Semantic Parsing

Announcements

- Plan to release midterm grades by Thursday
- One day behind on syllabus. Will likely drop image captioning.

What is semantic parsing?

- Mapping to a meaning representation
- Semantic representation with desiderata
  - Semantic roles
  - Compositionality
  - Truth preserving
- Application representation

Two Examples

- Parsing into Abstract Meaning Representation (AMR)
- Language to Code: learning parsers for if-this-then-that recipes
  - Simple rules that allow users to control aspects of their digital lives including smart phones
  - Large online naturally occurring repository of NL descriptions and associated code

Two Examples

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AMR characteristics

- Rooted, labeled graphs
- Abstract away from syntactic differences
  - He described her as a genius
  - His description of her: genius
  - She was a genius according to his description
- Use Propbank framesets
  - “bond investor”: invest-01
- Heavily biased towards English

- Variables (or nodes) for entities, events, properties, states
- Leaf nodes are labeled with concepts:
  - (b/boy) an instance of the concept boy
- Relations link entities
  - (d/die-01 :location(p/park)): there was a death in the park
- AMR concepts
  - English words (e.g., boy), Propbank framesets (e.g., want-01) or special keywords (entity-types, quantities or conjunctions)

AMR relations

- ~100 relations
- Frame arguments
  - Arg0, arg1, arg2, arg3, arg4, arg5 (Propbank)
- General semantic relations
  - :Accompanier, :age, :beneficiary, :cause, :compared-to, :concession, :condition, :consistof, :degree, :destination, :direction, :domain, :duration, :employed-by, :example, :extent, :frequency, :instrument, :li, :location, :manner, :medium, :mod, :mode, :name, :part, :path, :polarity, :poss, :purpose, :source, :subevent, :subset, :time, :topic, :value.
- Relations for quantity
  - :quant, :unit, :scale
- Relations for date entity
  - :day, :month, :year, :weekday, :time, :timezone, :quarter,:dayperiod, :season, :year2, :decade, :century, :calendar, :era.
- Relations for lists
  - :op1, :op2, …. :op10
- Plus inverses (e.g., :arg0-of, :location-of)

Framesets

- Examples of using Framesets to extract away from English syntax
- (d / describe-01
  - :arg0 (m/man)
  - :arg1 (m2 / mission)
  - :arg2 (d /disaster))
- :arg0 the describer, :arg1 the thing described, :arg2 what it is describing
- The man described the mission as a disaster. As the man described it, the mission was a disaster

General semantic relations

- Non-core relations
- (s :hum-02
  - :arg0 (s2 / soldier)
  - :beneficiary (g / girl)
  - :time (w / walk-01
    - :arg0 g
    - :destination (t/ town)))
- The soldier hummed to the girl as she walked to town.

Co-reference

- AMR abstracts away from surface forms for co-reference such as pronouns, zero-pronouns, reflexive, control structure. Instead, variables are re-used.

- See “g” in previous example.

Inverse relations

- In order to obtain rooted structures
- (s / sing-01
  - :arg0 (b /boy
    :source (c / college))
- The boy from the college sang.

- (b / boy
  - :arg0-of (s / sing-01)
    :source (c / college))

  the college boy who sang

Modals and Negation

- Negation is represented with :polarity and modality is represented with concepts

- ```
  (g / go-01
        :arg0 (b / boy)
        :polarity - )
  ```
  The boy did not go.
  ```

- ```
  (p / possible
        :domain (g / go-01
                    :arg0 (b /boy))
        :polarity -))
  ```

  The boy cannot go.
  It’s not possible for the boy to go.
  ```

- (p / obligate-01
      :arg0 (g / go-01
                  :arg0 (b / boy))
      :polarity -)

- The boy doesn’t have to go.
- The boy is not obligated to go.

Questions

- Amr-unknown to indicate wh-questions

- (f /find-01
  :arg0 (g /girl)
  :arg1 (a / amr-unknown))

  What did the girl find?

- (f / find-01)
  :arg0 (g /girl)
  :arg1 (b /boy)
  :location (a /amr-unknown))

  Where did the girl find the boy?

- (f / find-01

    arg0 (g /girl)

    arg1 (t / toy

        :poss (a /amr-unknown))

Sentence??

…e sentence for the AMR (f / find-01 arg0 (g /gi… / toy :poss (a /amr-unknown))

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Verbs

- Correspond to Propbank framesets

(l / look-05
    arg0: (b / boy)
    arg1: (a / answer)

The boy looked up the answer.
The boy looked the answer up.

Nouns

- PropBank verb framesets represent many nouns as well

(d / destroy-01
    arg0: (b / boy)
    arg1: (r / room)

the destruction of the room by the boy
the boy's destruction of the room
the boy destroyed the room

- Nominalization is a role

(s / see-01)
    arg0: (j / judge)
    arg1: (e / explode-01))

The judge saw the explosion

- How about?

```
(r / read-01
      :arg0 (j / judge)
      :arg1 (t / thing
                    :arg1-of (p /propose-01))
```

Sentence?

the sentence for (r / read-01 :arg0 (j / judge) : thing :arg1-of (p /propose-01))

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Adjectives

- Can also use framesets

  (s / spy
  	:arg0-of (a / attract-01))

  the attractive spy

- ```
  (s / spy
        :arg0-of (a / attract-01
                     :arg1 (w /woman)))
  ```

  NP?
  ```

s the NP for (s / spy :arg0-of (a / attract-01 :a /woman)))

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Compositionality

- The meaning of the whole is equal to the sum of the meaning of its parts
- How is AMR compositional?

  (d / describe-01
  - :arg0 (m/man)
    :arg1 (m2 / mission)
    :arg2 (d /disaster))

- (s / spy
  :arg0-of (a / attract-01))

- *What is the AMR for*

  the attractive spy described the mission as a disaster?

AMR data

- Available downloads: https://amr.isi.edu/download.html
  - Little Prince available to all
    - English and Chinese
  - Biomedical data
  - Generic, wide-ranging content: LDC

- References on AMR data
  - Abstract meaning representation for sembanking: https://amr.isi.edu/a.pdf
  - Guidelines for AMR annotation:
    amr.isi.edu/language.html

AMR parsing

- Many approaches
  - E.g., CCG, into logical form, graph parsing, syntax-based machine translation, hyperedge replacement grammars
- SemEval 2016: Track 8 on AMR parsing http://alt.qcri.org/semeval2016/task8/
- Today: A Parser for Abstract Meaning Representation Using Learning to Search

Learning to Search (L2S)

- Family of approaches that solves structured prediction problems
  - Decomposes the production of the structured output in terms of explicit search space
  - Learns hypotheses that control a policy that takes actions in the search space

- AMR is a structured semantic representation

- Model learning of concepts and relations in a unified setting.

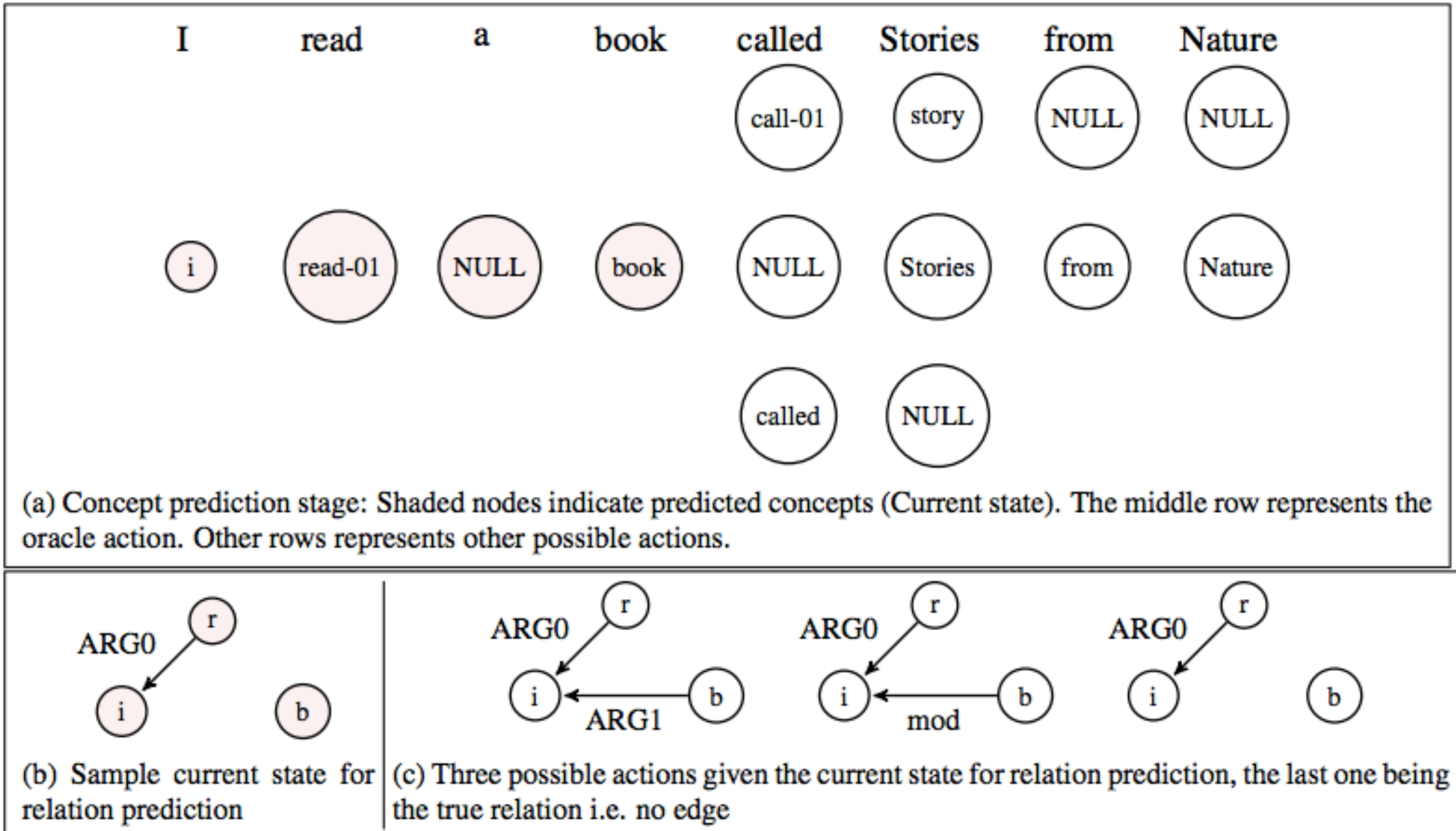
AMR parsing task decomposed

- Predicting concepts
- Predicting the root
- Predicting relations between predicated concepts

Search space

- State s = $\{x_1, x_2, \ldots, x_n, y_1, y_2, \ldots, y_{i-1}\}$ where the input $\{x_1, x_2, \ldots, x_n\}$ are the n words of the sentence
- Concept prediction: labels $y_1, y_2, \ldots, y_{i-1}$ are the concepts predicted up to i-1.
  - Next action: y_i is the concept for word x_i from a k-best list of concepts
- Relation prediction: labels are relations for predicted pairs of concepts
- Root prediction: multi-task classifier selects root concept from all predicted concepts

Example



(a) Concept prediction stage: Shaded nodes indicate predicted concepts (Current state). The middle row represents the oracle action. Other rows represents other possible actions.

(b) Sample current state for relation prediction

(c) Three possible actions given the current state for relation prediction, the last one being the true relation i.e. no edge

Figure 2: Using DAGGER for AMR parsing

Selecting k-best lists

- Concept candidates
  - The set of all concepts assigned to s_i in the entire training data
  - If s_i unseen -> lemmatized span, Propbank frames, and null
- Relation candidates (from c_i to c_j)
  - Union of
    - $\text{Pairwise}_{i,j}$: All directed relations from c_i to c_j when they occurred in the same AMR
    - Outgoing_i : All outgoing relations from c_i
    - Incoming_j : All incoming relations into c_j
  - When unseen in training data, all relations in the training data.

What does this look like?

Pre-processing for training

- Where do spans come from?
  - JAMR aligner to align sentences with AMR concepts and relations in training data
    - Single word to single concept
    - Span of words to graph fragment: “Stories from Nature” aligned to graph rooted at “name”
      - Named entities
      - Multiword expressions
    - Word aligned to null
      - Function words (e.g., “to”, “a”, “the”)

Single concept or multiple?

- Barack Obama
- At the drop of a hat (e.g., I would do anything for you at the drop of a hat).
- The President of the United States

Single concept or multiple: "Barack Obama"

single

multiple

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ngle concept or multiple: "At the drop of a ha

single

multiple

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concept or multiple: "The President of the U States"

single

multiple

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e concept or multiple: "President Donald Tru

single

multiple

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Alignment Details

- Forced alignments
  - Some concepts are not aligned to words
  - Force alignments based on count(unaligned concept aligned to unaligned words) across training corpus
- Test time
  - Each word a single span except
    - Named entities
    - Date and time multi-word expressions using regular expressions

Learning

- At each state, learn multiple classifiers
  - One concept (relation) against all others
- Predict the concept, relation, root sequence for the entire sentence
- Use Hamming distance to compute the loss
- Adjust prediction based on loss -> joint learning

Features for Learning Concepts

- Words in s_i and context
- POS of words in s_i and context
- Named entity tags for words in s_i
- Binary feature indicating whether words in s_i are stopwords
- All dependency edges emanating from words in s_i
- Binary feature indicating whether c is the concept most frequently aligned with s_i
- Predicted concepts for the two previous spans
- Concept label and its conjunction with all previous features
- If the label is a Frameset feature, then the frame and its sense

What does this look like?

Features for Learning Relations

- Given c_i c_j and r
- The two concepts (c_i c_j) and their conjunction
- Words in the corresponding spans and their conjunctions
- POS tags of words in spans and their conjunctions
- All dependency edges with tail in w_i and head in w_j
- Binary feature which is true iff I < j
- Relation label and its conjunction with all other labels

Features for Learning Root

- Concept label. If the concept is a Frameset, then the frame and its sense
- Words in the span corresponding to concept
- POS tags of words in the span
- Binary feature indicating whether one of the words in the span is the root of the dependency tree

Some Odds and Ends

- Connectivity:
  - For each disconnected component, find its root
  - Then connect root to root of sentence
- Cycles
  - No specific constraints against cycles in learning
  - In practice, only 5% of predicted AMR graphs have cycles

Dataset	Training	Dev	Test
BOLT DF MT	1061	133	133
Broadcast conversation	214	0	0
Weblog and WSJ	0	100	100
BOLT DF English	6455	210	229
Guidelines AMRs	689	0	0
2009 Open MT	204	0	0
Proxy reports	6603	826	823
Weblog	866	0	0
Xinhua MT	741	99	86

Table 4: Dataset statistics. All figures represent number of sentences.

Results

- Use a tool (Smatch) to compare predicted AMR with gold AMR

- F1 = .46
- P = .51
- R = .43

- Mean of all systems in shared task: F1 = .55, standard deviation .06

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Tasker and IFFT

- Simple programs with triggers and actions
- Phillips Hue light bulbs to flash red and blue when the Cubs hit a home run.
  Home automation sensors and controllers
  - Motion detectors
  - Thermostats
  - Location sensors
  - Garage door openers
- Users describe the recipes in natural language and publish them

Goal

- To build semantic parsers that map from NL description to the program automatically
- Collected 114,408 recipe-NL pairs from the http://ifttt.com website

Example Recipes

- Turn on my lights when I arrive home
- Text me if the door opnes
- Add receipt emails to a spreadsheet
- Remind me to drink water if I’ve been at a bar for more than 2 hours.

MT approach

- Created a context free grammar for programs
- Grammar for NL recipes
- Learn to map from one to the other
- Use separate classifiers for each possible action

- *Is it better to parse into AMR or directly into the command language?*

- *What are pros for using AMR?*

- *What are cons for using AMR?*

What are the pros for using AMR?

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What are the cons for using AMR?

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