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# Machine Translation

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31 August 2021



# What is This?



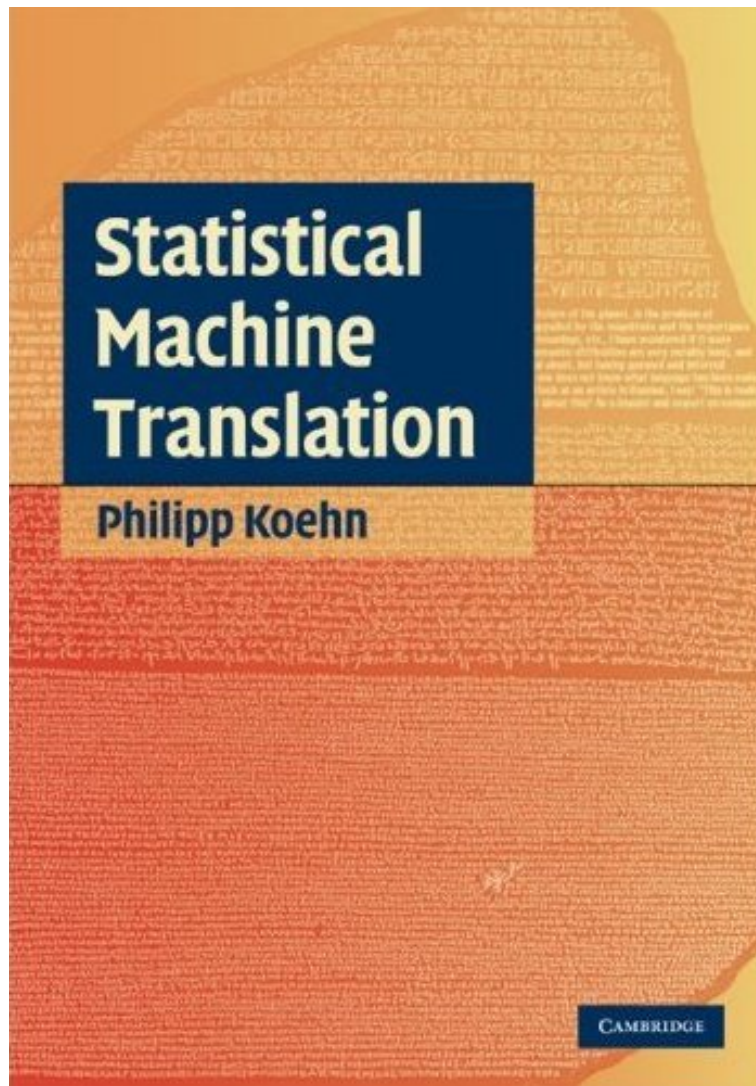
- A class on machine translation
- Taught at Johns Hopkins University, Fall 2021
- Class web site: <http://www.mt-class.org/jhu/>
- Tuesdays and Thursdays, 1:30-2:45, Hodson 213
- Instructor: Philipp Koehn
- TAs: Kelly Marchisio
- Grading
  - five programming assignments (12% each)
  - final project (30%)
  - in-class presentation: language in ten minutes (10%)

# Why Take This Class?



- Close look at an **artificial intelligence** problem
- Practical introduction to **natural language processing**
- Introduction to **deep learning** for structured prediction

# Textbooks



# some history

# An Old Idea



Warren Weaver on translation  
as code breaking (1947):

*When I look at an article in Russian, I say:  
"This is really written in English,  
but it has been coded in some strange symbols.  
I will now proceed to decode".*



# Early Efforts and Disappointment

- Excited research in 1950s and 1960s

1954

Georgetown experiment  
Machine could translate  
250 words and  
6 grammar rules■



- 1966 ALPAC report:
  - only \$20 million spent on translation in the US per year
  - no point in machine translation

# Rule-Based Systems



- Rule-based systems
  - build dictionaries
  - write transformation rules
  - refine, refine, refine
- Météo system for weather forecasts (1976)
- Systran (1968), Logos and Metal (1980s)

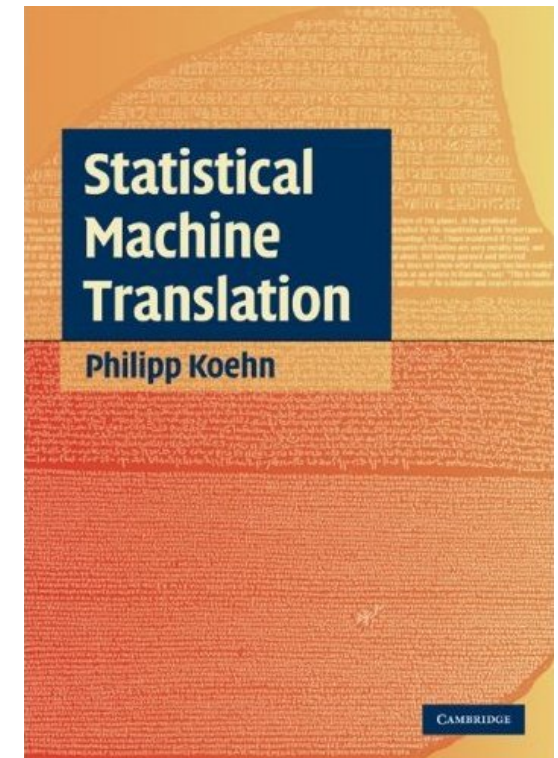
```
"have" :=  
  
if  
    subject(animate)  
    and object(owned-by-subject)  
then  
    translate to "kade... aahe"  
if  
    subject(animate)  
    and object(kinship-with-subject)  
then  
    translate to "laa... aahe"  
if  
    subject(inanimate)  
then  
    translate to "madhye...  
aahe"
```



# Statistical Machine Translation



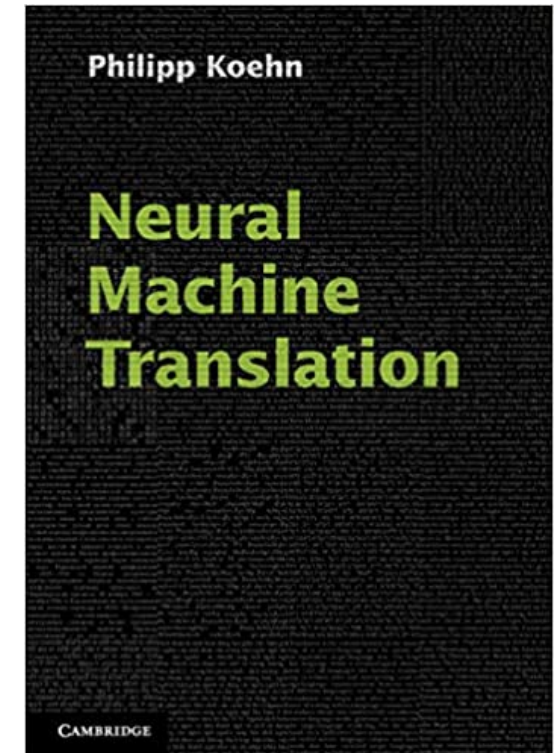
- 1980s: IBM
- 1990s: increased research
- Mid 2000s: Phrase-Based MT (Moses, Google)
- Around 2010: commercial viability



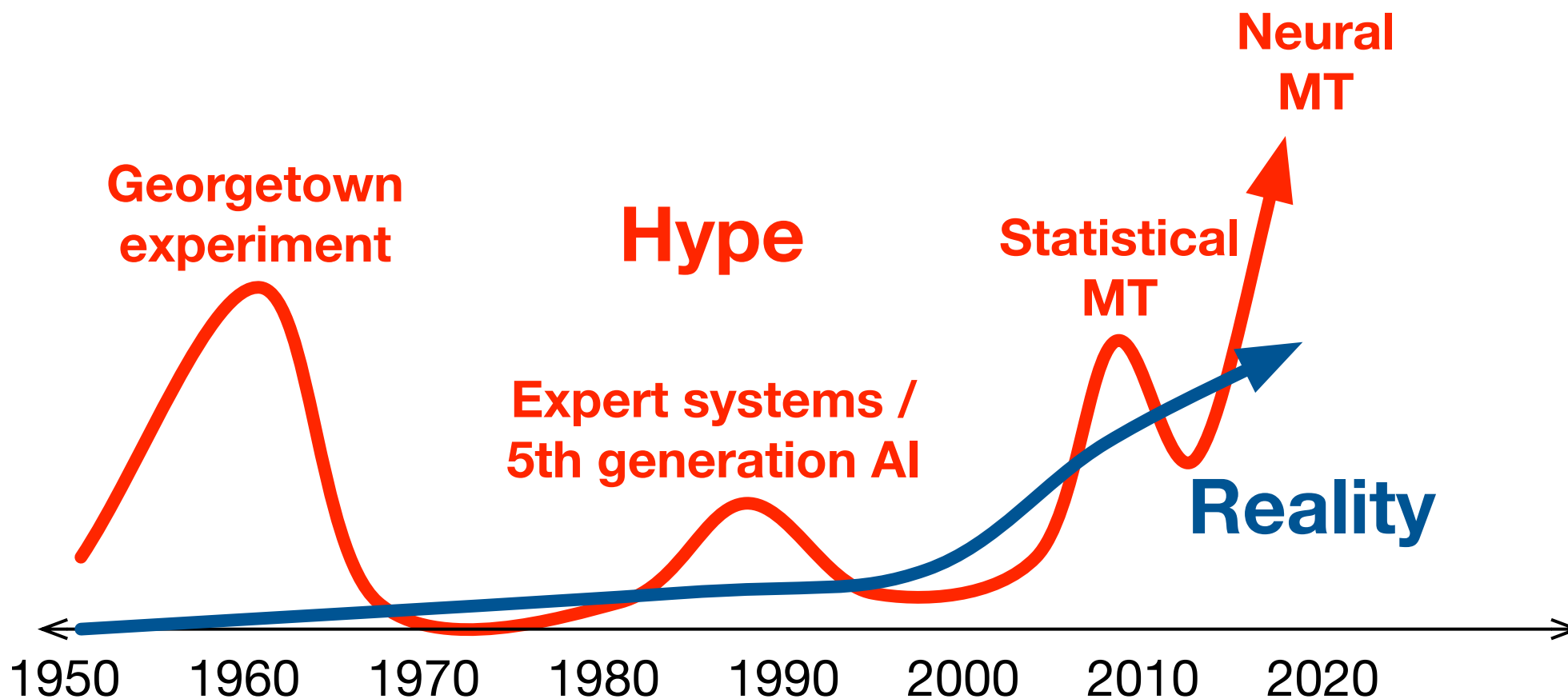
# Neural Machine Translation



- Late 2000s: neural models for computer vision
- Since mid 2010s: neural models for machine translation
- 2016: Neural machine translation the new state of the art



# Hype





how good is machine translation?

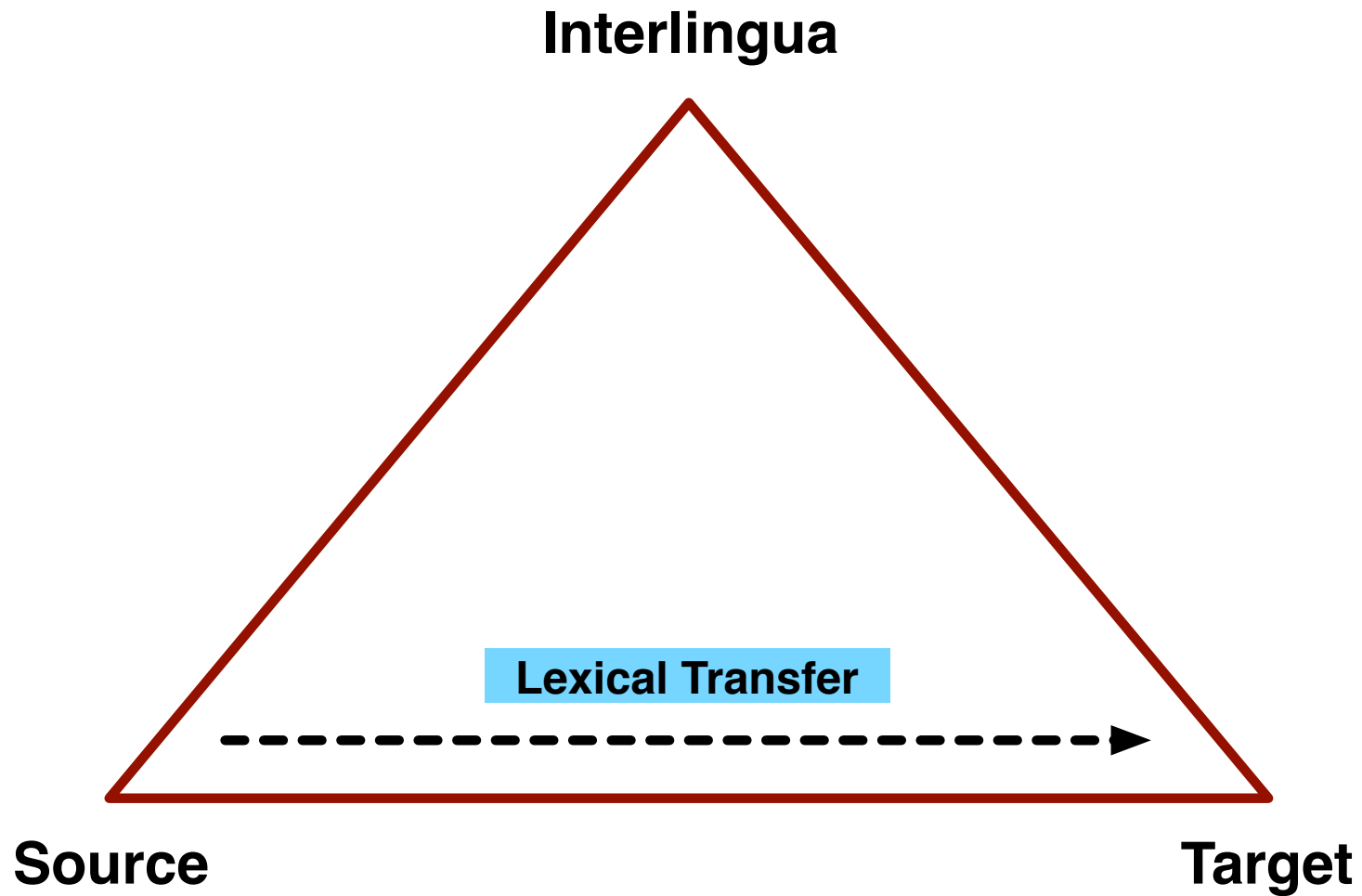
记者从环保部了解到,《水十条》要求今年年底前直辖市、省会城市、计划单列市建成区基本解决黑臭水体。截至目前,全国224个地级及以上城市共排查确认黑臭水体2082个,其中34.9%完成整治,28.4%正在整治,22.8%正在开展项目前期。

Reporters learned from the Ministry of Environmental Protection, "Water 10" requirements before the end of this year before the municipality, the provincial capital city, plans to build a separate city to solve the basic black and black water. Up to now, the country's 224 prefecture-level and above cities were identified to confirm the black and white water 2082, of which 34.9% to complete the renovation, 28.4% is remediation, 22.8% is carrying out the project early.

A l'orée de ce débat télévisé inédit dans l'histoire de la Ve République, on attendait une forme de «Tous sur Macron» mais c'est la candidate du Front national qui s'est retrouvée au cœur des premières attaques de ses quatre adversaires d'un soir, favorisées par le premier thème abordé, les questions de société et donc de sécurité, d'immigration et de laïcité.

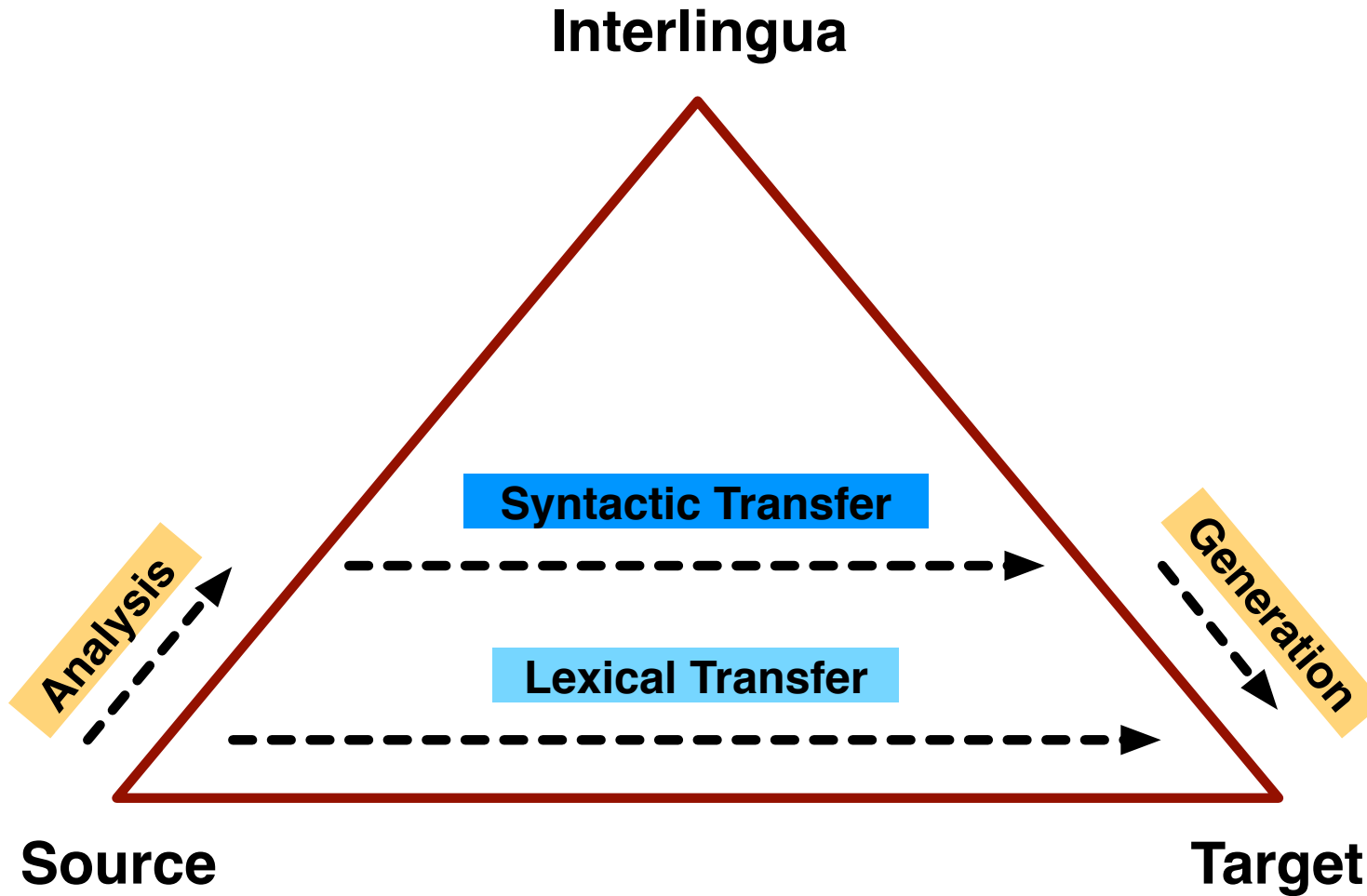
At the beginning of this televised debate, which was unheard of in the history of the Fifth Republic, a "Tous sur Macron" was expected, but it was the candidate of the National Front who found itself at the heart of the first attacks of its four Opponents of one evening, favored by the first theme tackled, the issues of society and thus security, immigration and secularism.

# A Clear Plan



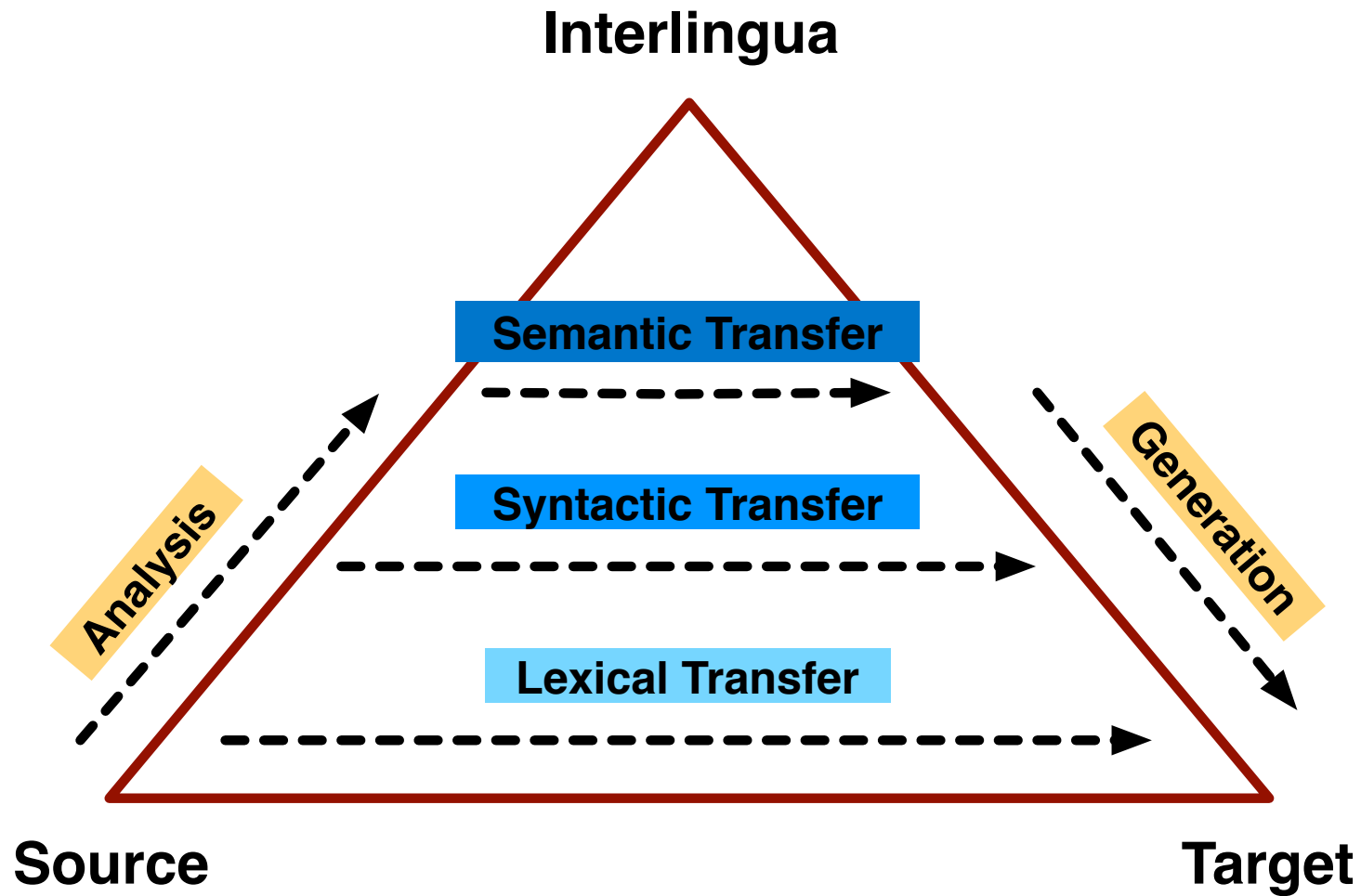


# A Clear Plan

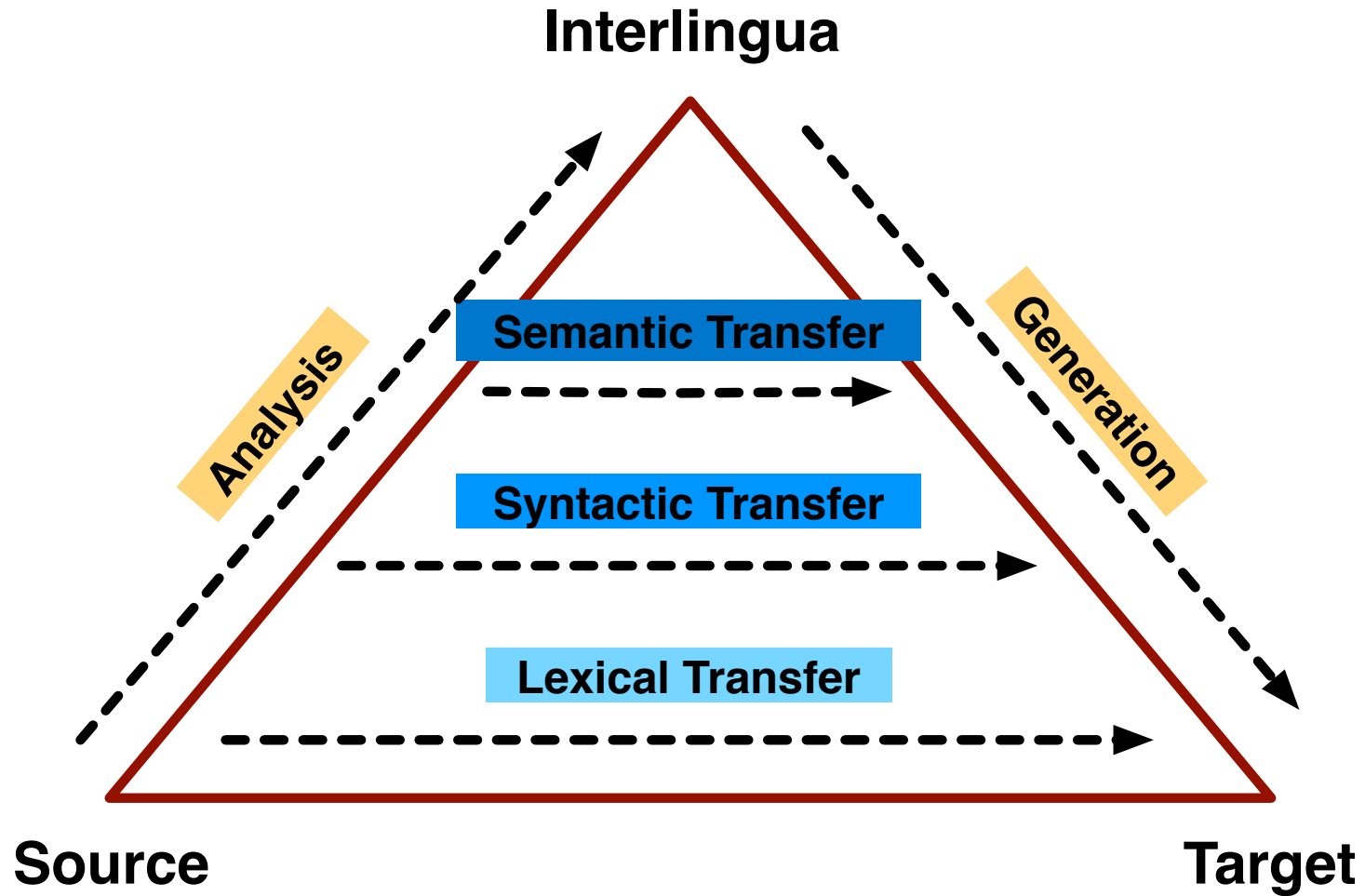




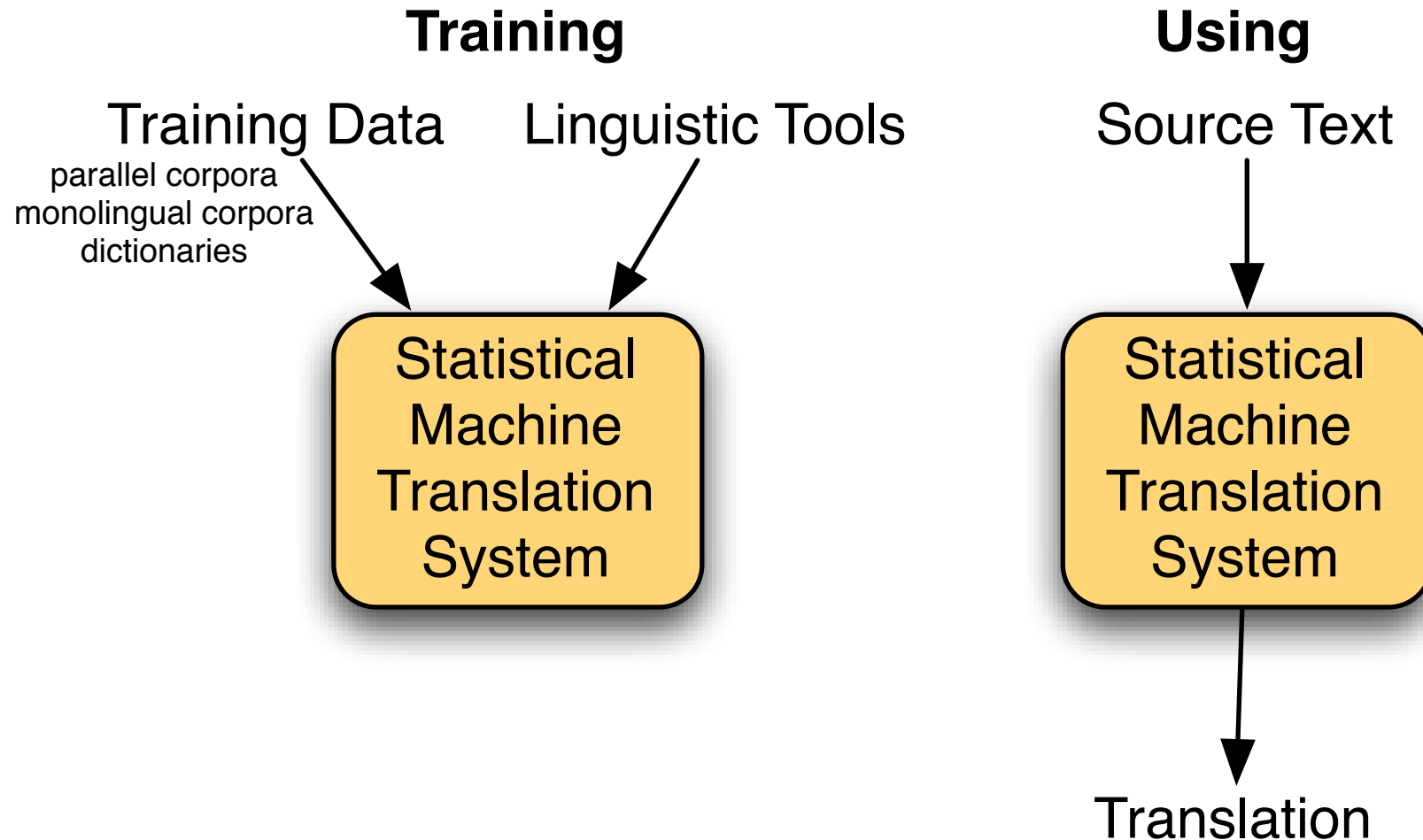
# A Clear Plan



# A Clear Plan



# Learning from Data



why is that a good plan?

# Word Translation Problems



- Words are ambiguous

He deposited money in a **bank** account  
with a high **interest** rate.

Sitting on the **bank** of the Mississippi,  
a passing ship piqued his **interest**.

- How do we find the right meaning, and thus translation?
- Context should be helpful

# Syntactic Translation Problems

- Languages have different sentence structure

das	behaupten	sie	wenigstens
this	claim	they	at least
the		she	

- Convert from object-verb-subject (OVS) to subject-verb-object (SVO)
- Ambiguities can be resolved through syntactic analysis
  - the meaning **the** of **das** not possible (not a noun phrase)
  - the meaning **she** of **sie** not possible (subject-verb agreement)

# Semantic Translation Problems



- Pronominal anaphora

I saw the movie and **it** is good.

- How to translate **it** into German (or French)?
  - **it** refers to **movie**
  - **movie** translates to **Film**
  - **Film** has masculine gender
  - ergo: **it** must be translated into masculine pronoun **er**
- We are not handling this very well [Le Nagard and Koehn, 2010]

# Semantic Translation Problems



- Coreference

Whenever I visit my uncle and his daughters,  
I can't decide who is my favorite **cousin**.

- How to translate **cousin** into German? Male or female?
- Complex inference required



# Semantic Translation Problems

- Discourse

Since you brought it up, I do not agree with you.

Since you brought it up, we have been working on it.

- How to translated *since*? Temporal or conditional?
- Analysis of discourse structure — a hard problem

# Learning from Data



- What is the best translation?

Sicherheit → security

Sicherheit → safety

Sicherheit → certainty

# Learning from Data

- What is the best translation?

Sicherheit → security 14,516

Sicherheit → safety 10,015

Sicherheit → certainty 334

- Counts in European Parliament corpus

# Learning from Data

- What is the best translation?

Sicherheit → security 14,516

Sicherheit → safety 10,015

Sicherheit → certainty 334

- Phrasal rules

Sicherheitspolitik → security policy 1580

Sicherheitspolitik → safety policy 13

Sicherheitspolitik → certainty policy 0

Lebensmittelsicherheit → food security 51

Lebensmittelsicherheit → food safety 1084

Lebensmittelsicherheit → food certainty 0

Rechtssicherheit → legal security 156

Rechtssicherheit → legal safety 5

Rechtssicherheit → legal certainty 723

# Learning from Data



- What is most fluent?

a problem for translation

a problem of translation

a problem in translation

# Learning from Data



- What is most fluent?

a problem for translation 13,000

a problem of translation 61,600

a problem in translation 81,700

- Hits on Google

# Learning from Data



- What is most fluent?

a problem for translation 13,000

a problem of translation 61,600

a problem in translation 81,700

a translation problem 235,000

# Learning from Data

- What is most fluent?

police disrupted the demonstration

police broke up the demonstration

police dispersed the demonstration

police ended the demonstration

police dissolved the demonstration

police stopped the demonstration

police suppressed the demonstration

police shut down the demonstration



# Learning from Data

- What is most fluent?

police disrupted the demonstration 2,140

police broke up the demonstration 66,600

police dispersed the demonstration 25,800

police ended the demonstration 762

police dissolved the demonstration 2,030

police stopped the demonstration 722,000

police suppressed the demonstration 1,400

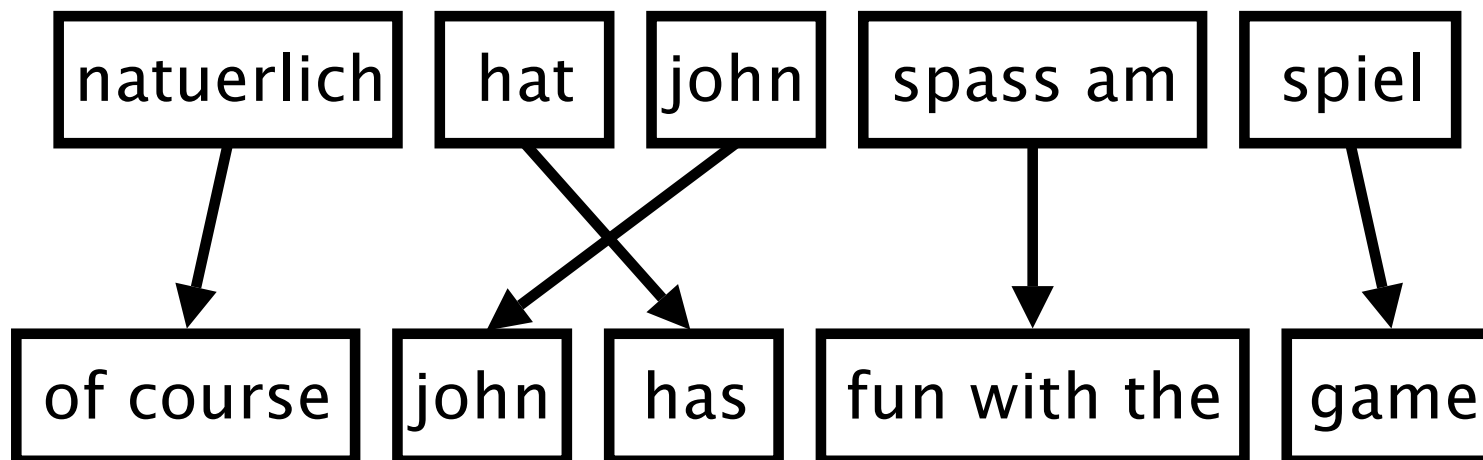
police shut down the demonstration 2,040

where are we now?

# Word Alignment

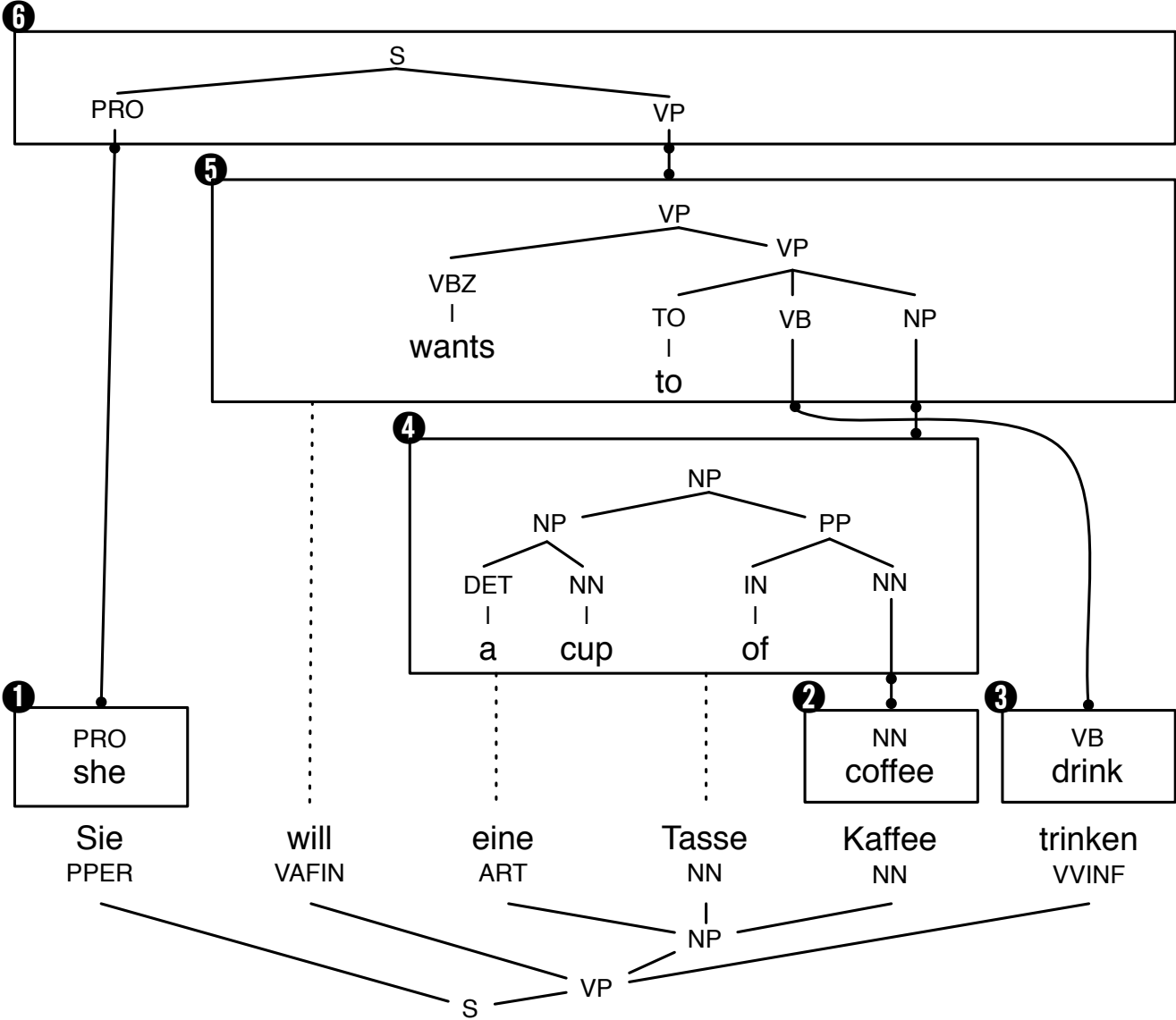
	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael	█									
assumes		█	█	█						
that						█				
he							█			
will										█
stay										█
in								█		
the								█		
house									█	

# Phrase-Based Model



- Foreign input is segmented in phrases
- Each phrase is translated into English
- Phrases are reordered
- Workhorse of today's statistical machine translation

# Syntax-Based Translation

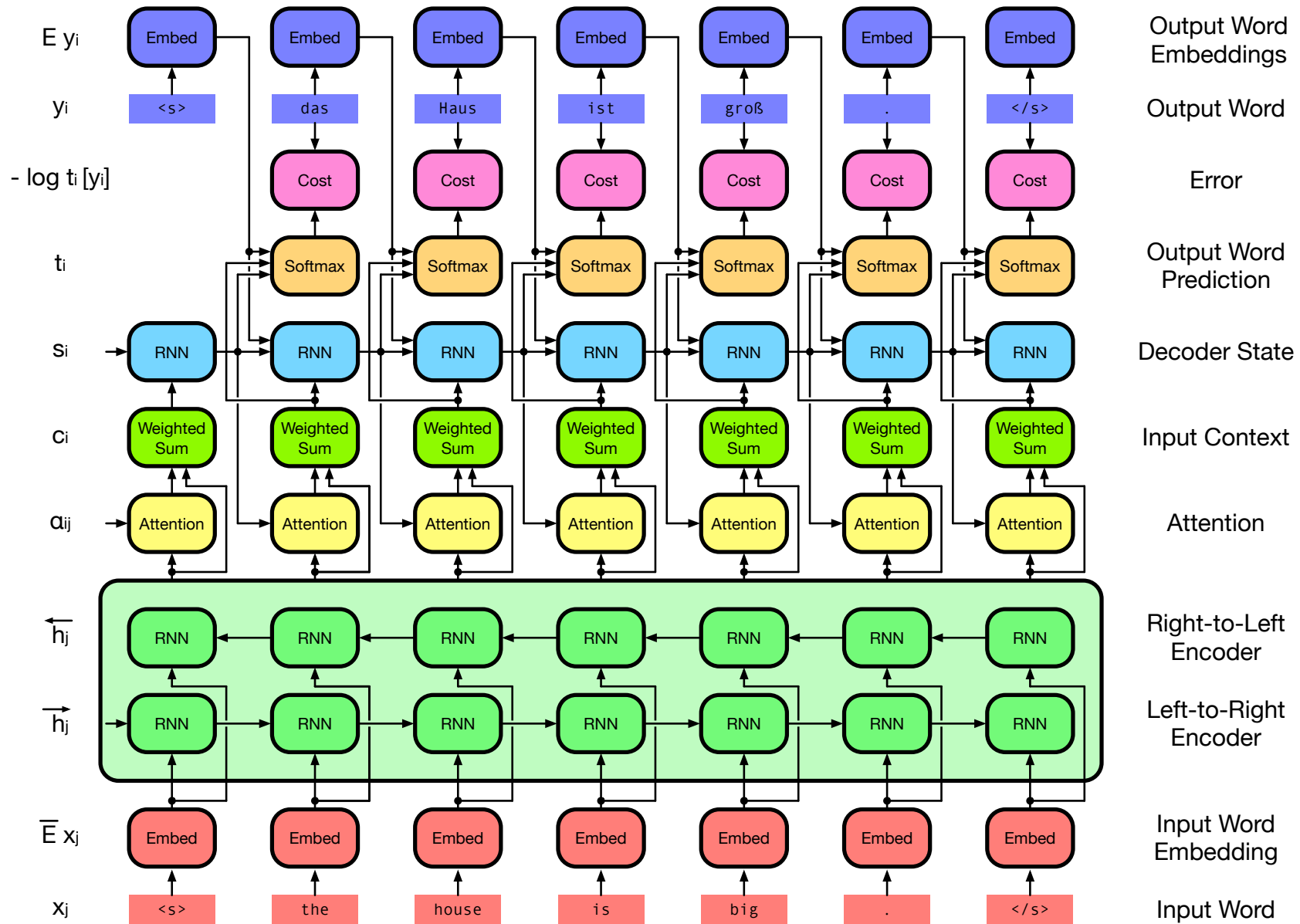


- Abstract meaning representation [Knight et al., ongoing]

```
(w / want-01
  :agent (b / boy)
  :theme (l / love
          :agent (g / girl)
          :patient b))
```

- Generalizes over equivalent syntactic constructs (e.g., active and passive)
- Defines semantic relationships
  - semantic roles
  - co-reference
  - discourse relations

# Neural Model



what is it good for?



what is it good *enough* for?

# Why Machine Translation?

**Assimilation** — reader initiates translation, wants to know content

- user is tolerant of inferior quality
- focus of majority of research (GALE program, etc.)■

**Communication** — participants don't speak same language, rely on translation

- users can ask questions, when something is unclear
- chat room translations, hand-held devices
- often combined with speech recognition, IWSLT campaign■

**Dissemination** — publisher wants to make content available in other languages

- high demands for quality
- currently almost exclusively done by human translators

# Problem: No Single Right Answer



这个 机场 的 安全 工作 由 以色列 方面 负责 .

Israeli officials are responsible for airport security.

Israel is in charge of the security at this airport.

The security work for this airport is the responsibility of the Israel government.

Israeli side was in charge of the security of this airport.

Israel is responsible for the airport's security.

Israel is responsible for safety work at this airport.

Israel presides over the security of the airport.

Israel took charge of the airport security.

The safety of this airport is taken charge of by Israel.

This airport's security is the responsibility of the Israeli security officials.

**HTER**    **assessment**

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0%	
10%	publishable
20%	editable
30%	gistable
40%	triagable
50%	

(scale developed in preparation of DARPA GALE programme)

# Applications

HTER	assessment	application examples
0%	publishable	Seamless bridging of language divide
10%		Automatic publication of official announcements
20%	editable	Increased productivity of human translators
30%		Access to official publications
40%	gistable	Multi-lingual communication (chat, social networks)
50%		Information gathering
	triagable	Trend spotting
		Identifying relevant documents

# Current State of the Art

HTER	assessment	language pairs and domains
0%	publishable	French-English restricted domain
10%		French-English news stories
	editable	German-English news stories
20%		Chinese-English news stories
30%	gistable	Swahili-English news stories
40%	triagable	Uyghur-English news stories
50%		

(informal rough estimates by presenter)

# Thank You



# questions?