Designing Abstract Meaning Representations for Machine Translation

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(Kevin Knight & Claire Bonial)
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What is meaning?

… just piling up words, one after the other, won't do much of anything until something else has been added.

Stanley Fish, How to Write a Sentence, 2011

- *And the words slide into the slots ordained by syntax, and glitter as with atmospheric dust with those impurities which we call meaning.*

Anthony Burgess, Enderby Outside, 1968

How do we sprinkle atmospheric dust?

- Some of the challenges
- AMR
- Challenges it addresses
- Challenges it doesn't
- What about Machine Translation?

Challenges

- Sense distinctions
- Semantic similarity
- Metaphors and world knowledge
- Constructions
- New usages
- Coercion, metonymy, implicit arguments, …

AMR development

- ISI, Colorado, LDC, SDL
  - Creating a large-scale semantics bank
  - “Abstract Meaning Representation for Sembanking”,
    - Banarescu, C. Bonial, S. Cai, M. Georgescu, K. Griffitt, U. Hermjakob, K. Knight, P. Koehn, M. Palmer, and N. Schneider,
  - LAW 2013
- Simple structures, like Penn Treebank
- Goal is supporting research in:
  - semantic parsing
  - natural language generation
  - machine translation

Meaning-based MT

source string → source tree → meaning representation → target tree → target string

- What content goes into the meaning representation?
  - Linguistic annotation

today's focus

Semantic Representation

LOGICAL FORM

"The boy wants to go."

∃ w, b, g : instance(w, WANT) ^
instance(g, GO) ^
instance(b, BOY) ^
agent(w, b) ^
patient(w, g) ^
agent(g, b)

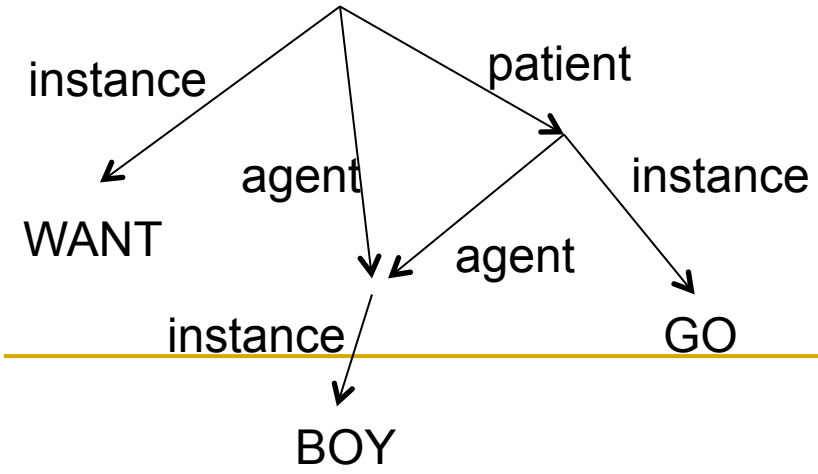
PENMAN

(w / WANT
:agent (b / BOY)
:patient (g / GO
:agent b)))

PATH EQUATIONS

((x0 instance) = WANT
((x1 instance) = BOY
((x2 instance) = GO
((x0 agent) = x1
((x0 patent) = x2
((x2 agent) = x1

DIRECTED ACYCLIC GRAPH



FEATURE STRUCTURE

instance: WANT
agent: 1 [instance: BOY]
patient: [instance: GO
agent: 1]

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Semantic Representation

"The boy wants to go."

LOGICAL FORM

∃ w, b, g : instance(w, WANT) ^
instance(g, GO) ^
instance(b, BOY) ^
agent(w, **b**) ^
patient(w, g) ^
agent(g, b)

PENMAN

(w / WANT
:agent (**b** / BOY)
:patient (g / GO
:agent **b**)))

PATH EQUATIONS

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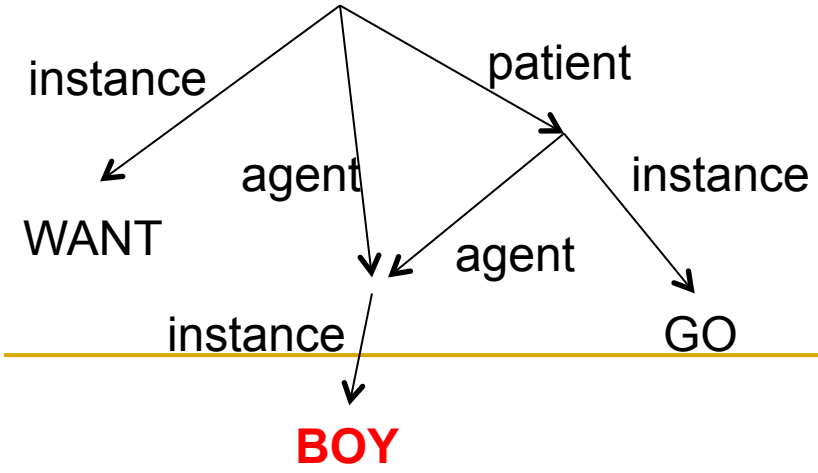

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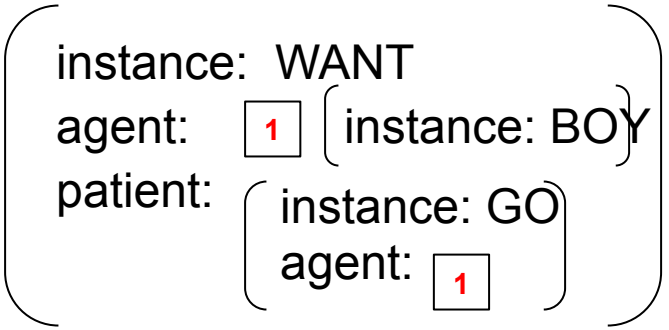

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Semantic Representation

LOGICAL FORM

“The boy wants to go.”

PATH EQUATIONS

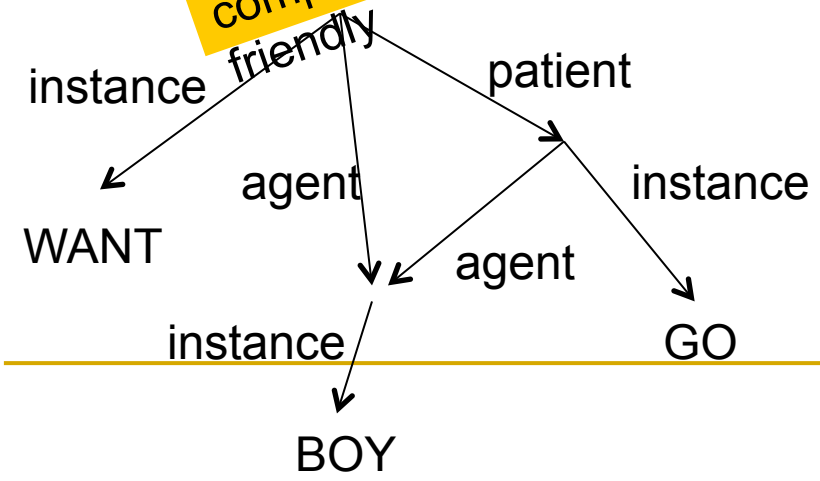
∃ w, b, g : instance(w, WANT) ^
instance(g, GO) ^
instance(b, BOY) ^
agent(w, b) ^
patient(w, g) ^
agent(g, b)

((x0 instance) = WANT
((x1 instance) = BOY
((x2 instance) = GO
((x0 agent) = x1
((x0 patent) = x2
((x2 agent) = x1

PL human friendly (AMR)

(w / WANT
:agent (b / BOY)
:patient (g / GO
:agent
b)))

DIRECTED ^C GRAPH computer friendly



FEATURE STRUCTURE

instance: WANT
agent: 1 instance: BOY
patient: instance: GO
agent: 1

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Abstract Meaning Representation (AMR)

- How to represent the meanings of sentences?
- Which concepts and relations?
- How to put them together?

- First guidelines released April 24, 2012
- 100 sentences from WSJ
- 244 sentences from webtext, 80 with consensus agreement
- The Little Prince, etc.

Abstract Meaning Representation (AMR)

- Basic “who-is-doing-what-to-whom”
- Cover all sentence content in single, rooted structure
- Builds upon PropBank
  - Uses PB rolesets: e.g. describe.01
    - Arg0: describer
    - Arg1: thing described
    - Arg2: secondary attribute, described-as
  - http://verbs.colorado.edu/propbank/framesets-english/

Abstract Meaning Representation (AMR)

- AMR composed of concepts and relations, not nouns and verbs
  - Currently ~100 relations, plus inverses
- AMR is not enslaved to syntax, or even mildly indentured:

He described her as a genius.	(d / describe-01
As he described her, she is a genius.	:ARG0 (h / he)
His description of her: a genius.	:ARG1 (s / she)
	:ARG2 (g / genius))

AMR vs. PB

He described her as a genius.
As he described her, she is a genius.
His description of her: a genius.

```
(d / describe-01
   :ARG0 (h / he)
   :ARG1 (s / she)
   :ARG2 (g / genius))
```

PropBank differences, 2 structures:

Describe-01: same except for empty ARG2
Be-01: she-ARG1, genius-ARG2, as he described her-ADV

Single rooted structures, abstracts away from surface syntax

```
(s / see-01
        :ARG0 (b / boy)
        :ARG1 (g / girl
                :ARG0-of (w / want-01
                        :ARG1 b)))
```

- *The boy saw the girl who wanted him.*
- *The boy saw the girl who he was wanted by.*
- *The girl who wanted the boy was seen by him.*

Maximal Use of PropBank Frame Files

He was not aware of research on smokers of the Kent cigarette

```
(r / realize-01
  :polarity -
 :ARG0 (h / he)
  :ARG1 (r3 / research-01
          :ARG1 (p4 / person
                  :ARG0-of (s / smoke-02
                             :ARG1 (c2 / cigarette
                                     :name (k / name
                                             :op1 "Kent"))))))
```

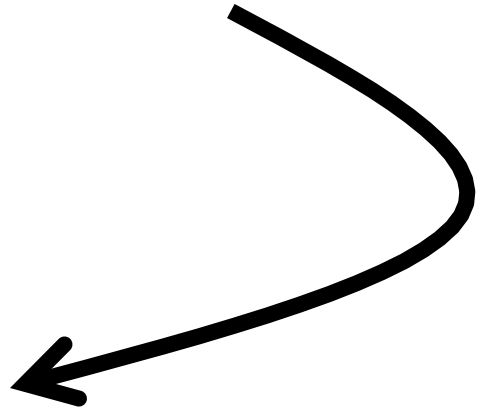
To get to canonical concept, we stem to English verbs where PropBank arguments are best described.

General direction of stemming:

adverb → adjective → noun → verb

"John could not have heard about the professor's creation of the microbial viruses that Mary sold to Russia yesterday."

```
(p2 / possible
    :polarity -
    :domain (h / hear-01
          :ARG0 (p / person
              :name (n / name :op1 "John"))
          :ARG1 (c / create-01
                  :ARG0 (p3 / professor)
                  :ARG1 (v / virus
                        :mod (m / microbe)
                        :ARG1-of (s / sell-01
                                :ARG0 (p4 / person
                                     :name (n2 / name :op1 "Mary"))
                                :ARG2 (c2 / country
                                     :name (n3 / name :op1 "Russia"))
                                          :time (y / yesterday))))))
```



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How is it really different from PropBank?

- Numbered Args, + ArgMs:
  - COM: Comitative
  - LOC: Locative
  - DIR: Directional
  - GOL: Goal
  - MNR: Manner
  - TMP: Temporal
  - EXT: Extent
  - REC: Reciprocals
  - PRD: Secondary Predication
  - PRP: Purpose
  - CAU: Cause
  - DIS: Discourse
  - ADV: Adverbials
  - ADJ: Adjectival
  - MOD: Modal
  - NEG: Negation
  - DSP: Direct Speech

How is it really different from PropBank? More semantic relations

- LOTS of additional relations/concepts in addition to numbered args, modifier tags of PB (types of ArgM's):
  - **General semantic roles:** :accompanier :age :beneficiary :cause :compared-to :concession :condition :consist-of :contrast :degree :destination :direction :domain :duration :employed-by : example :extent :frequency :instrument :li :location :manner :mod :mode :name :part :path :polarity :poss :purpose :source :subevent :subset :time :topic :value
  - **Quantities:** :quant :unit :scale
  - **Date-entity:** :day :month :year :weekday :time :timezone :quarter :dayperiod :season :decade :century :calendar :era :mod
  - **Ops:** :op1 :op2 :op3 :op4…

How is it really different from PropBank? Discourse relations

- Introduction of additional discourse elements:
  - *But* = contrast: “The House has voted to raise the ceiling to $ 3.1 trillion , **but** the Senate isn't expected to act until next week at the earliest.”
  - *Even though* = concession: “Workers described ‘clouds of blue dust’ that hung over parts of the factory, **even though** exhaust fans ventilated the area.”
- Penn Discourse Treebank – inter-sentential
- AMR – intra-sentential

How is it really different from PropBank?

- Provides more structuring of noun phrases & prepositional phrases, intra-sentential coreference and discourse relations
- Collapses more ways of saying the same thing, making much more use of PropBank predicates.
- Provides an interpretation for negation and modality; PropBank just marks them.

How is it really different from PropBank? Metonymy

- Introduction of understood, but not explicitly mentioned concepts:
  Gas could go to $ 10 a gallon

```
(p / possible
    :domain (g / go.01
        :ARG1 (t / thing
            :ARG2-of (p2 / price-01
                :ARG1 (g4 / gas
                    :quant (v2 / volume-quantity
                        :unit (g5 / gallon)
                        :quant 1))))
        :ARG4 (m2 / monetary-quantity
            :unit (d2 / dollar)
            :quant 10)))
```

When to do it?

PropBank Today – synching w/ AMR

- More flexible coverage
- Noun annotation (re-merging NomBank frames)
  - Eventive nouns: *destruction, escape*
  - Stative nouns: *fault, love*
  - NOT relational nouns
- Adjectives
  - *Comfortable, valuable*

Semantic similarity challenges

- Etymologically related terms are aliased, same representation
  - *destruction/destroy*
- What if they aren't etymologically related?
  - *fear.v/fear.n/afraid.adj*
  - *travel/take a trip*
  - *desire/want*
- Automatic clustering?

Light Verb Constructions- differs

- Similarly to PropBank, AMR isn't confounded by syntactic idiosyncrasies, function words, and light verb constructions.
- PB ("issue a warning"
  - issue → issue.lv
  - warning → warn.01,
  - final REL= issue_warning,
    with warn.01 arguments
- AMR ("issue a warning" → warn-01)

Issues: Distinguishing LVCs from heavy usages

- Several verbs seem to participate in complex predication but contribute at varying levels to semantics:
  - light: *produce an alteration* *'alter'*
  - light: *issue a complaint* *'complain'*
  - heavy: *register a complaint*
- So what about sense distinctions?

SUBJ IOBJ

We serve men

We serve food to men.
We serve our community.
serve —IndirectObject→ men

Sense Distinctions?

SUBJ DOBJ

We serve men

We serve organic food.
We serve coffee to connoiseurs.
serve —DirectObject→ men

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Sense Distinctions AMR makes

- call.02 *He calls me every day at 8am and 5pm*.
- call.03 *Secretary of State Baker , in a foreign policy speech , called for the reunification of Germany.*

- AMR makes the same distinctions PropBank makes.

Trickier distinctions…

- *take-vpc-v*
  - take.11: *obtain* (“take out a pencil, take out an ad”)
  - **take.26: *project anger* (“take it out on her”)**
  - take.27: *kill* (“take out the enemy”)
  - take.28: *vacation* (“take out a year”)

- *take* has 256 multi-word expressions

39 more MWE's for "take"

- TAKE A CHILL
  TAKE A HIT
  TAKE A POWDER
  TAKE ABACK
  TAKE ADVANTAGE
  TAKE AFTER
  TAKE BACK
  TAKE CARE
  TAKE DOWN
  TAKE FOR GRANTED
  TAKE HOME
  TAKE IN VAIN
  TAKE IN CHARGE
  TAKE ISSUE
  TAKE IT EASY
  TAKE ITS/HIS/HER TOLL

SEMLINK

- Extended VerbNet: 6,340 senses
  - 92% PB tokens (8114 verb senses/12,646 all)
- Type-type mapping
  - PB/VN, VN/FN, VN/WN, VN/ON (groupings of WN senses)
- Semi-automatic mapping of WSJ PropBank instances to VerbNet classes and thematic roles, hand-corrected. ***(now FrameNet also)***
- VerbNet class tagging as automatic WSD

Brown, Dligach, Palmer, IWCS 2011; Croce, et. al., ACL2012

Accuracy & Agreement

- AMR uses the *smatch* metric to calculate agreement rates against consensus AMR annotations
- 4 annotators provided AMRs for all 180 adjudicated sentences (100 wsj, 80 webtext)
- average *smatch* agreement rates with consensus AMRs were 0.83 (wsj) and 0.73 (webtext)
- PB IAA generally between 92-98%

Summarizing

- A more abstract labeled dependency tree
  - w/out function words
  - many nouns/adjectives have predicate-argument structures as well as verbs
  - wikified NE's
  - abstract discourse relations
  - interpretation of modality and negation
  - "some" implicit arguments/relations
  - AND equivalence relations for coreference – makes it a graph.

Challenges AMR doesn't address

- Sense distinctions
- Semantic similarity
- Metaphors and world knowledge
- Constructions
- New usages
- Coercion, metonymy, implicit arguments, …

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Metaphors

- *His cigarette ash fell on the diva's skirt.*
- *The curtain fell on the diva.*

- *By the time the Iron Curtain fell in 1989, differences ran deep indeed.*

Jena Hwang – *Adapting to New Usages: Incorporating Constructions into VerbNet*

- Why constructions?

"They threw him out of the university"

Ellos le echaron fuera de la universidad.

- They *threw* him out of the university.
- They *hissed* him out of the university.

Le silbó fuera de la universidad.

"They whistled to him outside the university"

New usages

- *Not all yarn frogs easily.*

amr.isi.edu

- LDC release – 13K
  http://amr.isi.edu/download.html
- Publications
  - Pourdamghani, N, Yang Gao, Ulf Hermjakob and Kevin Knight, Aligning English Strings with AMR Graphs, EMNLP 2014
  - Braune, F., D. Bauer, and K. Knight, Mapping between English Strings and Reentrant Semantic Graphs" LREC 2014.
  - Flanigan, J., S. Thomson, J. Carbonell, C, A Discriminative Graph-Based Parser for the Abstract Meaning Representation, ACL 2014

So what about Machine Translation?

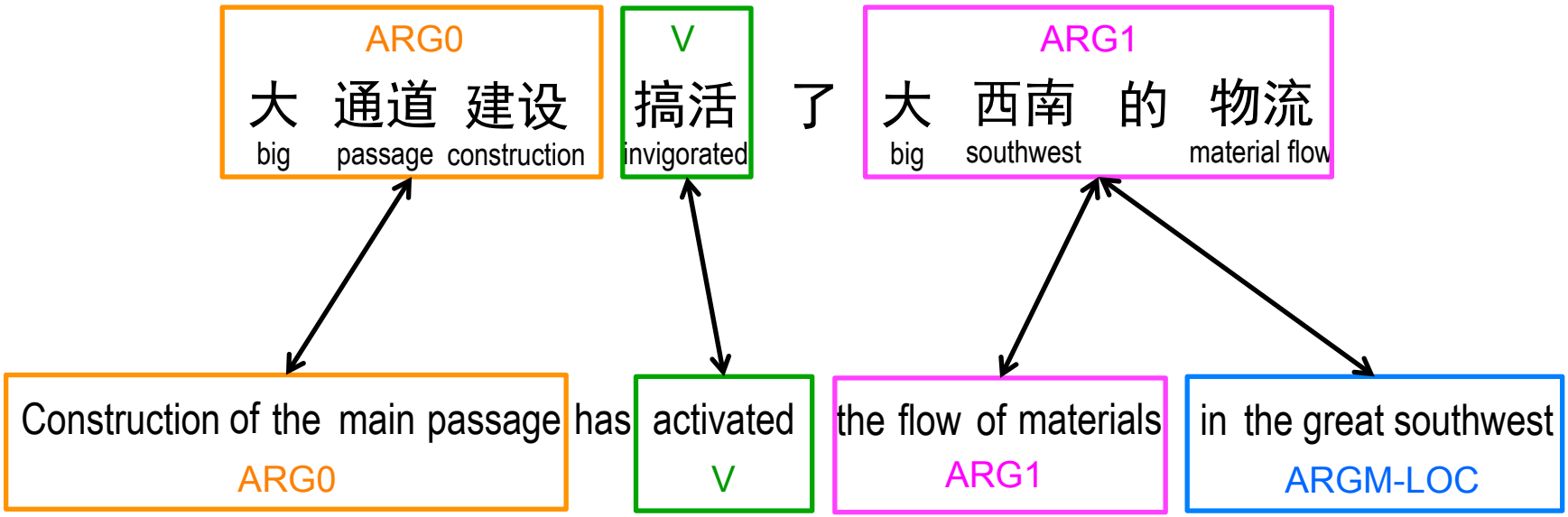
- JHU NSF Fred Jelinek Memorial Workshop
  - July, 2014, 4 weeks, Charles University, Prague, the Czech Republic

Aligning parallel corpora

- Subtrees of dependency parses of parallel English/Chinese corpora only have isomorphic matches about 30% of the time.
  - Yuan Ding, Thesis, 2005
- Parallel PropBank structures match almost 60%.
  - Wu & Palmer, SSST, 2011
- What about AMR's? Will they align even more?
  - Xue, Bojar, Hajič, Palmer, Urešová, Zhang, Not an Interlingua, but Close: Comparison of English AMRs to Chinese and Czech LREC 2014

Semantic Mapping

- Mapping predicate-arguments between languages



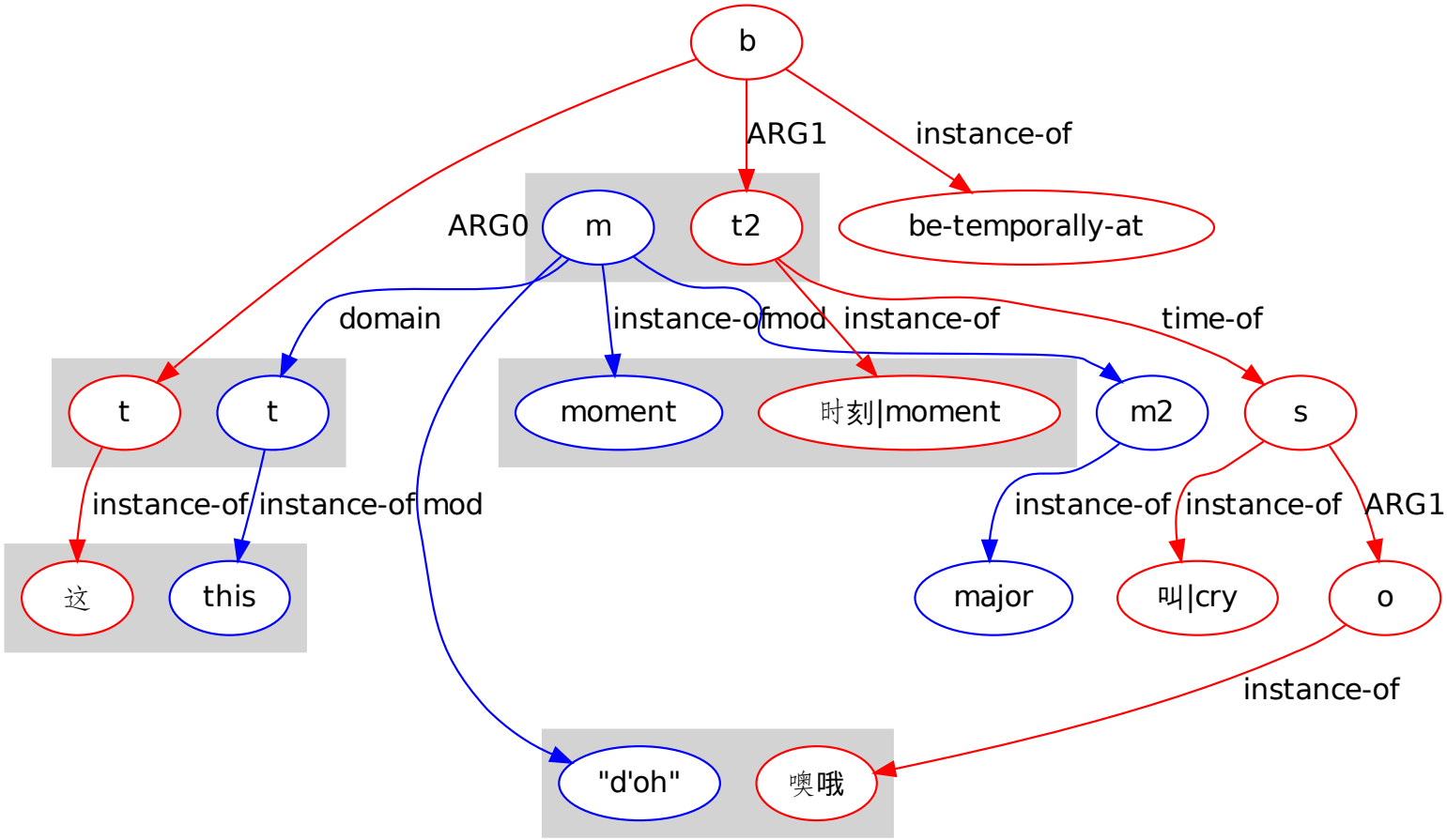
Prague CL-AMR workshop: Preparatory Efforts

- English, Chinese, and Czech AMR's of the same 100 sentences and their translations.
- A preliminary mapping from TR to AMR.
- Given a 1M word WSJ English corpus with parallel Czech translations, both in TR
  - And automatically produced AMR's (from OntoNotes, thanks to Ulf Hermjakob) for the same data

Differences in Lexicalization and Annotation Choice

这 是 一 个 大 叫 “ 噢哦 ！ ” 的 时刻 。

This is a major `` D'oh! '' moment .



Annotation Choice Differences

- Annotation choice
  - To reify or not to reify?
- Chinese: reifies “be_temporally_located_at”
- English drops “be” and puts “this” as the :domain of “moment”:
  - (m / moment
    :mod (m2 / major)
    :domain (t / this)
    :mod (d / d'oh :mode expressive))

Alternative Annotation Choices for English

- English could just as easily reify “is moment” as ***temporal_location.01***
  - (t / temporal_location.01
    - :Arg1 (t2 / this)
    - :mod (m / major)
    - :mod (d / d'oh :mode expressive))
- Closer match for English and Chinese
- How often is this the case?

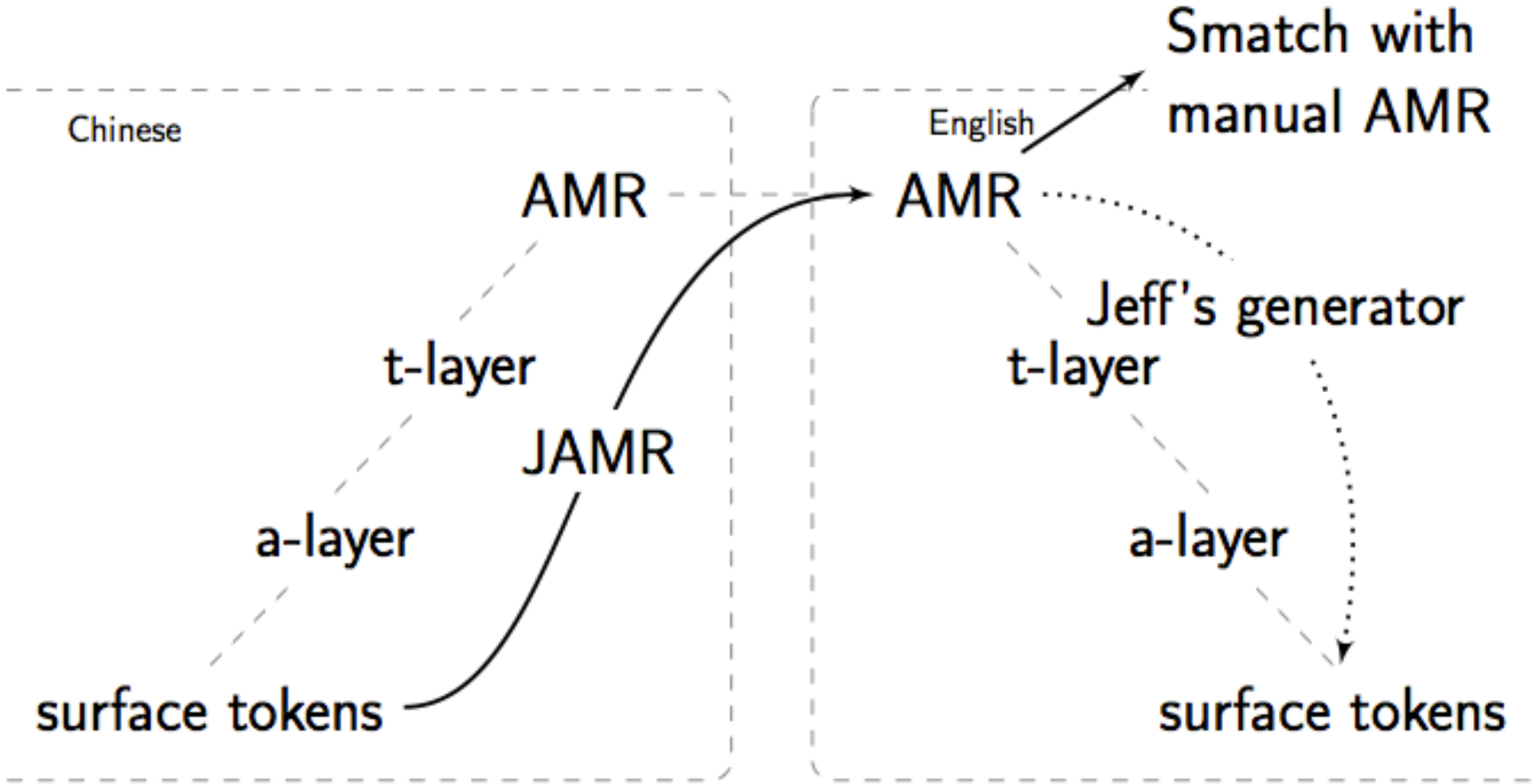
Lexicalization differences

- Language specific lexicalization differences
- Simply different word choices
  - “major” vs. 울/ cry
- Often a single lexical item in one language is a multi-word expression elsewhere, w/ structure
  - “tells the tale” vs. popsány..
    - (t / tell.01 (p / popsat.1
      :Arg1 (t2 / tale) (no :Arg1)
  - “*překračovat povolenou rychlost*” vs. “speeding”
- Should AMR make more of an effort to treat MWE’s as single lexical items?

Questions to investigate

- Deterministically produce variations for annotation choices = sets of semantically equivalent AMRs ➔better matches?
- Resources for language-specific alternative lexicalizations, both manual and automatic?
- How much should AMR abstract away from Multi-word expressions?
- When to reify? And when not?
- Etc.,

Prague Workshop: MT with AMRs
Renduchintala and Flanigan



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Results

Alignment Scheme	Precision	Recall	F-score
Full sentence	0.261	0.363	0.303
Serialized concepts	0.155	0.290	0.202

Future directions for AMR

- Inter-sentential coreference and discourse relations
- Integrating this with RED (Richer Event Descriptions)
  - Temporal and causal relations between events
- ????

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