat
A syntax-semantics mapping rule for interlingua-based MT

(emap *insert
  <=l=> insert ((CAT v) (SUBCAT trans))
  (role =sem (*physical-action))
  (:agent =syn (SUBJECT))
  (:theme =syn (DOBJECT))
  (:goal =syn (PPADJUNCT
               ((PREP into) (CAT n)))))

In KBMT 89, each language had an inheritance hierarchy for semantic mapping rules verb classes.

Takeda, Uramoto, Nasukawa, and Tsutsumi: Shaltz – a symmetric machine translation system with conceptual transfer, COLING 1992
The importance of constructions

Constructional Divergences

(10)  a. You’d better go.

b. Itta hoo ga ii.
   go-PAST alternative SUBJ good
   “The alternative that you went is good.”

c. Tebe stoi pojti.
   you-DATIVE cost-IMPPERSONAL go-INFINTIVE
   “To you costs to go.”

Typology in the days of interlingua-based machine Translation

Constructional Divergences

(10) a. You’d better go.

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Highly grammaticalized relative clause

Typology in the days of interlingua-based machine Translation

Constructional Divergences

(10) a. You’d better go.

b. Itta hoo ga ii.
go-PAST alternative SUBJ good
“The alternative that you went is good.”

c. Tebe stoit pojti.
you-DATIVE cost-IMPERSINAL go-INFINITIVE
“To you costs to go.”

Dative Case

a. You’d better go.

b. Itta hoo ga ii.
   go-PAST alternative SUBJ good
   “The alternative that you went is good.”

c. Tebe stoit poji.
   you-DATIVE cost-IMPERSONAL go-INFINITIVE
   “To you costs to go.”

Figure 6. TMR for the sentences in (10).
Good Practice

• The design phase of the KBMT 89 project included with two linguists (Levin and Mitamura) who had written dissertations on argument realization in multiple languages.

• The KBMT 89 system was clean and modular based on Lexical Functional Grammar:
  • Grammatical encoding: morphosyntactic strategies
  • Lexical mapping: argument realization

• The C-STAR and NESPOLE! consortia:
  • Task-oriented spoken language: meeting scheduling and travel reservations
  • The interlingua represented domain-specific speech acts
  • Developers for seven languages met for 3-5 days twice a year
    • Ensured that every decision we made worked for all languages
A Classifier for Definiteness

- The complexity of semantic maps
- Intersecting meaning systems
- Background in linguistics literature
- Read reference grammars
A Classifier for Definiteness

• ‘A Unified Annotation Scheme for the Semantic/Pragmatic Components of Definiteness’, Archna Bhatia, Mandy Simons, Lori Levin, Yulia Tsvetkov, Chris Dyer, Jordan Bender, LREC 2014

A semantic map for some aspects of definiteness

Discourse-old
I met a student. The student was tall.

Specific
I’m looking for a student. Her name is Chris.

Genericity

Discourse
Predictable
I went to a wedding. The bride and groom looked great.

Uniqueness

Non Specific
I’m looking for a student. I need one to help me with something.

Abstract nouns

Proper nouns

Familiarity/Context
Hand me the pen on the desk.

Mass nouns
Hmong and Hausa “aforementioned” definiteness markers

Definiteness markers in Hmong and Hausa

Discourse-old
I met a student. The student was tall.

Discourse Predictable
I went to a wedding. The bride and groom looked great.

Specific
I’m looking for a student. Her name is Chris.

Non Specific
I’m looking for a student. I need one to help me with something.

Genericity

Uniqueness

Abstract nouns

Familiarity/Context
Hand me the pen on the desk.

Mass nouns
Farsi and Turkish differential object marking for specificity

Discourse-old
I met a student. The student was tall.

Discourse Predictable
I went to a wedding. The bride and groom looked great.

Specific
I'm looking for a student. Her name is Chris.

Non Specific
I'm looking for a student. I need one to help me with something.

Familiarity/Context
Hand me the pen on the desk.

Genericity

Uniqueness

Abstract nouns

Mass nouns

Accusative marker in Farsi, Turkish, and all the related languages is used only for indefinite specific.
Even English and French do not have the same contour

Discourse-old
I met a student. The student was tall.

Discourse-Predictable
I went to a wedding. The bride and groom looked great.

Specific
I'm looking for a student. Her name is Chris.

Non Specific
I'm looking for a student. I need one to help me with something.

Genericity

Uniqueness

English and French differ here.

Abstract nouns
La gloire (glory)

Mass nouns
Du vin (wine)

Familiarity/Context
Hand me the pen on the desk.

Genericity
Communicative Functions of Definiteness: semantic map/annotation scheme

- **NONANAPHORA** [-A, -B]
  - **UNIQUE [+U]**
    - **UNIQUE_HEARER_OLD [+F, -G, +S]**
      - **UNIQUE_PHYSICAL_COPRESENCE [+R]**
      - **UNIQUE_LARGER_SITUATION [+R]**
      - **UNIQUE_PREDICATIVE_IDENTITY [+P]**
      - **UNIQUE_HEARER_NEW [-F]**
    - **NONUNIQUE [-U]**
      - **NONUNIQUE_HEARER_OLD [+F]**
        - **NONUNIQUE_PHYSICAL_COPRESENCE [-G, +R, +S]**
        - **NONUNIQUE_LARGER_SITUATION [-G, +R, +S]**
        - **NONUNIQUE_PREDICATIVE_IDENTITY [+P]**
      - **NONUNIQUE_HEARER_NEW_SPEC [-F, -G, +R, +S]**
      - **NONUNIQUE_NONSPEC [-G, -S]**
    - **GENERIC [+G, -R]**
      - **GENERIC_KIND_LEVEL**
      - **GENERIC_INDIVIDUAL_LEVEL**
      - **ANAPHORA [+A]**
        - **BASIC_ANAPHORA [-B, +F]**
          - **SAME_HEAD**
          - **DIFFERENT_HEAD**
        - **EXTENDED_ANAPHORA [+B]**
          - **BRIDGING_NOMINAL [-G, +R, +S]**
          - **BRIDGING_EVENT [+R, +S]**
          - **BRIDGING_RESTRICTIVE_MODIFIER [-G, +S]**
          - **BRIDGING_SUBTYPE_INSTANCE [-G]**
          - **BRIDGING_OTHER_CONTEXT [+F]**
      - **MISCELLANEOUS [-R]**
        - **PLEONASTIC [-B, -P]**
        - **QUANTIFIED**
        - **PREDICATIVE_EQUATIVE_ROLE [-B, +P]**
        - **PART_OF_NONCOMPOSITIONAL_MWE**
        - **MEASURE_NONREFERENTIAL**
        - **OTHER_NONREFERENTIAL**

<table>
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<tr>
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<th>Anaphoric</th>
<th>Generic</th>
<th>Predicative</th>
<th>Specific</th>
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<tr>
<td>+</td>
<td>1574</td>
<td>131</td>
<td>72</td>
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<td>-</td>
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<td>3180</td>
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<td>1905</td>
<td>621</td>
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<tr>
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<td>1327</td>
<td>267</td>
<td>1711</td>
<td><strong>Referential</strong></td>
</tr>
</tbody>
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<th>+</th>
<th>-</th>
<th>0</th>
<th>+</th>
<th>-</th>
<th>0</th>
<th>+</th>
<th>-</th>
<th>0</th>
</tr>
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<td>1711</td>
<td>Referential</td>
<td>690</td>
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<tr>
<td>Unique</td>
<td>287</td>
<td>581</td>
<td>2437</td>
<td>Specific</td>
<td>1305</td>
<td>181</td>
<td>1819</td>
<td>Unique</td>
<td>287</td>
</tr>
</tbody>
</table>
Example of definiteness annotation

Once upon a time there was a dear little girl who was loved by everyone who looked at her, but most of all by her grandmother, and there was nothing that she would not have given to the child.

Once she gave her a little riding hood of red velvet, which suited her so well that she would never wear anything else; so she was always called ‘Little Red Riding Hood.’

Figure 2: An annotated sentence from “Little Red Riding Hood.” The previous sentence is shown for context.

The annotated corpus:

17 documents: TED talks (75%), presidential speech (16%), fictional narrative (5%).
13,860 words
868 sentences
3,422 NPs
Details of the definiteness classifier

• Models
  • Log Linear (interpretable)
  • Random Forest (more accurate)

• Percepts (features)
  • The head of the NP (token, lemma, POS, token length, token position)
  • The dependents of the NP (token, lemma, POS)
  • The governor (immediate parent) of the NP
  • The dependency label attaching the NP to the governor
  • The closest dominating verb (left or right of NP)
  • The auxiliaries of the closest dominating verb
  • Whether the closest dominating verb is negated
  • Path length from the head of NP to the root of the tree
  • And more

• Goal: predict a communicative function given a set of percepts (features)
<table>
<thead>
<tr>
<th>+Specific</th>
<th>Percepts</th>
<th>-Specific</th>
</tr>
</thead>
<tbody>
<tr>
<td>First dependent’s POS</td>
<td>PRP$</td>
<td>First dependent’s lemma</td>
</tr>
<tr>
<td>Head’s left neighbor’s POS</td>
<td>PRP$</td>
<td>Last dependent’s lemma</td>
</tr>
<tr>
<td>Last dependent’s lemma</td>
<td>you</td>
<td>Num. of dependents, dependent’s lemma</td>
</tr>
<tr>
<td>Num. of dependents, dependent’s lemma</td>
<td>1, you</td>
<td>Head’s left neighbor’s POS</td>
</tr>
<tr>
<td>Num. of dependents, dependent’s POS</td>
<td>1, PRP$</td>
<td>Last dependent’s POS</td>
</tr>
<tr>
<td>Governor’s right neighbor’s POS</td>
<td>PRP$</td>
<td>Num. of dependents, dependent’s lemma</td>
</tr>
<tr>
<td>Last dependent’s POS</td>
<td>NNP</td>
<td>First dependent’s lemma</td>
</tr>
<tr>
<td>Last dependent’s POS</td>
<td>PRP$</td>
<td>Last dependent’s lemma</td>
</tr>
<tr>
<td>First dependent’s lemma</td>
<td>the</td>
<td>Num. of dependents, dependent’s POS</td>
</tr>
<tr>
<td>Governor’s lemma</td>
<td>from</td>
<td>Governor’s left neighbor’s POS</td>
</tr>
</tbody>
</table>

Figure 3: Percepts receiving highest positive weights in association with values of the Specific attribute.
<table>
<thead>
<tr>
<th>Example</th>
<th>Relevant percepts from fig. 3</th>
<th>CFD annotation</th>
</tr>
</thead>
</table>
| This is just for the United States of America. | Last dependent's POS: NNP  
First dependent's lemma: the | Unique_Larger_Situation |
| We were driving from our home in Nashville to a little farm we have 50 miles east of Nashville — driving ourselves. | First dependent's POS: PRP$  
Head's left neighbor's POS: PRP$  
Governor's right neighbor's POS: PRP$  
Governor's lemma: from | Bridging_Restrictive_Modifier |

Figure 4: Sentences from our corpus illustrating percepts fired for gold NPs and their CFD annotations.
Overlapping semantic spaces

- The limits of our work on definiteness
  - In languages that do not have non-deictic determiners, some communicative functions of definiteness are accomplished with different morphosyntactic mechanisms such as word order, special constructions, and differential object marking.
  - But it is not clear that these morphosyntactic mechanisms are actually definiteness. They may be grammaticalizations of other semantic spaces that happen to intersect with definiteness:
    - Old and new information, affectedness, completedness
A Classifier for Causality

- Morphosyntactic Recruitment
- Two-phase annotation: expert and less expert
Collaborators and acknowledgements

• Collaborators: Jesse Dunietz, Jaime Carbonell,
  - Jesse Dunietz, Jaime Carbonell and Lori Levin, “DeepCx: A transition-based approach for shallow semantic parsing with complex constructional triggers”. *EMNLP* 2018

• Thank you: Nathan Schneider, Miriam Petruck, Alexis Palmer
Annotating Causality

- **Why** is California on fire?
- **The hot summer** set the stage for **the devastating fires**.

Connective and Argument spans:

- **CAUSATION** (ENABLEMENT)
- **CAUSE**
- **EFFECT**
We annotate three types of causality.

The system failed because of a loose screw.  

Mary left because John was there.  

Mary left in order to avoid John.
Causation can be positive or negative.

This has often caused problems elsewhere.

He kept the dog from leaping at her.
# The Because Corpus

<table>
<thead>
<tr>
<th>Source</th>
<th>Documents</th>
<th>Sentences</th>
<th>Causal</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York Times Washington section</td>
<td>59</td>
<td>1924</td>
<td>717</td>
</tr>
<tr>
<td>Penn TreeBank WSJ</td>
<td>47</td>
<td>1542</td>
<td>534</td>
</tr>
<tr>
<td>2014 NLP Unshared Task in PoliInformatics</td>
<td>3</td>
<td>772</td>
<td>324</td>
</tr>
<tr>
<td>Manually Annotated Sub-Corpus</td>
<td>12</td>
<td>629</td>
<td>228</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>121</strong></td>
<td><strong>4790</strong></td>
<td><strong>1803</strong></td>
</tr>
</tbody>
</table>

**BECAUSE** = **Bank of Effects and Causes Stated Explicitly**
Annotators were guided by a “constructicon.”

<table>
<thead>
<tr>
<th>Connective pattern</th>
<th>&lt;cause&gt; prevents &lt;effect&gt; from &lt;effect&gt;</th>
<th>&lt;enough cause&gt; for &lt;effect&gt; to &lt;effect&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annotatable words</td>
<td>prevent, from</td>
<td>enough, for, to</td>
</tr>
<tr>
<td>WordNet verb senses</td>
<td>prevent.verb.01</td>
<td>prevent.verb.02</td>
</tr>
<tr>
<td>Type</td>
<td>Verbal</td>
<td>Complex</td>
</tr>
<tr>
<td>Degree</td>
<td>INHIBIT</td>
<td>FACILITATE</td>
</tr>
<tr>
<td>Type restrictions</td>
<td>Not PURPOSE</td>
<td></td>
</tr>
<tr>
<td>Example</td>
<td>His actions prevented disaster.</td>
<td>There’s enough time for you to find a restroom.</td>
</tr>
</tbody>
</table>
Causality uses structures from other domains

*After* a drink, she felt much better. (Temporal)

They’re *too* big to fail. (Extremity)

The more I read his work, the *less* I like it. (Correlation)

The police *let* his sister visit him briefly. (Permission)

*As* voters get to know Mr. Romney, his poll numbers will *rise*. (Temporal + Correlation)
We annotate 7 different types of overlapping relations.

<table>
<thead>
<tr>
<th>Type</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TEMPORAL</strong></td>
<td>After; once; during</td>
</tr>
<tr>
<td><strong>CORRELATION</strong></td>
<td>As; the more…the more…</td>
</tr>
<tr>
<td><strong>HYPOTHETICAL</strong></td>
<td>If…then…</td>
</tr>
<tr>
<td><strong>OBLIGATION/PERMISSION</strong></td>
<td>Require; permit</td>
</tr>
<tr>
<td><strong>CREATION/TERMINATION</strong></td>
<td>Generate; eliminate</td>
</tr>
<tr>
<td><strong>EXTREMITY/SUFFICIENCY</strong></td>
<td>So…that…; sufficient…to…</td>
</tr>
<tr>
<td><strong>CONTEXT</strong></td>
<td>Without; when (circumstances where…</td>
</tr>
</tbody>
</table>
Overlapping Relation Examples

• Temporal
  • Within minutes after the committee released its letter, Torricelli took the senate floor to apologize to the people of New Jersey.

• Correlation
  • Auburn football players are reminded of last year’s losses every time they go into the weight room.

• Hypothetical
  • Previously, he allowed increases in emissions as long as they did not exceed the rate of economic growth.
Overlapping Relation Examples

• Obligation/Permission
  • He will roll back a provision known as a new source review that compels utilities to install modern pollution controls whenever the significantly upgrade older plants.
    • “whenever” is also a connective

• Creation/Termination
  • Many expected synergies of financial service activities gave rise to conflicts and excessive risk taking.

• Context
  • With Hamas controlling Gaza, it was not clear that Mr. Abbas had the power to carry out his decrees.
Temporal with and without causal interpretation

After last year’s fiasco, everyone is being cautious.

After last year’s fiasco, they’ve rebounded this year.
Conditional hypotheticals don’t have to be causal, but most are.

Non-causal: If he comes, he’ll bring his wife.
Causal: If I told you, I’d have to kill you.

84% carry causal meaning
Causality has seeped into the temporal and hypothetical domains.

Of the causal expressions in the corpus:

- > 14% are piggybacked on temporal relations
- ~7% are expressed as hypotheticals
Opinions and Advice
How to run a multi-lingual design project

• Know your phenomenon and your languages: read reference grammars and talk to linguists
  • Semantic maps
  • Morphosyntactic strategies
  • Overlapping semantic domains
  • Morphosyntactic Recruitment

• Iterations
  • Do not get too big to fail all at once. Make a few preliminary versions that you intend to revise.

• Reconcile together:
  • Developers for different languages should meet regularly with each other.

• How do you know when it is good enough?
Your new hobbies

• Reading typology papers and reference grammars
  • If you can’t do it: always consult a typologist

• Reading papers on classifiers in Semeval and Non-prop/ex-prop, and LAW
Opinion on crowdsourcing

• I don’t recommend it for most types of meaning
• But you can factor out some of the more expert part from some of the less expert part.
  • PropBank
  • Because Constructicon

Naïve science: not recommended for real-world applications
Lobby for increased funding for resource creation

• Resource creation is not funded by the National Science Foundation in the US
• There is intellectual merit
• There are intrinsic and extrinsic evaluation metrics
  • We need to make this case to the funding agencies
End