

Semantics-based Machine Translation

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About this lecture

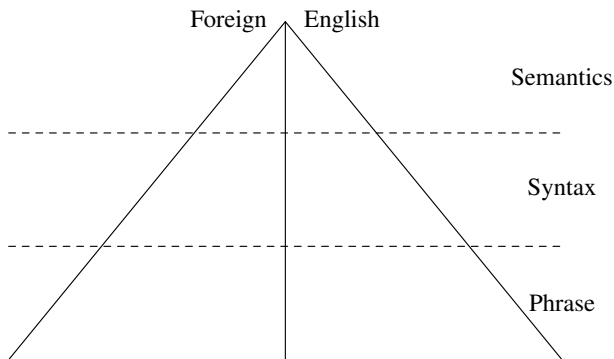
About me

- ▶ I am a Ph.D. student in Andreas Maletti's project
- ▶ Working on tree acceptors and transducers for syntax-based MT

About my ISI visit

- ▶ I visited USC/ISI for three months last year
- ▶ At ISI, I worked in KEVIN KNIGHT's group
- ▶ They produce state-of-the art results in syntax-based MT
- ▶ ...but they are working on *semantics-based MT* now!
- ▶ This lecture is mostly about **what they have in mind**, not what has happened already!

Motivation



Why semantics-based MT?

The more linguistic structure we use, the better the translation can be!

Motivation (2)

But what's wrong with phrase-based and syntax-based MT?

- ▶ We want to get the “**who did what to whom**” (WWW) right
- ▶ Preservation of meaning can be more important than grammaticality/fluency
- ▶ We are aiming for **useful** translation!

But haven't people tried and failed?

Yes, but. . .

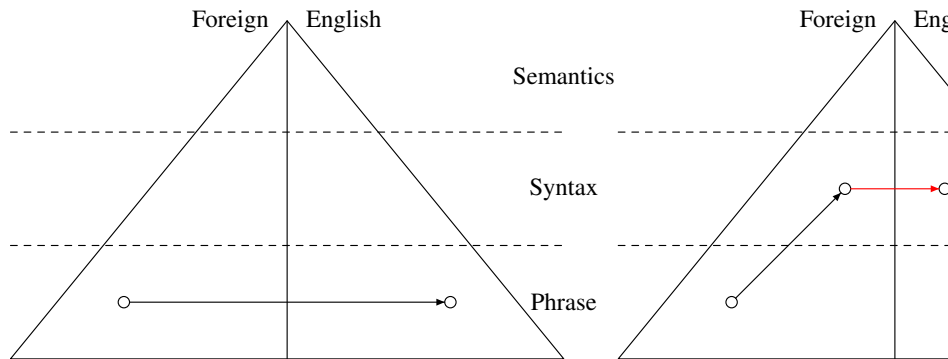
- ▶ that was before **statistics**
- ▶ small-scale, hand-crafted
- ▶ people said the same about syntax-based MT and look where it's now!

Words of wisdom

KEVIN KNIGHT: “As long as we get the **WWW** wrong, we are optimizing with respect to the wrong metric (BLEU)!”

WARREN WEAVER: “Thus it may be true that the way to translate from Chinese to Arabic [. . .] is not to attempt the direct route, shouting from tower to tower. Perhaps the way is to descend, from each language, down to the common base of human communication – the real but as yet undiscovered universal language – and then re-emerge by whatever particular route is convenient.”

Different MT paradigms

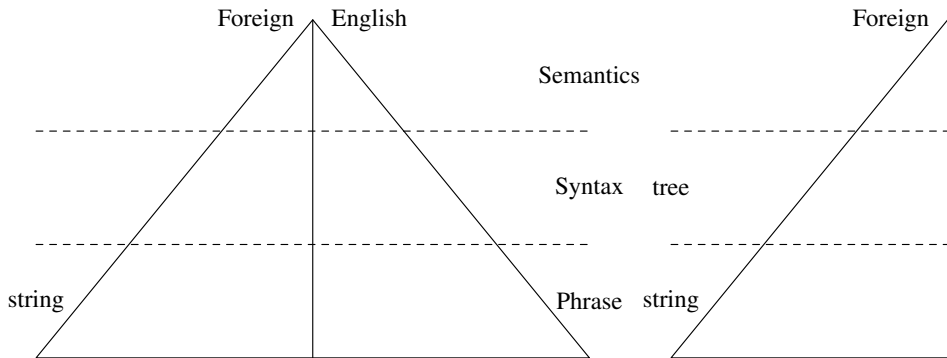


phrase-based MT: *n*-grammatical

syntax-based MT: grammatical

semantics-based MT: **sensible** and grammatical

Different MT paradigms (2)

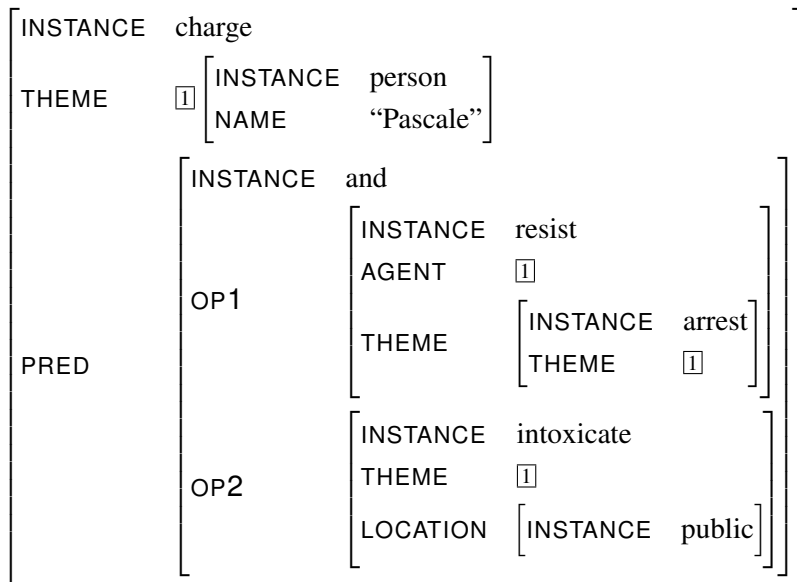


Phrases: represented as **strings**

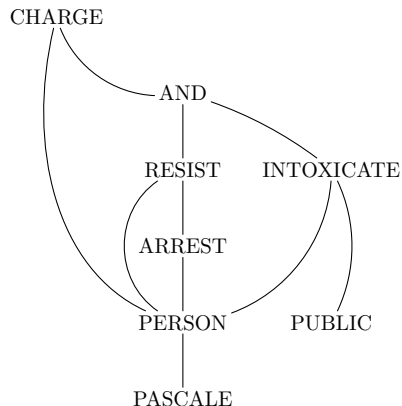
Syntax: represented by **trees**

Semantics: represented by **directed acyclic graphs**

Feature structures



Directed acyclic graphs



CHARGE \mapsto charge(theme, pred)

AND \mapsto and(op1, op2)

RESIST \mapsto resist(agent, theme)

ARREST \mapsto arrest(theme)

INTOXICATE \mapsto intoxicate
(theme, location)

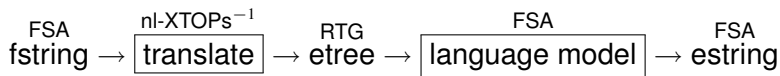
PUBLIC \mapsto public()

PERSON \mapsto person(name)

PASCALE \mapsto "Pascale"

Translation pipelines

Syntax-based MT pipeline

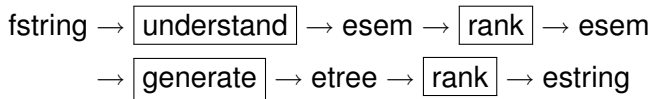


- ▶ The individual components are efficiently represented as **weighted tree acceptors and transducers**.

`estring = BESTPATH(INTERSECT(language model,
YIELD(BACKWARDS(translate, fstring))))).`

Translation pipelines (2)

Semantics-based MT pipeline



- ▶ No suitable automaton framework is known!

Algorithms and automata

	string automata	tree automata	graph automata
<i>k</i> -best	paths through a WFSAs	trees in a weighted forest	?
EM training	Forward-backward EM	Tree transducer EM training	?
Determinization	of weighted string acceptors	of weighted tree acceptors	?
Transducer composition	WFST composition	Many transducers not closed under composition	?
General tools	AT&T FSM, Carmel, OpenFST	Tiburon	?

Table: General-purpose algorithms for strings, trees and feature structures.

Algorithms and automata (2)

Our goal

- ▶ Find an adequate automaton model for the pipeline parts
- ▶ Investigate algorithms and fill all the blanks!

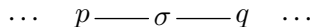
Candidates

- ▶ Treating everything as a tree (too weak?)
- ▶ Unification grammars (HPSG, LFG) (too powerful?)
- ▶ Hyperedge replacement grammar (too powerful?)
- ▶ Some straightforward extension of tree automata?

Dag automata

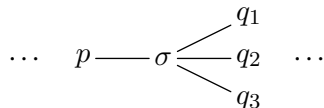
finite string automaton: (FSA)

one input state, one input symbol, one output state



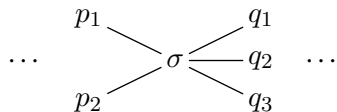
finite tree automaton: (FTA)

one input state, one input symbol, many output states



finite dag automaton: (FDA?)

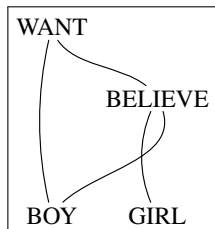
many input states, one input symbol, many output states



Dag automata (2)

KAMIMURA and SLUTZKI (1981, 1982)

- ▶ Dag acceptors and dag-to-tree transducers
- ▶ They proved a couple of technical properties, no algorithms
- ▶ We investigate their model with some adjustments:
 - ▶ not only adjacent leaves can be connected
 - ▶ top-down transducers instead of bottom-up
 - ▶ we add weights (probabilities)



Example dag automaton

$q \rightarrow \text{WANT}(r, q) \langle 0.3 \rangle$

$q \rightarrow \text{BELIEVE}(r, q) \langle 0.2 \rangle$

$q \rightarrow r \langle 0.4 \rangle \mid \emptyset \langle 0.1 \rangle$

$r \rightarrow \text{BOY} \langle 0.3 \rangle \mid \text{GIRL}$

$\langle 0.3 \rangle \mid \emptyset \langle 0.1 \rangle$

$[r, r] \rightarrow r \langle 0.2 \rangle$

$[r, r, r] \rightarrow r \langle 0.1 \rangle$

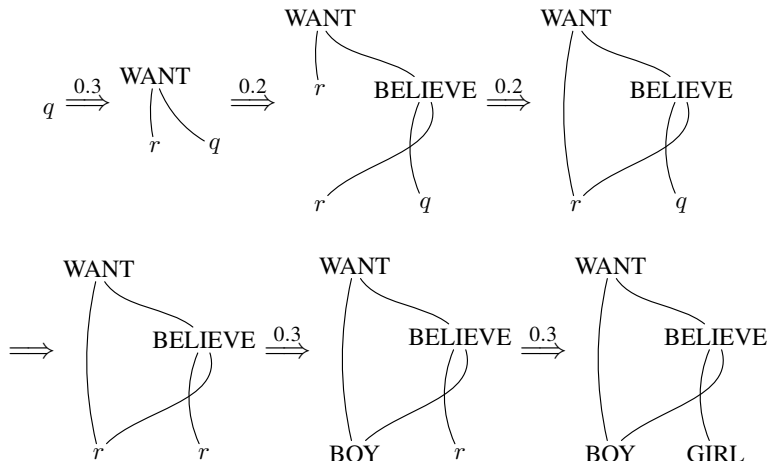
$\text{WANT} \mapsto \text{want}(\text{agent}, \text{theme})$

$\text{BELIEVE} \mapsto \text{believe}(\text{agent}, \text{theme})$

$\text{BOY} \mapsto \text{boy}()$

$\text{GIRL} \mapsto \text{girl}()$

Example dag generation



Example dag transducer rules

- ▶ Rules have m incoming edges with states and produce m trees
- ▶ Rules have n outgoing edges and n variables to pass states down

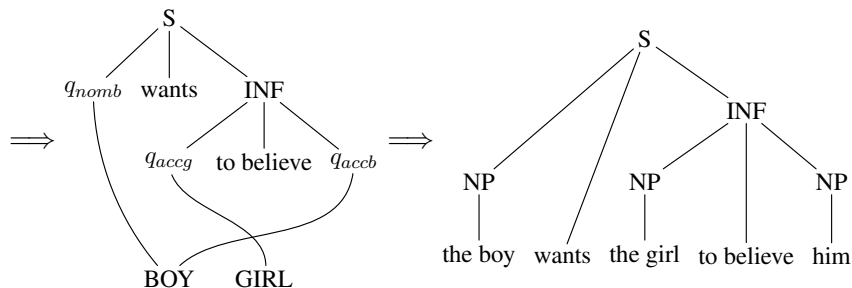
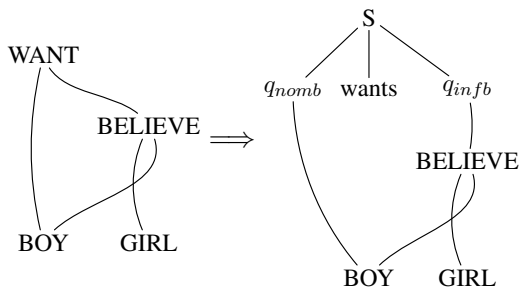
$[q_{nomb}, q_{accb}].\text{BOY} \rightarrow \text{NP}(\text{the boy}), \text{NP}(\text{him})$

$q_{accg}.\text{GIRL} \rightarrow \text{NP}(\text{the girl})$

$q_s.\text{WANT}(x, y) \rightarrow \text{S}(q_{nomb}.x, \text{wants}, q_{infb}.y)$

$q_{infb}.\text{BELIEVE}(x, y) \rightarrow \text{INF}(q_{accg}.x, \text{to believe}, q_{accb}.y)$

Example dag transduction



Toolkit

I implemented in Python...

- ▶ unweighted and weighted **membership checking**
- ▶ unweighted and weighted **dag-to-tree transductions**

- ▶ packing the **set of derivations** into a dag acceptor
- ▶ packing the **set of output trees** into an RTG

- ▶ unweighted and weighted ***n*-best generation**
- ▶ **backward application** (tree to dag)

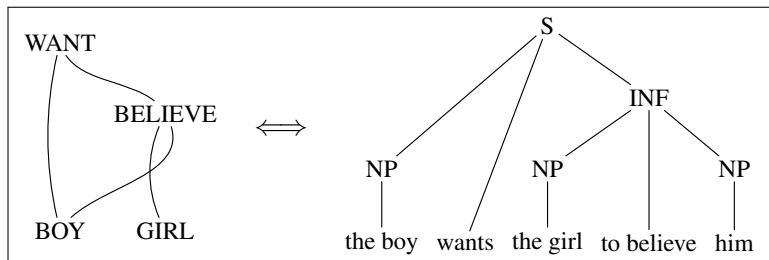
- ▶ product construction: **intersection and union**

- ▶ nice **visualization** of trees and graphs using GraphViz

Building an NLP system

With the theoretical background, it should be possible to carry out the same program that worked for syntax-based MT:

- ▶ Collect lots of training data



- ▶ Train models for parts of the translation pipeline
- ▶ Use them in a bucket-brigade approach or in an integrated decoder

Where does our training data come from?

Training data

- ▶ Goal: gold standard esem bank
- ▶ In the meantime: annotate data automatically using other resources (e.g. Propbank/OntoNotes) and manually correct them

After training: evaluation

Is BLEU the right metric?

BLEU and other n -gram based automated metrics. . .

- ▶ . . . favor translations that make the same lexical choices as the reference translations
- ▶ . . . capture translation fluency, but often disagree with human judgment
- ▶ . . . are still the metrics of choice of most people!

What makes a good metric

- ▶ It should favor useful (meaning-preserving) translations
- ▶ It should not require identical lexical choices
- ▶ It should be relatively cheap

A semantically motivated metric

MEANT (Lo and Wu 2011)

- ▶ measures accuracy (precision and recall) of semantic frames
- ▶ → it scores the **who did what to whom**
- ▶ can be performed by monolinguals, no bilinguals needed
- ▶ less labor-intensive than other adequacy-oriented metrics
- ▶ good correlation coefficient with human judgment

The end beginning

Thank you for your attention! – Questions?

What are you
in for?

```
(c / charge-05
 :theme (m / me)
 :predicate (a / and
 :op1 (r / resist-01
 :agent m
 :theme (a2 / arrest-01
 :theme m)))
 :op2 (i / intoxicate-01
 :theme m
 :location (p2 / public))))
```



You got arrested
for resisting
arrest?

I know, right?
This policeman grabs
me, and I'm like
what the f--



Sounds like
you are playing
four different
roles here.

It's just
semantics.

