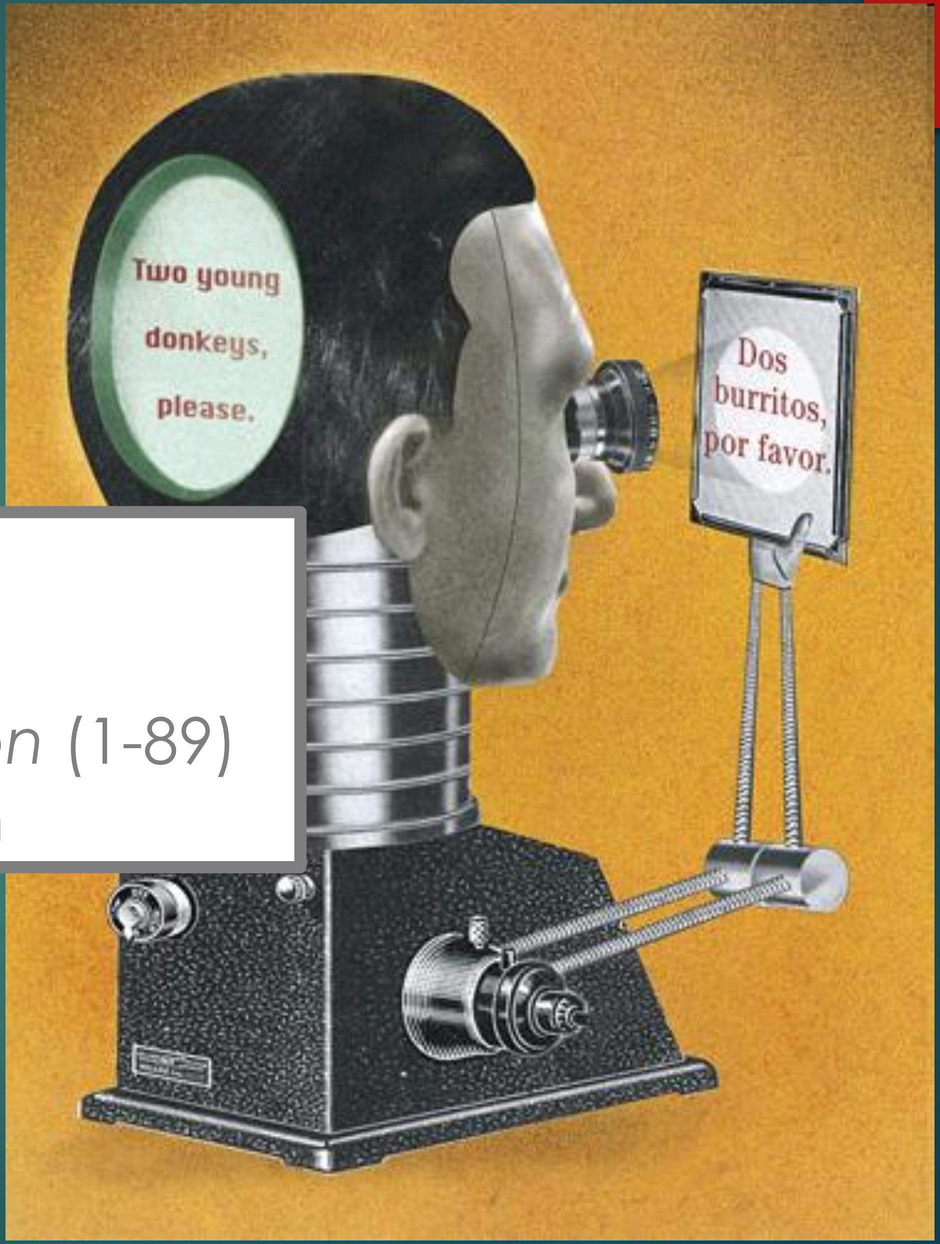
COMS 493

AI, ROBOTS & COMMUNICATION

Agenda

- Review
- Natural Language Processing
- Preview

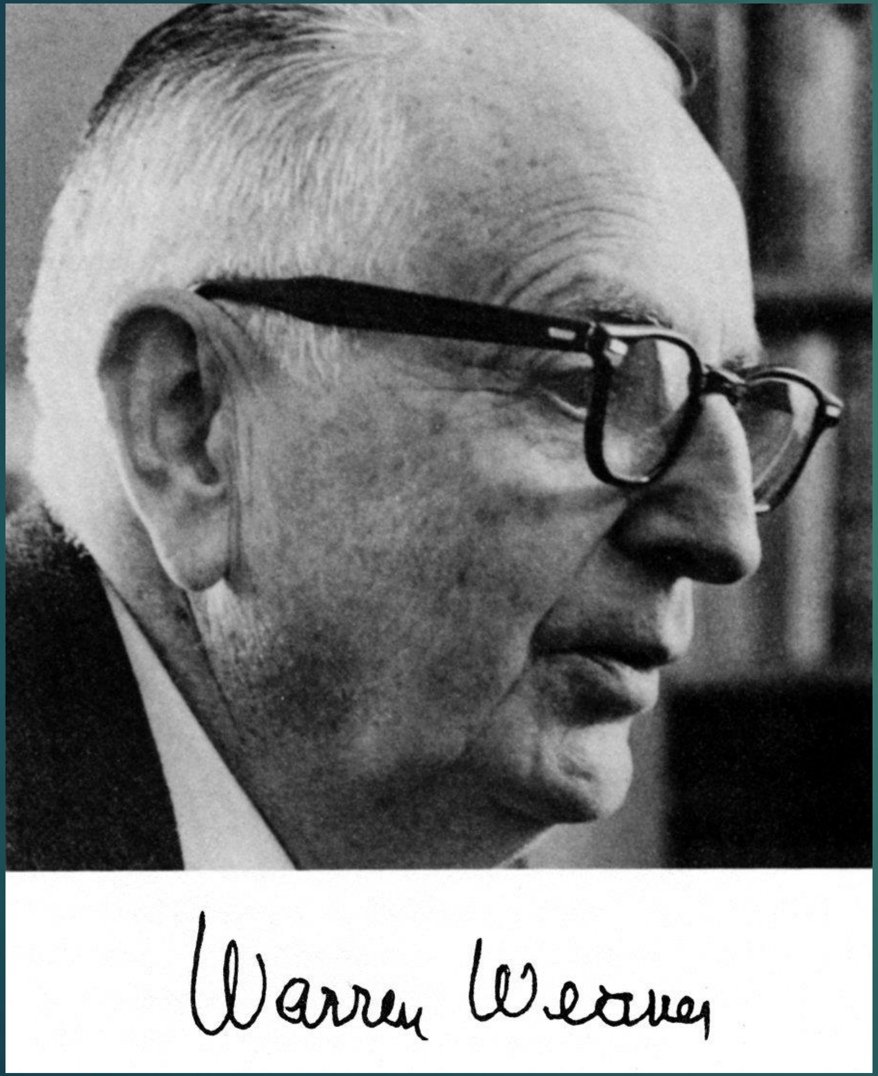
Review



Machine Translation

- Weaver Memo
- Poibeau - *Machine Translation* (1-89)
- Gunkel - Machine Translation

Review



History of Machine Translation

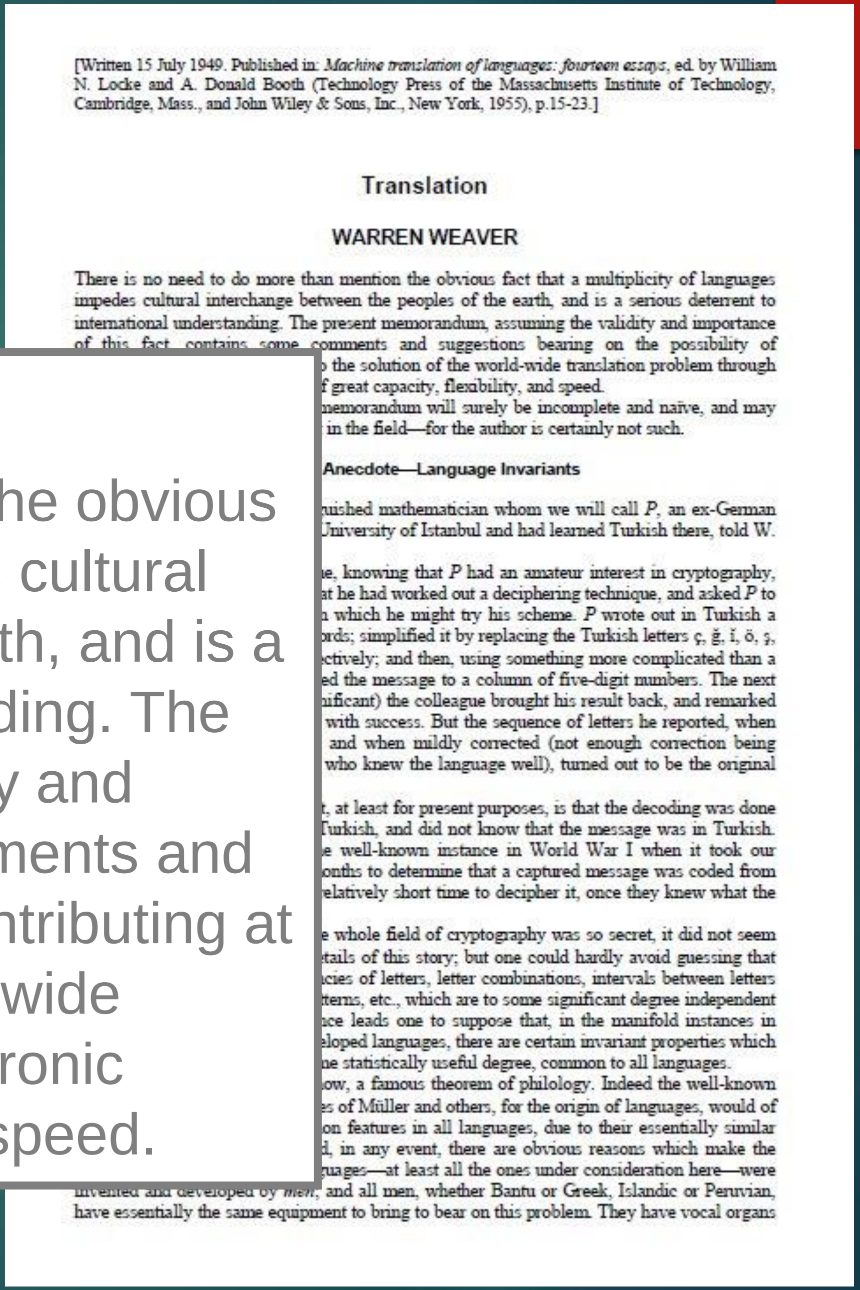
- Warren Weaver
- Co-author (with Claude Shannon) of the *Mathematical Theory of Communication*
- Translation Memorandum (1947)

Review

What assumptions are operative here?

Objective:

There is no need to do more than mention the obvious fact that a multiplicity of languages impedes cultural interchange between the peoples of the earth, and is a serious deterrent to international understanding. The present memorandum, assuming the validity and importance of this fact, contains some comments and suggestions bearing on the possibility of contributing at least something to the solution of the world-wide translation problem through the use of electronic computers of great capacity, flexibility, and speed.



[Written 15 July 1949. Published in: *Machine translation of languages: fourteen essays*, ed. by William N. Locke and A. Donald Booth (Technology Press of the Massachusetts Institute of Technology, Cambridge, Mass., and John Wiley & Sons, Inc., New York, 1955), p.15-23.]

Translation

WARREN WEAVER

There is no need to do more than mention the obvious fact that a multiplicity of languages impedes cultural interchange between the peoples of the earth, and is a serious deterrent to international understanding. The present memorandum, assuming the validity and importance of this fact, contains some comments and suggestions bearing on the possibility of
o the solution of the world-wide translation problem through
f great capacity, flexibility, and speed.
memorandum will surely be incomplete and naïve, and may
in the field—for the author is certainly not such.

Anecdote—Language Invariants

uished mathematician whom we will call *P*, an ex-German
University of Istanbul and had learned Turkish there, told W.

e, knowing that *P* had an amateur interest in cryptography,
at he had worked out a deciphering technique, and asked *P* to
n which he might try his scheme. *P* wrote out in Turkish a
ords; simplified it by replacing the Turkish letters ç, ğ, ĭ, ö, ş,
ctively; and then, using something more complicated than a
ed the message to a column of five-digit numbers. The next
nificant) the colleague brought his result back, and remarked
with success. But the sequence of letters he reported, when
and when mildly corrected (not enough correction being
who knew the language well), turned out to be the original

t, at least for present purposes, is that the decoding was done
Turkish, and did not know that the message was in Turkish.
e well-known instance in World War I when it took our
onths to determine that a captured message was coded from
elatively short time to decipher it, once they knew what the

e whole field of cryptography was so secret, it did not seem
tails of this story; but one could hardly avoid guessing that
cies of letters, letter combinations, intervals between letters
terns, etc., which are to some significant degree independent
nce leads one to suppose that, in the manifold instances in
eloped languages, there are certain invariant properties which
ne statistically useful degree, common to all languages.
ow, a famous theorem of philology. Indeed the well-known
s of Müller and others, for the origin of languages, would of
on features in all languages, due to their essentially similar
d, in any event, there are obvious reasons which make the
uages—at least all the ones under consideration here—were
men; and all men, whether Bantu or Greek, Islandic or Peruvian,
have essentially the same equipment to bring to bear on this problem. They have vocal organs

Review

Operative Assumptions

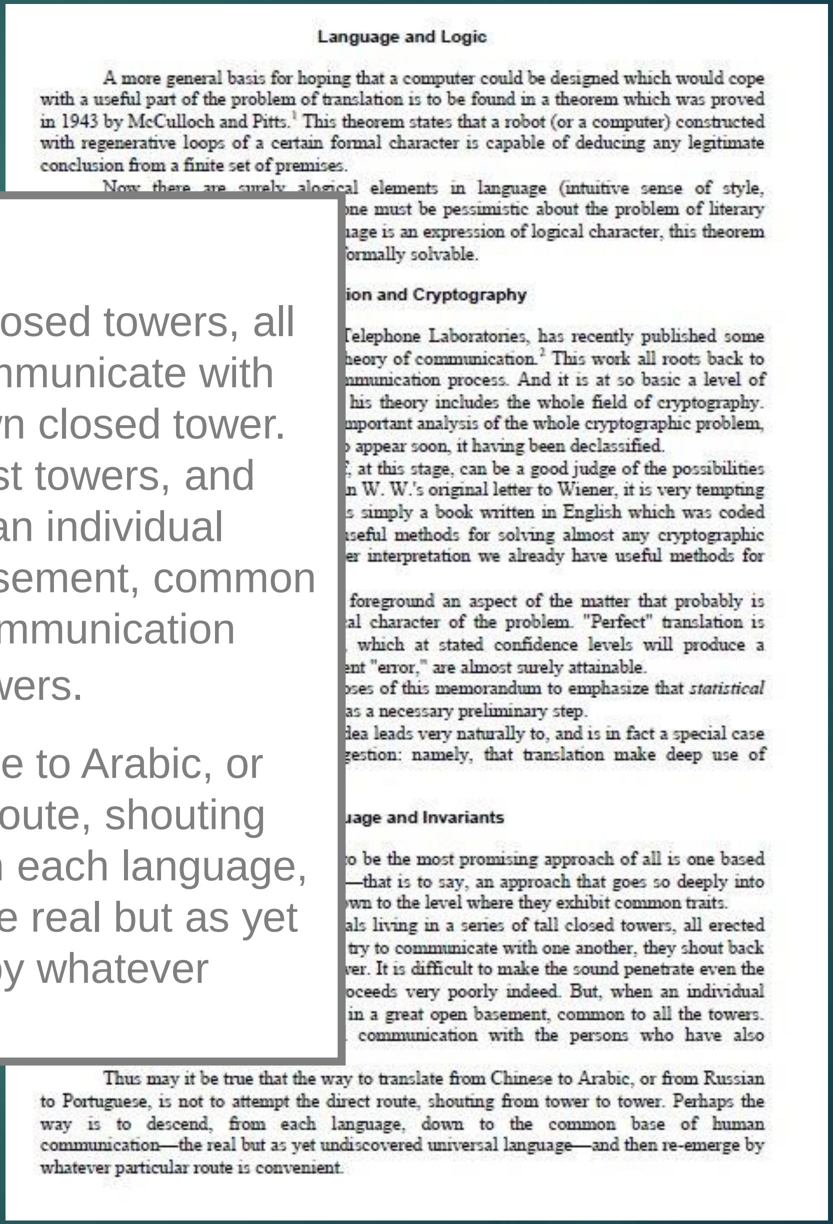
- Utopian Vision and Objective
- Linguistic Difference is a problem
- Technological Determinism
- Communication = Cooperation

Review

Translation Methodology:

Think, by analogy, of individuals living in a series of tall closed towers, all erected over a common foundation. When they try to communicate with one another, they shout back and forth, each from his own closed tower. It is difficult to make the sound penetrate even the nearest towers, and communication proceeds very poorly indeed. But, when an individual goes down his tower, he finds himself in a great open basement, common to all the towers. Here he establishes easy and useful communication with the persons who have also descended from their towers.

Thus may it be true that the way to translate from Chinese to Arabic, or from Russian to Portuguese, 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.



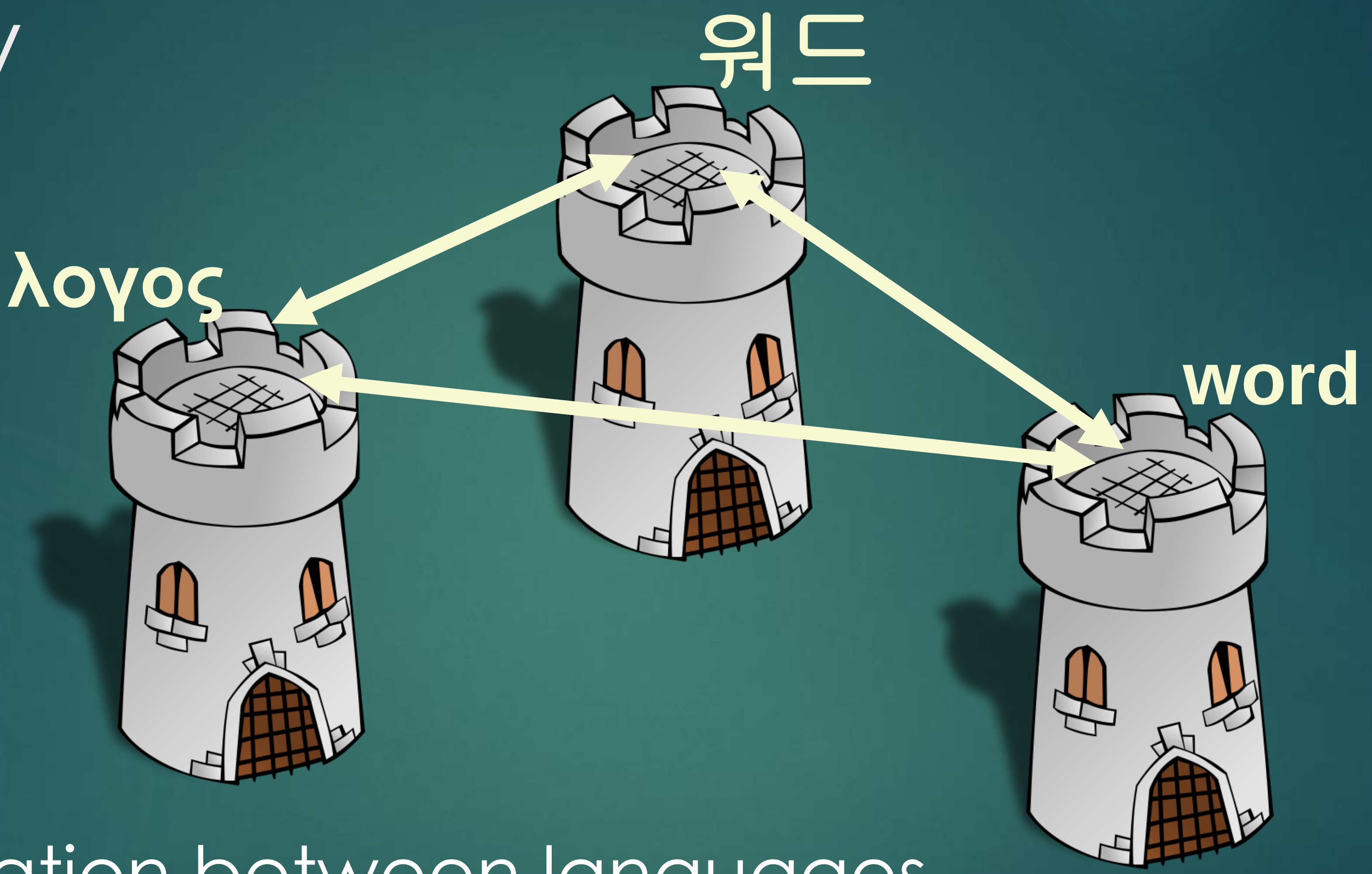
Language and Logic

A more general basis for hoping that a computer could be designed which would cope with a useful part of the problem of translation is to be found in a theorem which was proved in 1943 by McCulloch and Pitts.[1] This theorem states that a robot (or a computer) constructed with regenerative loops of a certain formal character is capable of deducing any legitimate conclusion from a finite set of premises.

Now there are surely alogical elements in language (intuitive sense of style, …

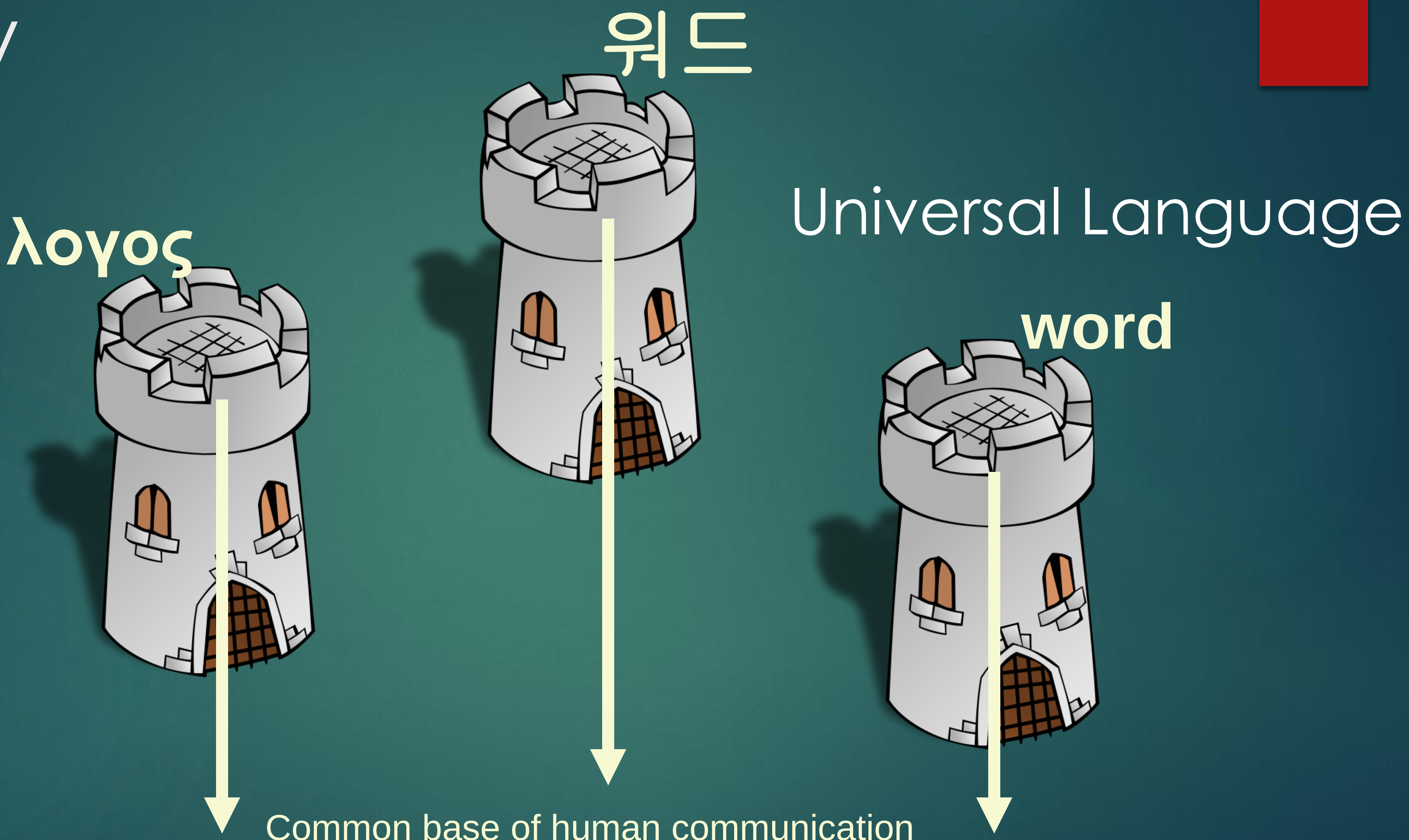
Thus may it be true that the way to translate from Chinese to Arabic, or from Russian to Portuguese, is not to attempt the direct route, shouting from tower to tower. Perhaps the way is to descend, from each language, down to the common base of human communication—the real but as yet undiscovered universal language—and then re-emerge by whatever particular route is convenient.

Review



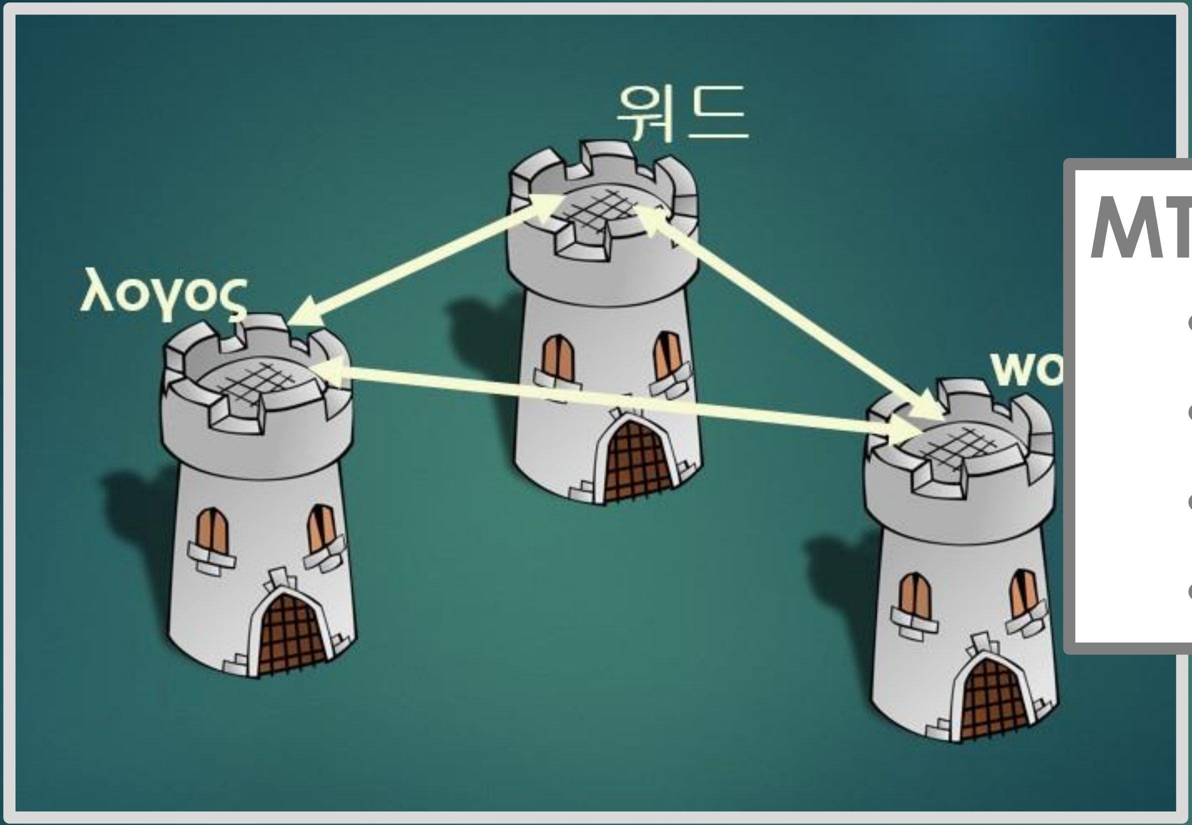
Translation between languages

Review



Common base of human communication
The real but as yet undiscovered universal language

Review



MT Methods

- Rule Based MT
- Example Based MT
- Statistical MT
- Machine Learning MT

1. Rule-Based MT

- Words in one language are cross referenced to words in another language (i.e. bilingual dictionary)
- "Translation module" links the two languages through a series of transformation steps that are specific to that particular pair.

SURVIVAL PHRASES

Hello.	Guten Tag.	*goo*·ten tahk
Goodbye.	Auf Wiedersehen.	owf *vee*·der·zay·en
Please.	Bitte.	*bi*·te
Thank you.	Danke.	*dang*·ke
You're welcome.	Bitte (sehr).	*bi*·te (zair)
Yes./No.	Ja./Nein.	yah/nain
Excuse me.	Entschuldigung.	ent·*shul*·di·gung
Sorry!	Entschuldigung.	ent·*shul*·di·gung
I don't understand.	Ich verstehe nicht.	ikh fer·*shtay*·e nikht
One moment, please.	Eine Moment, bitte.	*ai*·ne maw·*ment* *bi*·te
Help!	Hilfe!	*hil*·fe
How much is this?	Wie viel kostet das?	vee feel kos·tet das
Where is the toilet?	Wo ist die Toilette?	vo ist dee to·a·*le*·te
Cheers!	Prost!	prawst

NUMBERS

1	eins	ains	**6**	sechs	zeks
2	zwei	tsvai	**7**	sieben	zee·ben
3	drei	drai	**8**	acht	akht
4	vier	feer	**9**	neun	noyn
5	fünf	fünf	**10**	zehn	tsayn

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1. Rule-Based MT


```

<html>

<script>
function xlate()
 {
  source = document.getElementById("english").value;

  if (source=="hello") target = "Guten Tag";
  else if (source=="goodbye") target = "Auf Wiedersehen";
  else if (source=="please") target = "Bitte";
  else if (source=="thank you") target = "Danke schon";
  else if (source=="you're welcome") target = "Bitte sehr";
  else if (source=="yes") target = "Ja";
  else if (source=="no") target = "Nein";
  else if (source=="excuse me") target = "Entschuldigung";
  else if (source=="no thank you") target = "Nein, danke";
  else if (source=="beer") target = "ein bier";
  else if (source=="water") target = "wasser"
  else target = "Sorry, I do not know that one."

  document.getElementById("german").value = target;

 }
</script>

<body>
 <form>
  Basic Translator - English to German
  <p><input type="text" id="english">
     <input type="button" value=">>" onClick="xlate()">
     <input type="text" id="german"></p>
</form>

</body>
</html>

```

1. Rule-Based MT

- Problems/Limitations of Rule Based MT
  - **Exceptions** – Language use does not follow exact grammatical rules. There are numerous exceptions and variations.
  - **Language Pairs** – Rule based MT is organized around language pairs. This creates a problem when you try to scale the approach to multiple languages

1. Rule-Based MT

- Rule Based MT Mathematics
  - Language Pairs = n (n-1) translation modules
    - 2 languages: 2 (2-1) = 2 translation modules

German to Japanese	Japanese to German

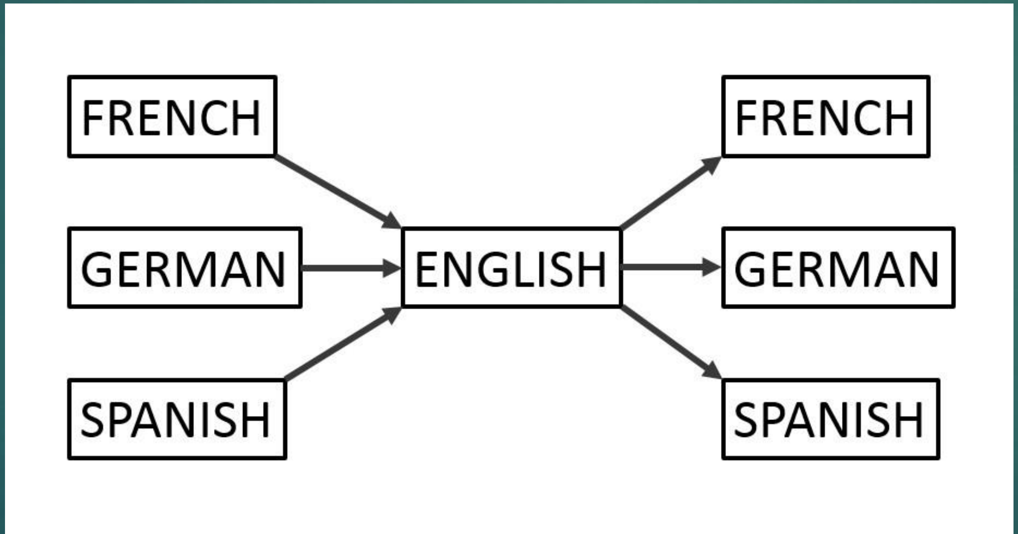
    - 3 languages: 3 (3-1) = 6 translation modules

German to Japanese	English to Japanese	German to English
Japanese to German	Japanese to English	English to German

    - 9 languages: 9 (9-1) = 72 translation modules

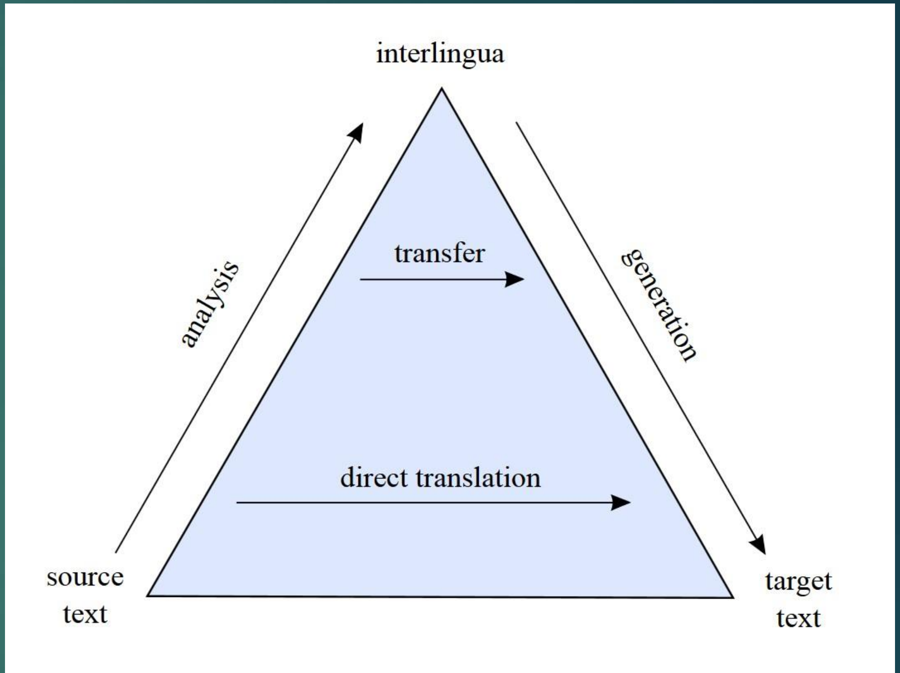
1. Rule-Based MT

- Possible Solution = Interlingua
  - An intermediary language that mediates between different languages
  - 2n translation modules - 3 languages = 6 MT modules



1. Rule-Based MT

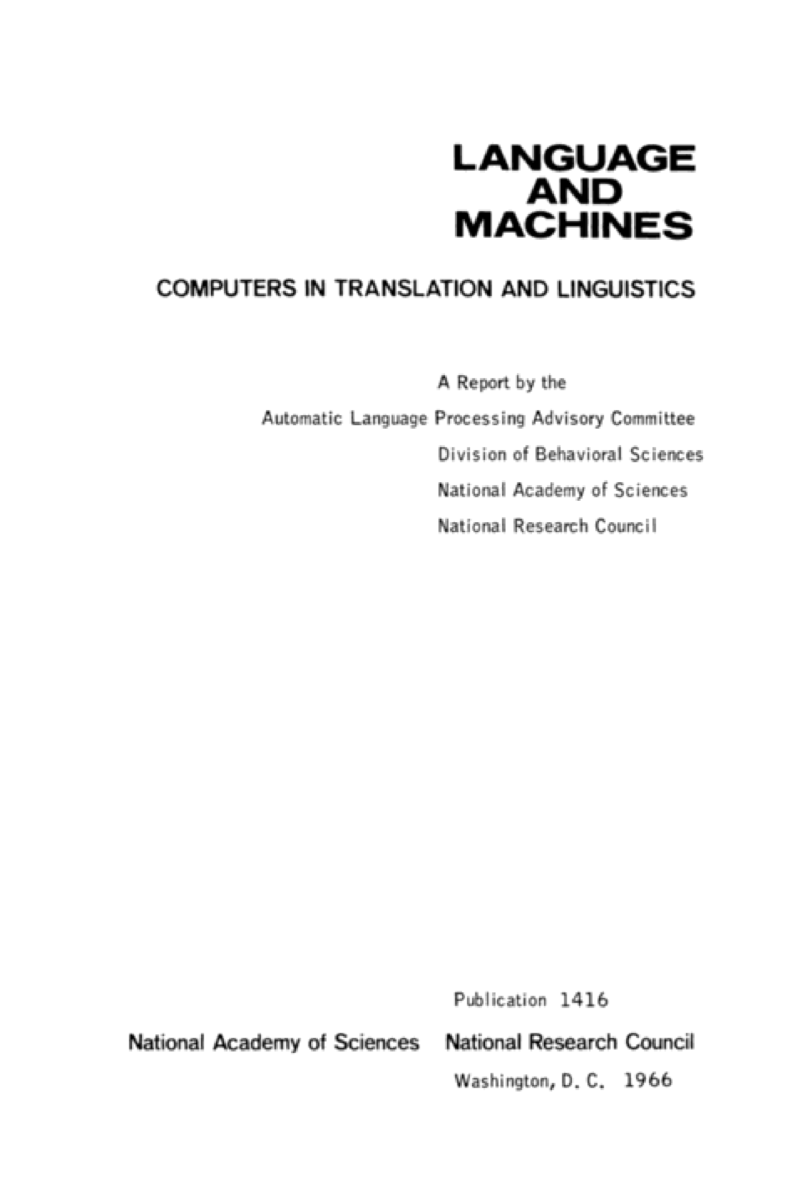
The different approaches to rule-based MT—or what is also called "classical MT" (Jurafsky and Martin 2017)—can be organized into three main variants: Direct, Transfer, Interlingua. "These three kinds of approaches," As Thierry Poubeau (2017, 28-29) explains "can be considered to form a continuum, going from a strategy that is very close to the surface of the text (a word-for-word translation) up to systems trying to develop a fully artificial and abstract representation that is independent of any language."



Vauquois Triangle

1. Rule-Based MT

The three methods of rule based MT (direct, transfer and interlingua) experienced enthusiastic support in the wake of Weaver's Translation memo. But already by the late 1950s, optimism for success with these MT efforts began to lose ground and were increasingly the target of criticism.


LANGUAGE
AND
MACHINES

COMPUTERS IN TRANSLATION AND LINGUISTICS

A Report by the
Automatic Language Processing Advisory Committee
Division of Behavioral Sciences
National Academy of Sciences
National Research Council

Publication 1416
National Academy of Sciences National Research Council
Washington, D. C. 1966

ALPAC Report - 1966

1. Rule-Based MT

Altavista’s Babel Fish – Systran (1990s)

2. Example Based MT

- Parallel corpora = textual pairings of the same content in at least two different languages
- Use parallel corpora to provide example translations.

First Reading of Senate Public Bills	Première lecture des projets de loi d'intérêt public émanant du Sénat
S-205 — October 25, 2016 — An Act to amend the Canada Border Services Agency Act (Inspector General of the Canada Border Services Agency) and to make consequential amendments to other Acts.	**S-205** — 25 octobre 2016 — Loi modifiant la Loi sur l'Agence des services frontaliers du Canada (inspecteur général de l'Agence des services frontaliers du Canada) et d'autres lois en conséquence.
S-215 — January 30, 2017 — An Act to amend the Criminal Code (sentencing for violent offences against Aboriginal women).	**S-215** — 30 janvier 2017 — Loi modifiant le Code criminel (peine pour les infractions violentes contre les femmes autochtones).
S-225 — June 16, 2016 — Mr. Carrie (Oshawa) — An Act to amend the Controlled Drugs and Substances Act (substances used in the production of fentanyl).	**S-225** — 16 juin 2016 — M. Carrie (Oshawa) — Loi modifiant la Loi réglementant certaines drogues et autres substances (substances utilisées dans la production de fentanyl).

Canadian Parliament's *Order Paper and Notice Paper*

2. Example Based MT

Makato Nagao - 1985

ARTIFICIAL AND HUMAN INTELLIGENCE (A. Elithorn and R. Banerji, editors).
Elsevier Science Publishers. B.V.

Chapter 11

A FRAMEWORK OF A MECHANICAL TRANSLATION BETWEEN JAPANESE AND ENGLISH BY ANALOGY PRINCIPLE

MAKOTO NAGAO
Department of Electrical Engineering, Kyoto University, Kyoto, Japan

Summary

Problems inherent in current machine translation systems have been reviewed and have been shown to be inherently inconsistent. The present paper defines a model based on a series of human language processing and in particular the use of analogical thinking.

Machine translation systems developed so far have a kind of inherent contradiction in themselves. The more detailed a system has become by the additional improvements, the clearer the limitation and the boundary will be for the translation ability. To break through this difficulty we have to think about the mechanism of human translation, and have to build a model based on the fundamental function of language processing in the human brain. The following is an attempt to do this based on the ability of analogy finding in human beings.

1. Prototypical consideration

Let us reflect about the mechanism of human translation of elementary sentences at the beginning of foreign language learning. A student memorizes the elementary English sentences with the corresponding Japanese sentences. The first stage is completely a drill of memorizing lots of similar sentences and words in English, and the corresponding Japanese. Here we have no translation theory at all to give to the student. He has to get the translation mechanism through his own instinct. He has to compare several different English sentences with the corresponding Japanese. He has to guess, make inferences about the structure of sentences from a lot of examples.

Along the same lines as this learning process, we shall start the consideration of our machine translation system, by giving lots of example sentences with their corresponding translations. The system must be able to recognize the similarity and the difference of the given example sentences. Initially a pair of sentences are given, a simple English sentence and the corresponding Japanese sentence. The next step is to give another pair of sentences (English and Japanese), which is different from the first only by one word.

2. Example Based MT

Example-based MT garnered considerable attention during the 1980s and was especially attractive for systems designed to handle Asian languages. But this approach to developing MT applications does have important limitations.

1) It requires a large number of parallel corpora that are aligned, if at all possible, at the sentence level. Fortunately this kind of data became increasingly accessible throughout the 80's as documents were digitized and uploaded to the Internet.

2) But even though the number of parallel corpora have increased considerably since the privatization of the Internet, there are still situations where aligned fragments cannot be identified. When this occurs, example-based MT systems either fail or need to fall back on direct word-for-word translations.

3. Statistical MT

- Translation model based on probably and statistics instead of grammatical rules.
- *Parallel corpora* provide translation data. Large number of bilingual texts.

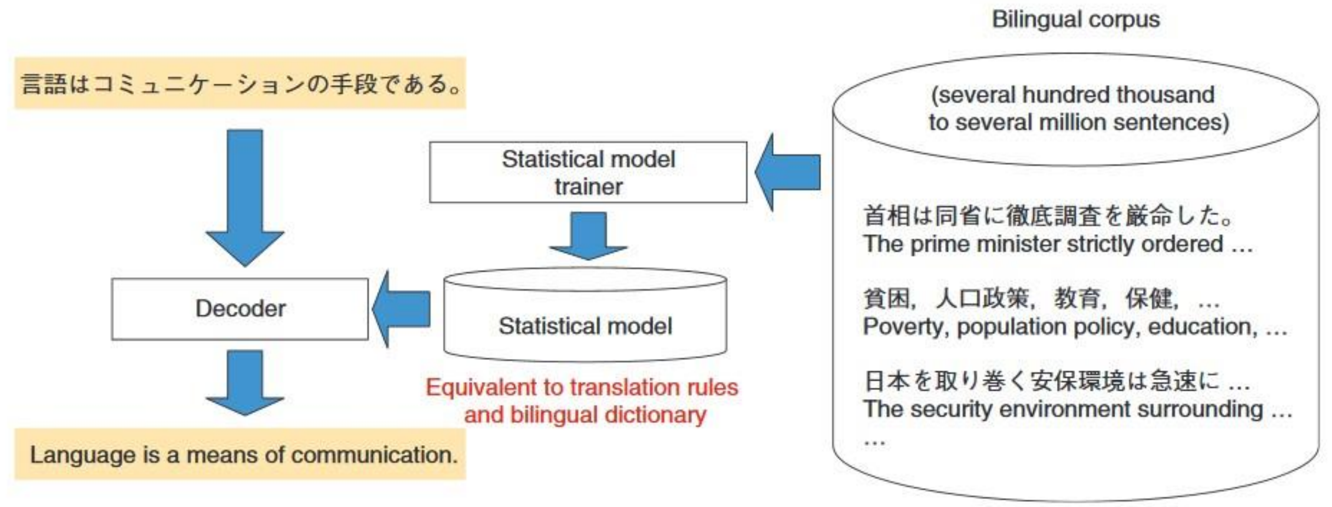


Fig. 1. Outline of statistical machine translation.

3. Statistical MT

<u>Quiero</u> <u>ir</u> <u>a</u> <u>la playa</u> <u>más bonita</u>.

I love | to leave | at | the seaside | more tidy.

I mean | to be on | to | the open space | most lovely.

I like | to be |on | per the seaside | more lovely.

I mean | to go | to | the open space | most tidy.

1) Sentence to be translated is broken up into linguistic chunks, i.e. individual words or sequence of words.

2) Translation program looks to the bilingual corpora to find all the different ways human translators have translated these words (or sequence of words) in the past.

3) The program generates 1000's of different possible translations. It then rates these different translations based on the probability that they actually have occurred in the target language. Some are more like to occur than others; program picks the most likely version.

3. Statistical MT

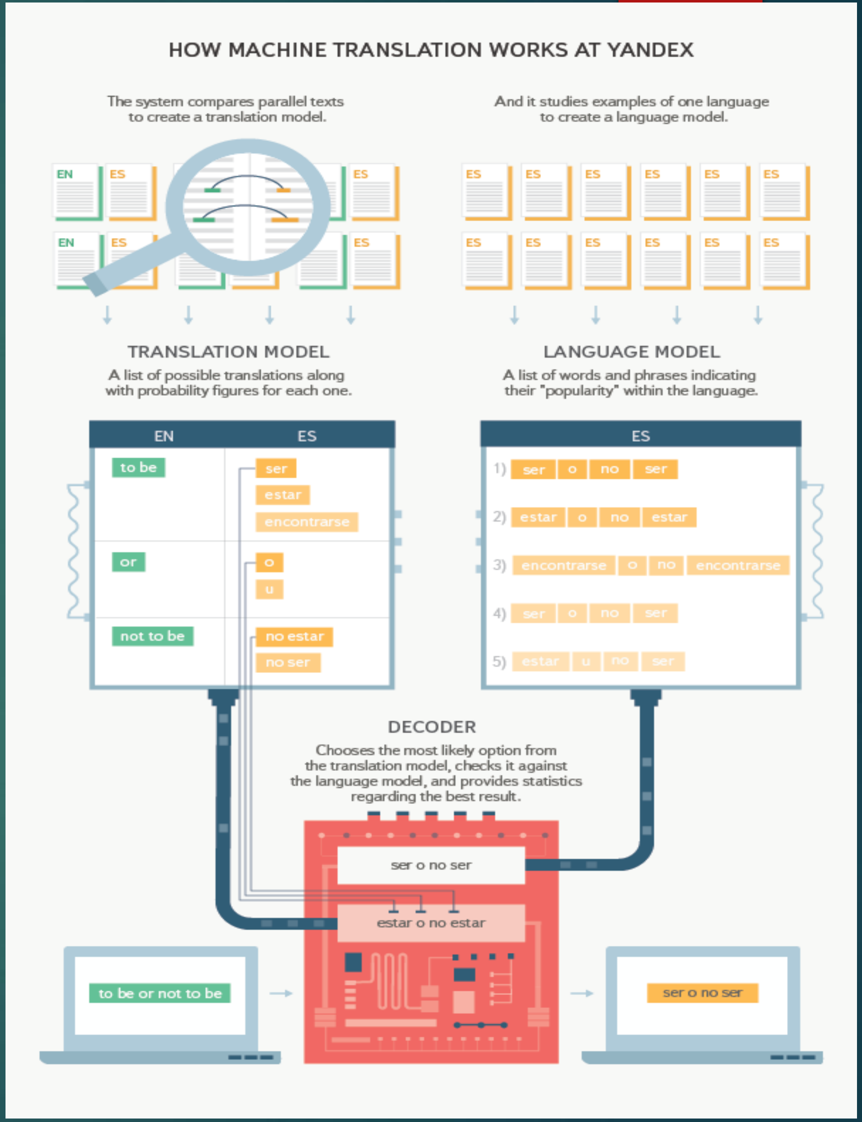
Google Translate (2006-2016)

- Statistical Machine Translation (SMT)
- Quality varies between different language pairs due to number of available translated documents
- Supported 103 different languages

http://translate.google.com/about/intl/en_ALL/

3. Statistical MT

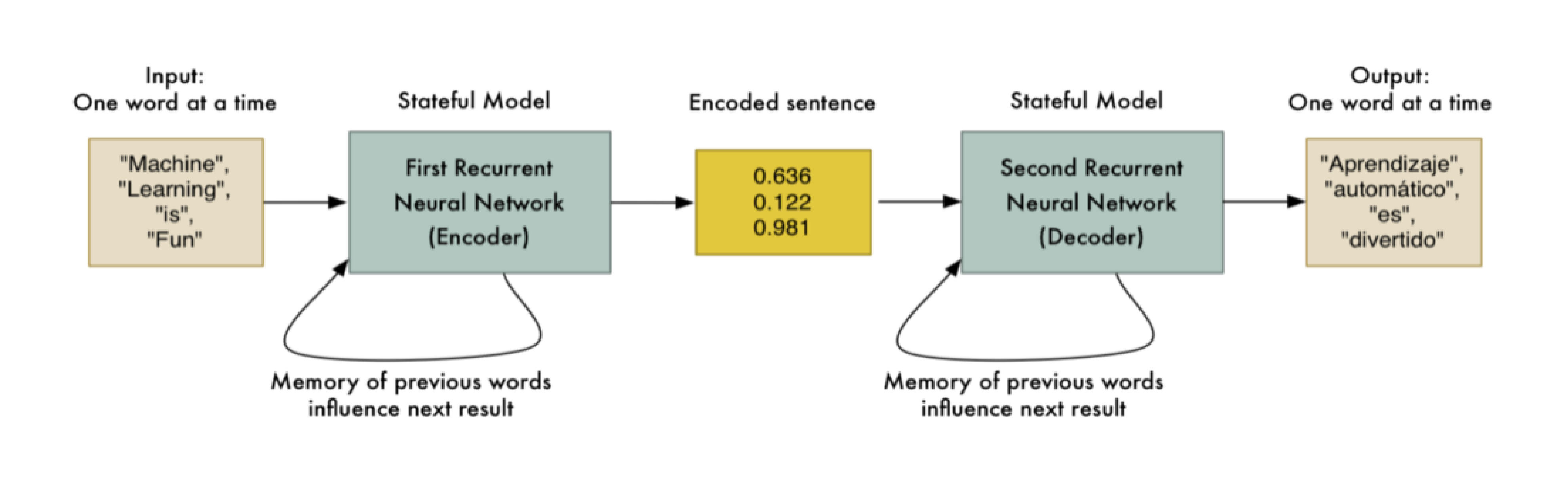
- Problems/Limitations of SMT
  - **Complexity** – SMT is complicated to build and maintain. Every new pair of languages requires experts to tweak and tune a new multi-step translation process.
  - **Data Limitations** – Need a lot of parallel texts. Some language pairs have a lot, others have very little. Translation quality depends on the number of available texts.



https://yandex.com/company/technologies/translation/

4. Machine Learning MT

- Use a neural network to discover translation patterns in data
- Feed the network the parallel corpora and the machine discovers the translation by itself



https://medium.com/@ageitgey/machine-learning-is-fun-part-5-language-translation-with-deep-learning-and-the-magic-of-sequences-2ace0acca0aa

4. Machine Learning MT

Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation

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Abstract

In this paper, we propose a novel neural network model called RNN Encoder–Decoder that consists of two recurrent neural networks (RNN). One RNN encodes a sequence of symbols into a fixed-length vector representation, and the other decodes the representation into another sequence of symbols. The encoder and decoder of the proposed model are jointly trained to maximize the conditional probability of a target sequence given a source sequence. The performance of a statistical machine translation system is empirically found to improve by using the conditional probabilities of phrase pairs computed by the RNN Encoder–Decoder as an additional feature in the existing log-linear model. Qualitatively, we show that the proposed model learns a semantically and syntactically meaningful representation of linguistic phrases.

1 Introduction

Deep neural networks have shown great success in various applications such as objection recognition

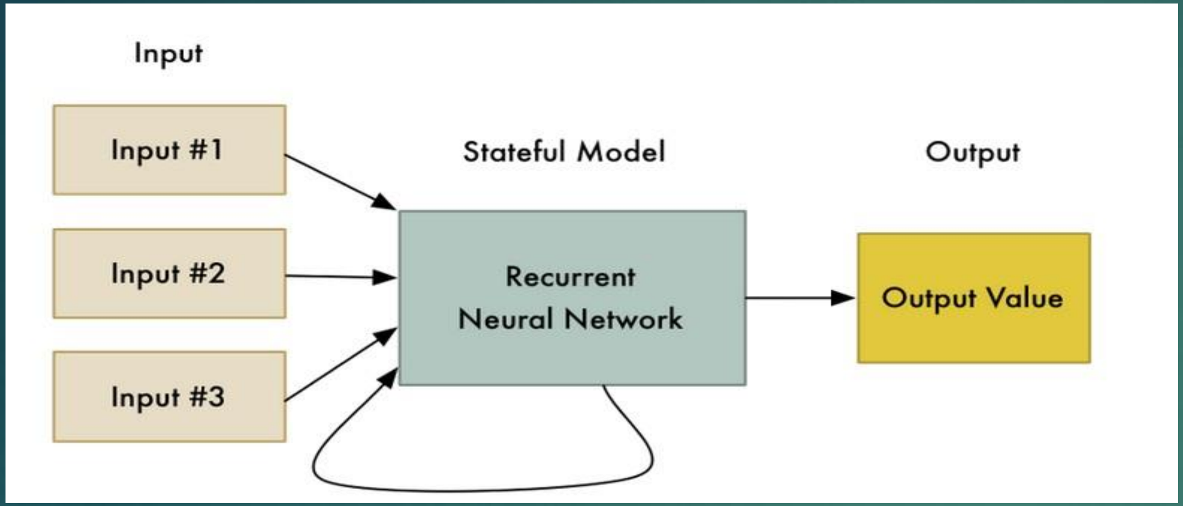
Along this line of research on using neural networks for SMT, this paper
ral network architecture th
of the conventional phra
The proposed neural netw
we will refer to as an *RNN*
sists of two recurrent neur
act as an encoder and a
coder maps a variable-leng
fixed-length vector, and th
tor representation back to
sequence. The two netwo
maximize the conditional
sequence given a source s
we propose to use a rath
unit in order to improve both the memory capacity and the ease of training.

The proposed RNN Encoder–Decoder with a novel hidden unit is empirically evaluated on the task of translating from English to French. We train the model to learn the translation probability of an English phrase to a corresponding French phrase. The model is then used as a part of a standard phrase-based SMT system by scoring each phrase pair in the phrase table. The empirical evaluation reveals that this approach of scoring phrase

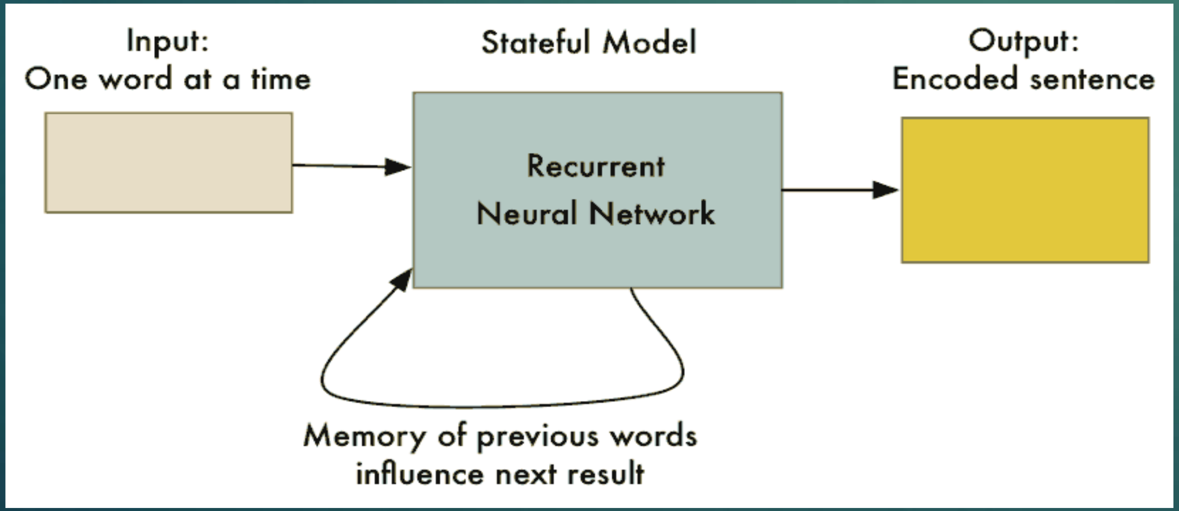
Learning Phrase Representations…

- Scientific Paper published in 2014
- Demonstrate the feasibility of RNN for machine translation tasks

4. Machine Learning MT

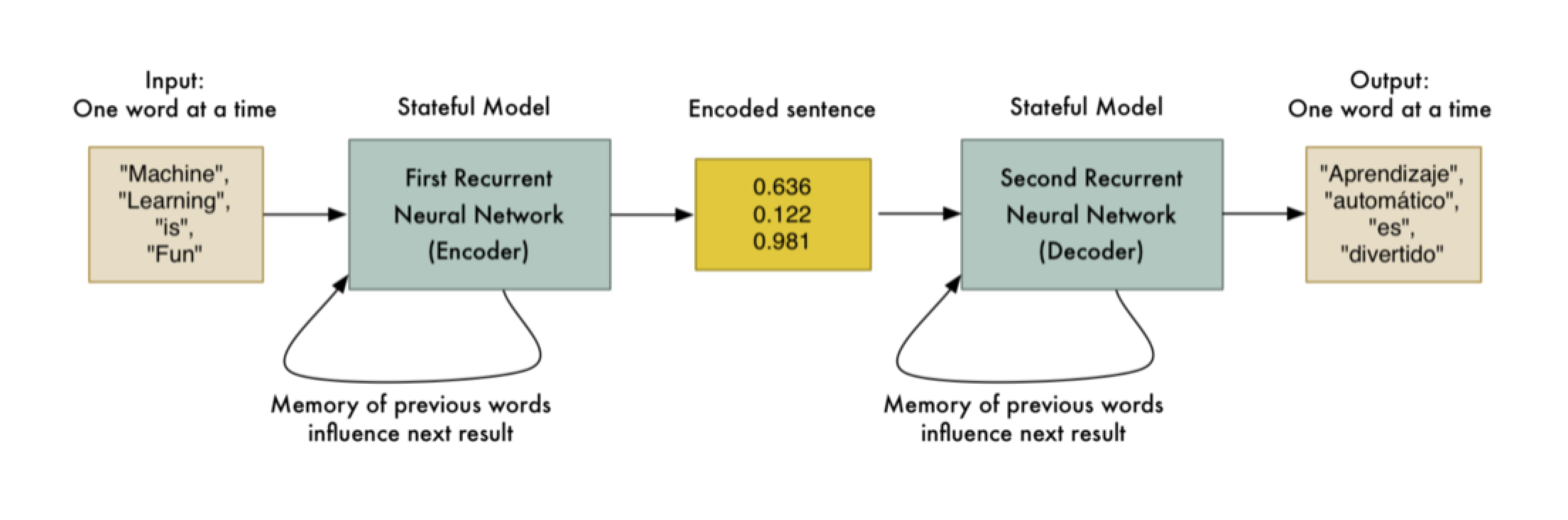


1) Recurrent Neural Network (RNN)
A neural network where the previous state of the network is used as one of the inputs to the next calculation. This allows the network to find patterns in a sequence of data.



2) Encoding/Decoding
Turn words into a series of numerical measurements. This permits us to represents every possible different sentence in any language as a series of unique numbers and vice versa.

4. Machine Learning MT



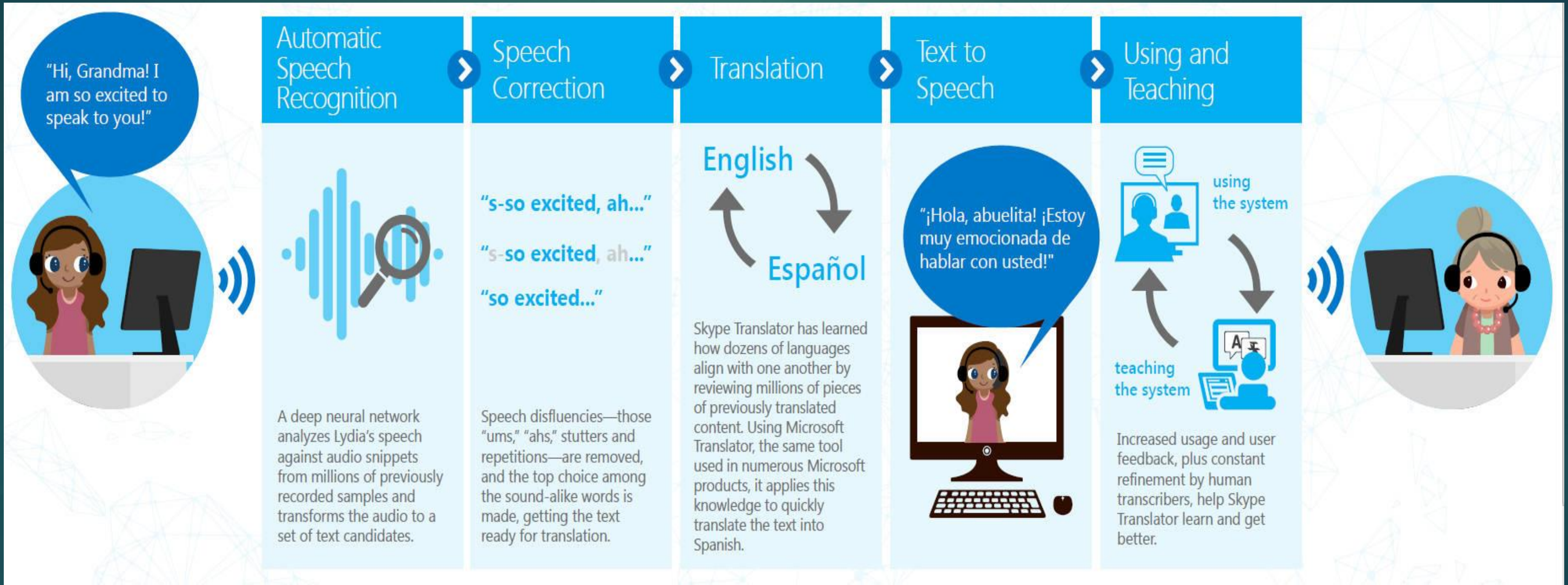
3) Sequence-to-Sequence Translation
Put two RNNs together.
The first RNN generates the encoding that represents an English sentence.
The second RNN takes that encoding and decodes it into Spanish.

4. Machine Learning MT

- Features/Limitations
  - Do not need to know how to translate between languages. The computer figures this out for itself.
  - Limited by the amount of training data and available computer power to process the data.
  - Examples
    - Google Neural Machine Translation (GNMT) – 2016
    - Microsoft Skype (2017)

4. Machine Learning MT

Microsoft Skype



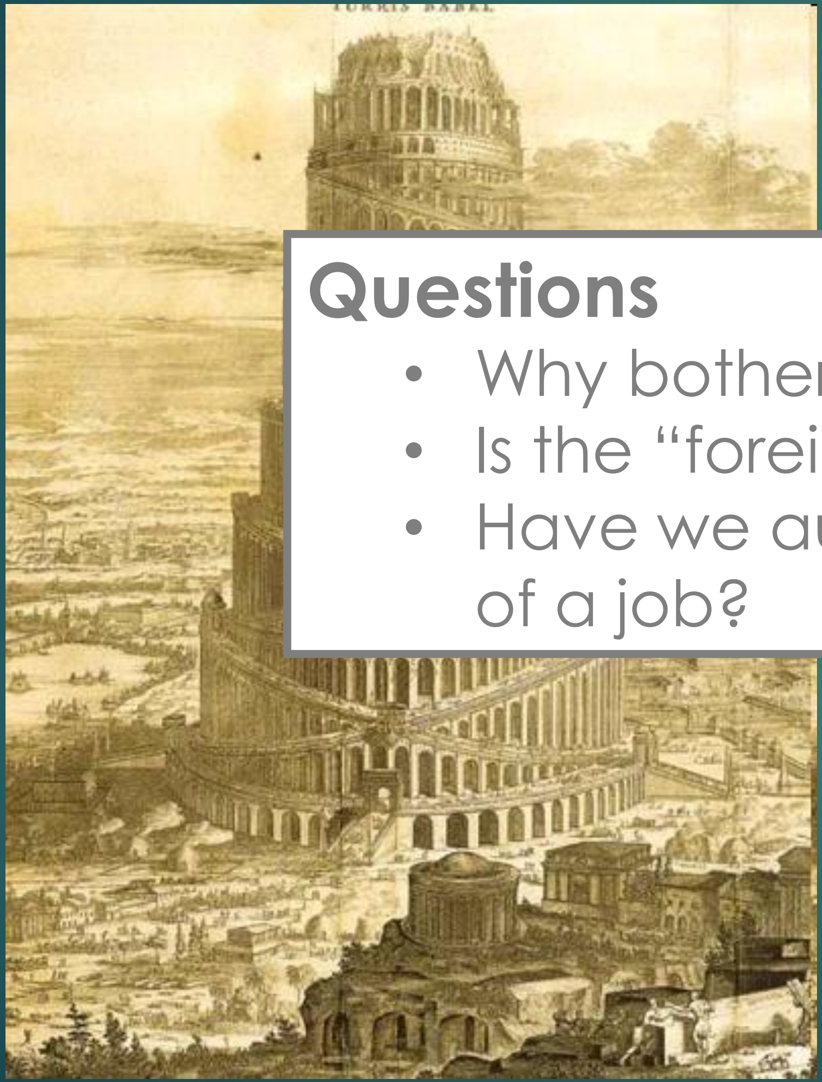
https://www.youtube.com/watch?v=JrlTzS7Fk6o

Review

MT Objective = Real-Time Translation

- *Star Trek* "Universal Translator"
- Overcome linguistic difference

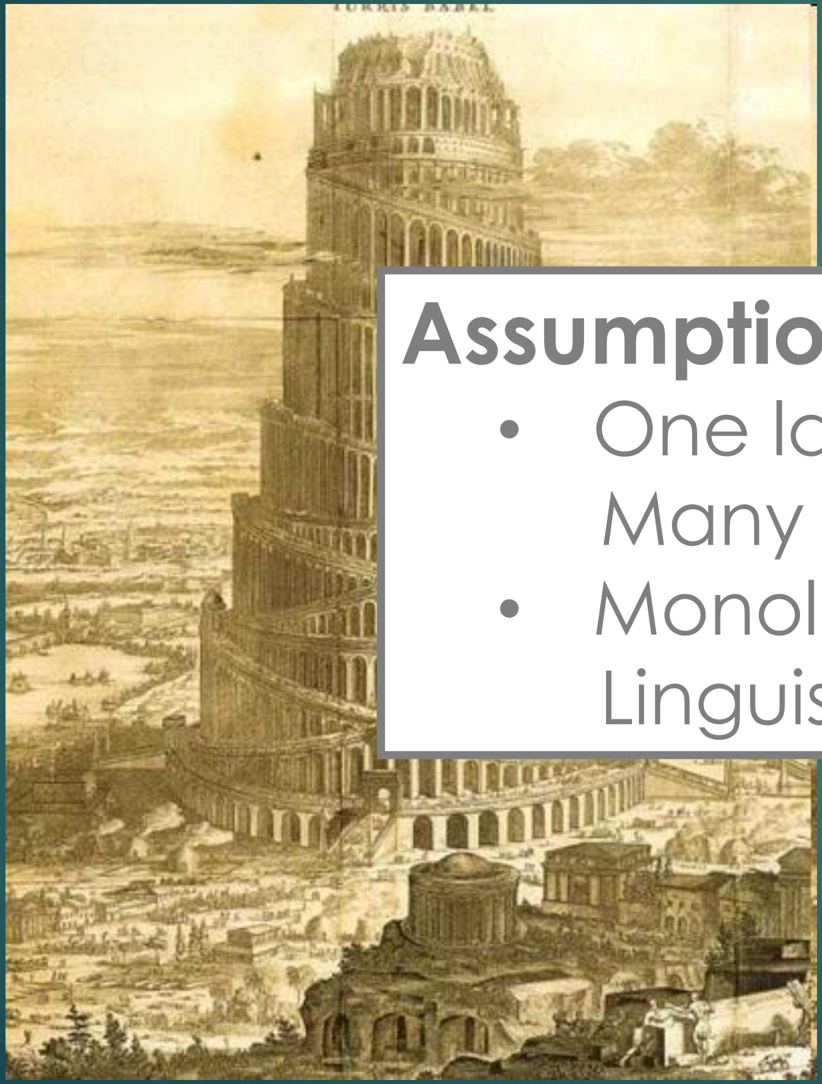
Review



Questions

- Why bother learning another language?
- Is the “foreign language” requirement obsolete?
- Have we automated foreign language learning out of a job?

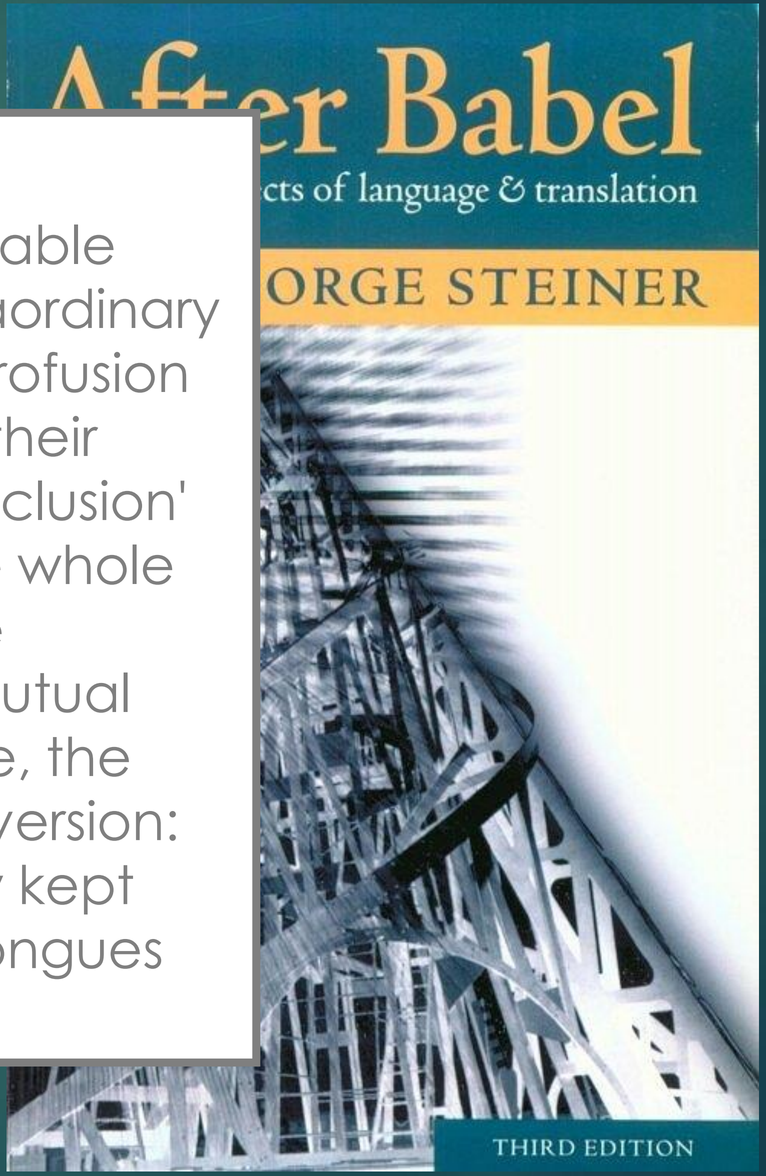
Review



Assumptions from Babel

- One language = Good
  Many languages = Bad
- Monolinguism = God-like Powers
  Linguistic Diversity = Impotence

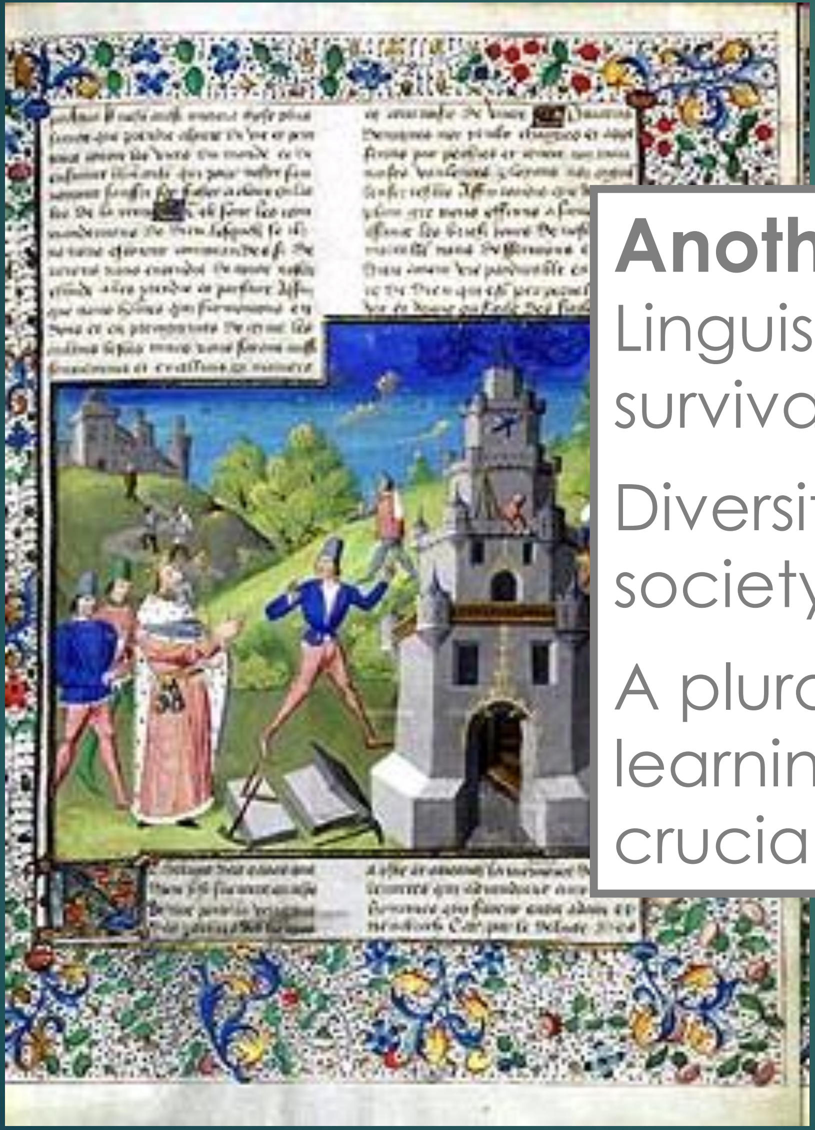
Review



Rethinking Babel

The ripened humanity of language, its indispensable conservative and creative force live in the extraordinary diversity of actual tongues, in the bewildering profusion and eccentricity (though there is no center) of their modes. The psychic need for particularity, for 'inclusion' and invention is so intense that it has, during the whole of man's history until very lately, outweighed the spectacular, obvious material advantages of mutual comprehension and linguistic unity. In that sense, the Babel myth is once again a case of symbolic inversion: mankind was not destroyed but on the contrary kept vital and creative by being scattered among tongues (George Steiner).

Review



Another Perspective on Babel

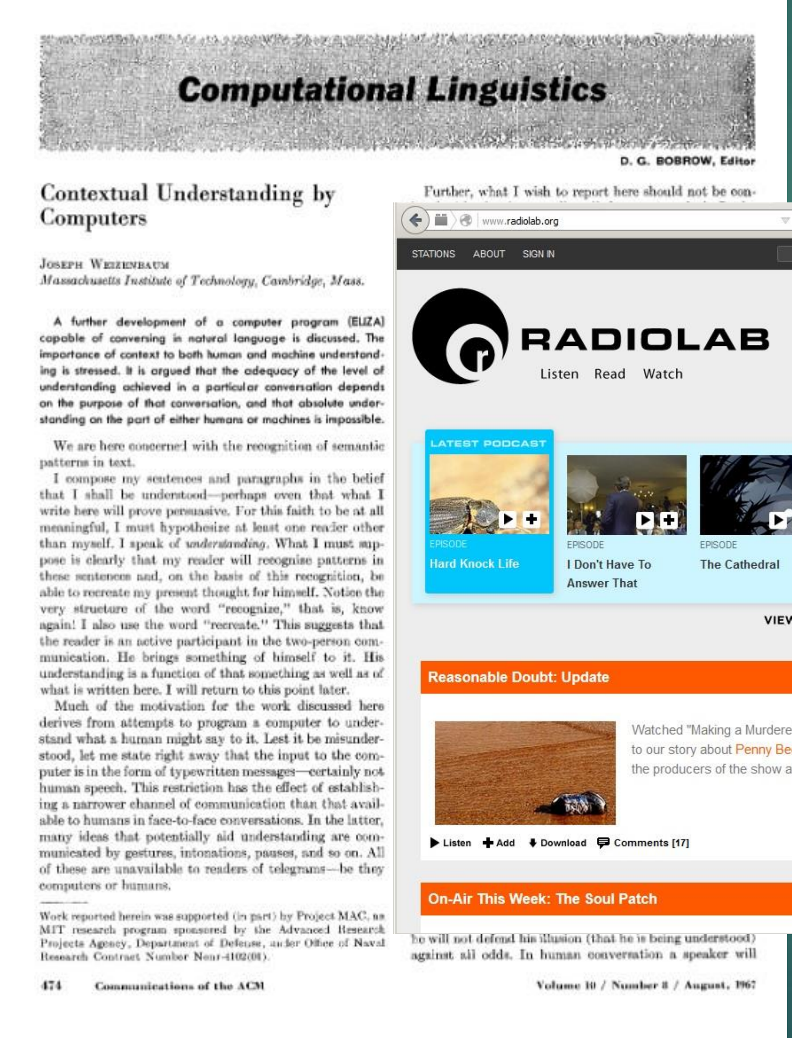
Linguistic diversity is not a bad thing. It is a survival mechanism, like bio-diversity.

Diversity of tongues did not ruin human society but kept it vital and creative.

A plurality of languages is positive and learning to operate in different languages is crucial to human innovation and success.

Today

Natural Language Processing (NLP)



Computational Linguistics

D. G. BOBROW, Editor

Contextual Understanding by Computers

Joseph Weizenbaum
Massachusetts Institute of Technology, Cambridge, Mass.

A further development of a computer program (ELIZA) capable of conversing in natural language is discussed. The importance of context to both human and machine understanding is stressed. It is argued that the adequacy of the level of understanding achieved in a particular conversation depends on the purpose of that conversation, and that absolute understanding on the part of either humans or machines is impossible.

We are here concerned with the recognition of semantic patterns in text.

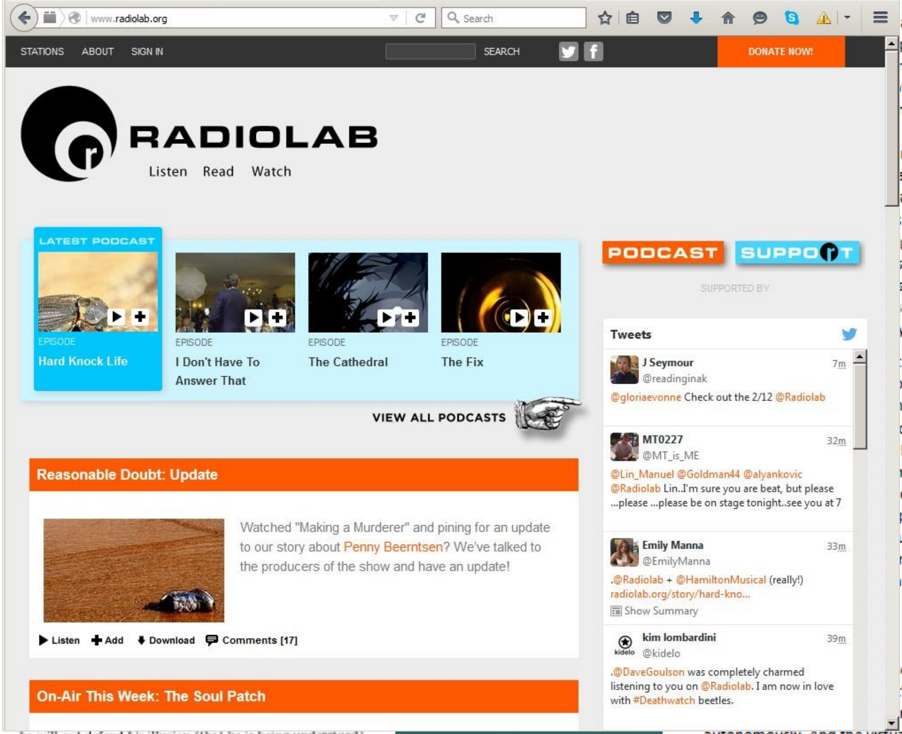
I compose my sentences and paragraphs in the belief that I shall be understood—perhaps even that what I write here will prove persuasive. For this faith to be at all meaningful, I must hypothesize at least one reader other than myself. I speak of *understanding*. What I must suppose is clearly that my reader will recognize patterns in these sentences and, on the basis of this recognition, be able to recreate my present thought for himself. Notice the very structure of the word "recognize," that is, know again! I also use the word "recreate." This suggests that the reader is an active participant in the two-person communication. He brings something of himself to it. His understanding is a function of that something as well as of what is written here. I will return to this point later.

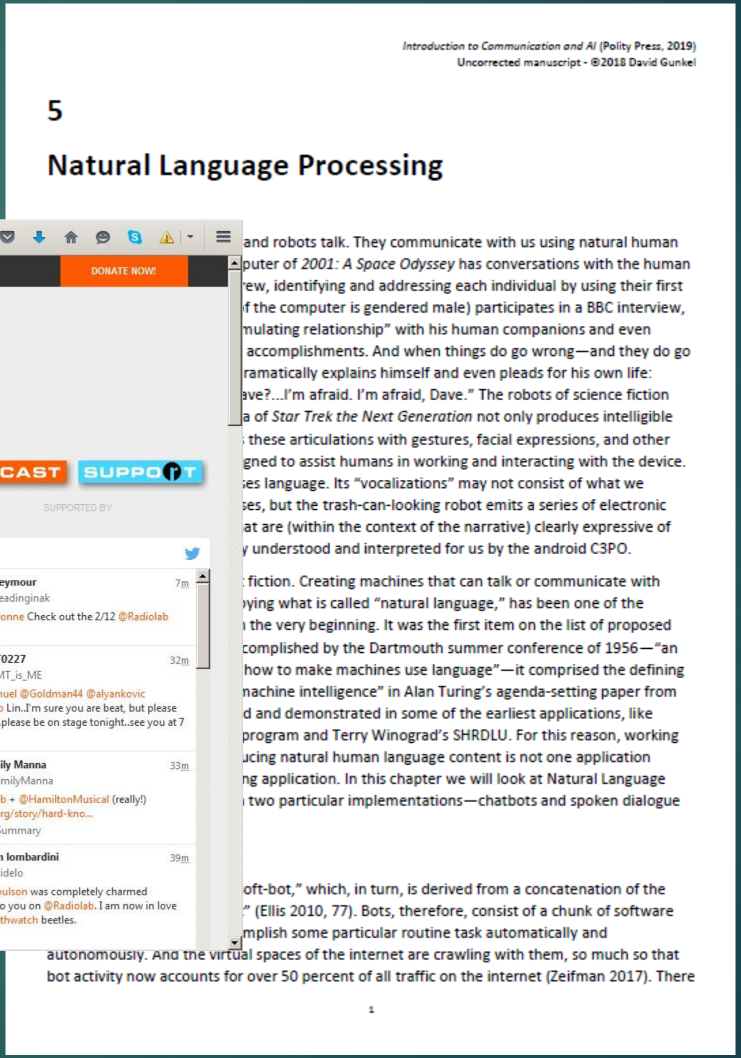
Much of the motivation for the work discussed here derives from attempts to program a computer to understand what a human might say to it. Lest it be misunderstood, let me state right away that the input to the computer is in the form of typewritten messages—certainly not human speech. This restriction has the effect of establishing a narrower channel of communication than that available to humans in face-to-face conversations. In the latter, many ideas that potentially aid understanding are communicated by gestures, intonations, pauses, and so on. All of these are unavailable to readers of telegrams—be they computers or humans.

Work reported herein was supported (in part) by Project MAC, an MIT research program sponsored by the Advanced Research Projects Agency, Department of Defense, under Office of Naval Research Contract Number Nonr-4102(01).

Further, what I wish to report here should not be con-

he will not defend his illusion (that he is being understood) against all odds. In human conversation a speaker will





5

Natural Language Processing

and robots talk. They communicate with us using natural human
puter of *2001: A Space Odyssey* has conversations with the human
rew, identifying and addressing each individual by using their first
f the computer is gendered male) participates in a BBC interview,
mulating relationship" with his human companions and even
accomplishments. And when things do go wrong—and they do go
ramatically explains himself and even pleads for his own life:
ave?...I'm afraid. I'm afraid, Dave." The robots of science fiction
a of *Star Trek the Next Generation* not only produces intelligible
these articulations with gestures, facial expressions, and other
gned to assist humans in working and interacting with the device.
es language. Its "vocalizations" may not consist of what we
es, but the trash-can-looking robot emits a series of electronic
at are (within the context of the narrative) clearly expressive of
y understood and interpreted for us by the android C3PO.

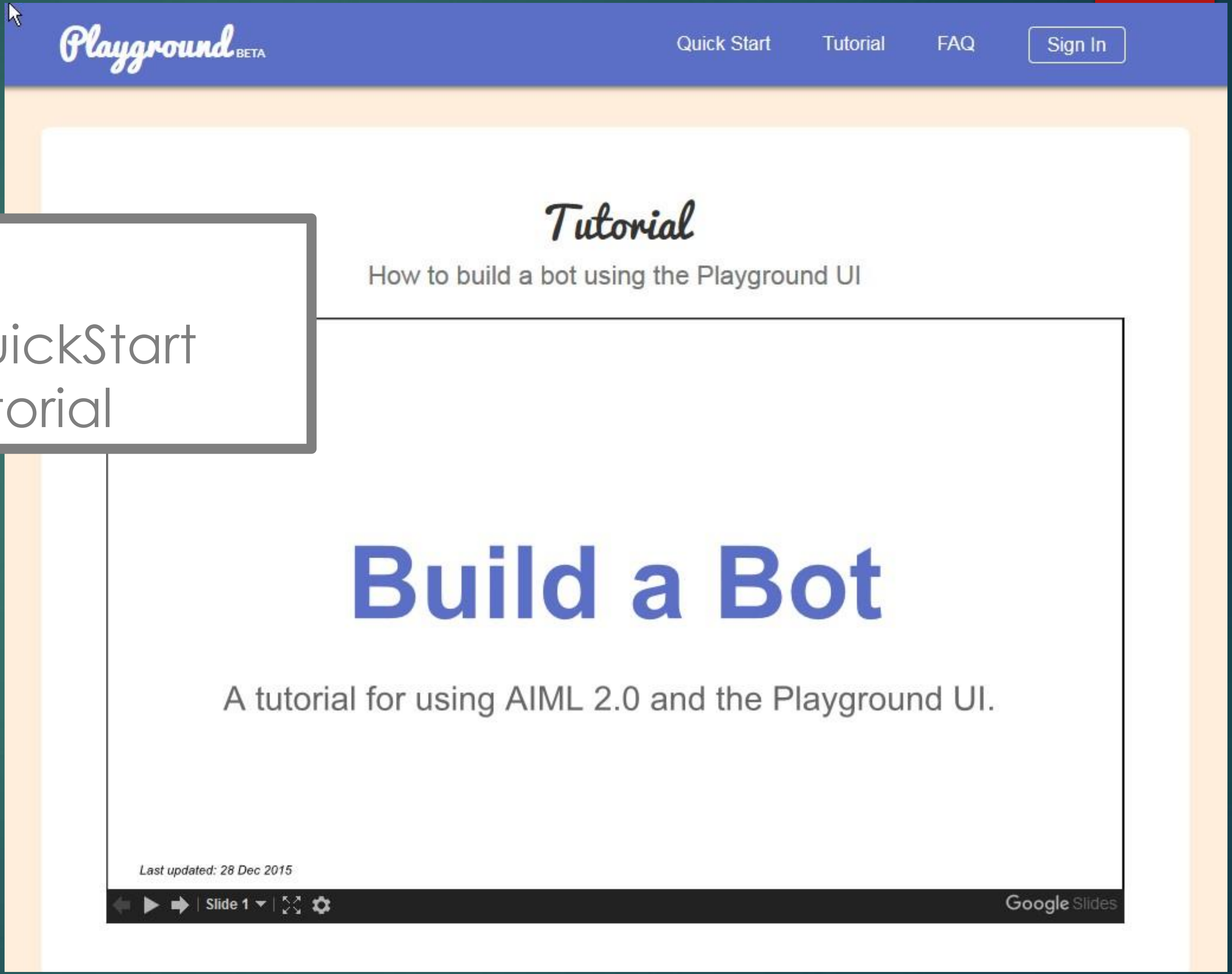
fiction. Creating machines that can talk or communicate with
ying what is called "natural language," has been one of the
the very beginning. It was the first item on the list of proposed
complished by the Dartmouth summer conference of 1956—"an
how to make machines use language"—it comprised the defining
nachine intelligence" in Alan Turing's agenda-setting paper from
d and demonstrated in some of the earliest applications, like
program and Terry Winograd's SHRDLU. For this reason, working
ucing natural human language content is not one application
ng application. In this chapter we will look at Natural Language
two particular implementations—chatbots and spoken dialogue

oft-bot," which, in turn, is derived from a concatenation of the
" (Ellis 2010, 77). Bots, therefore, consist of a chunk of software
mplish some particular routine task automatically and
autonomously. And the virtual spaces of the internet are crawling with them, so much so that
bot activity now accounts for over 50 percent of all traffic on the internet (Zeifman 2017). There

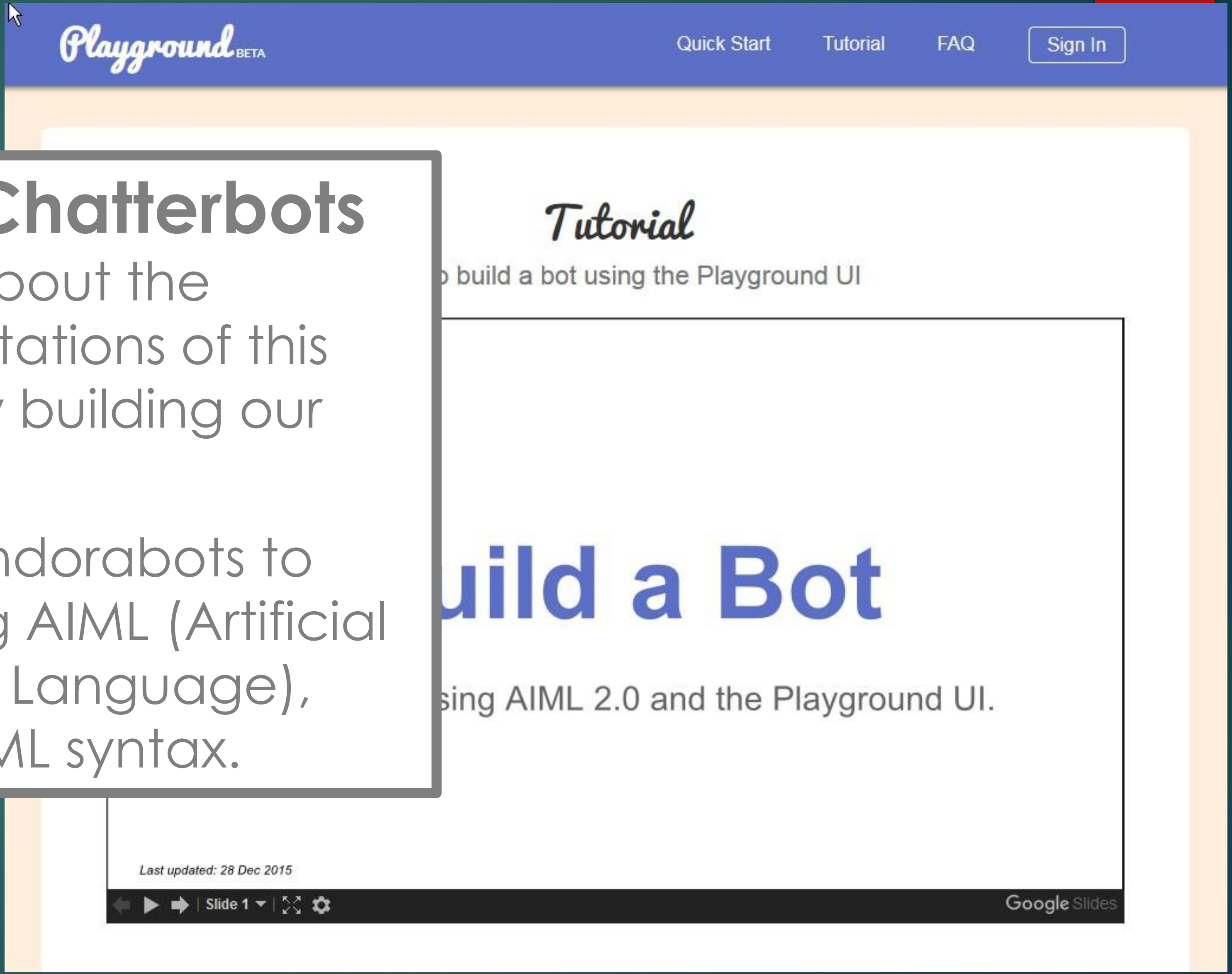
Exercise

Chatterbots

- PandoraBot QuickStart
- PandoraBot Tutorial



Exercise



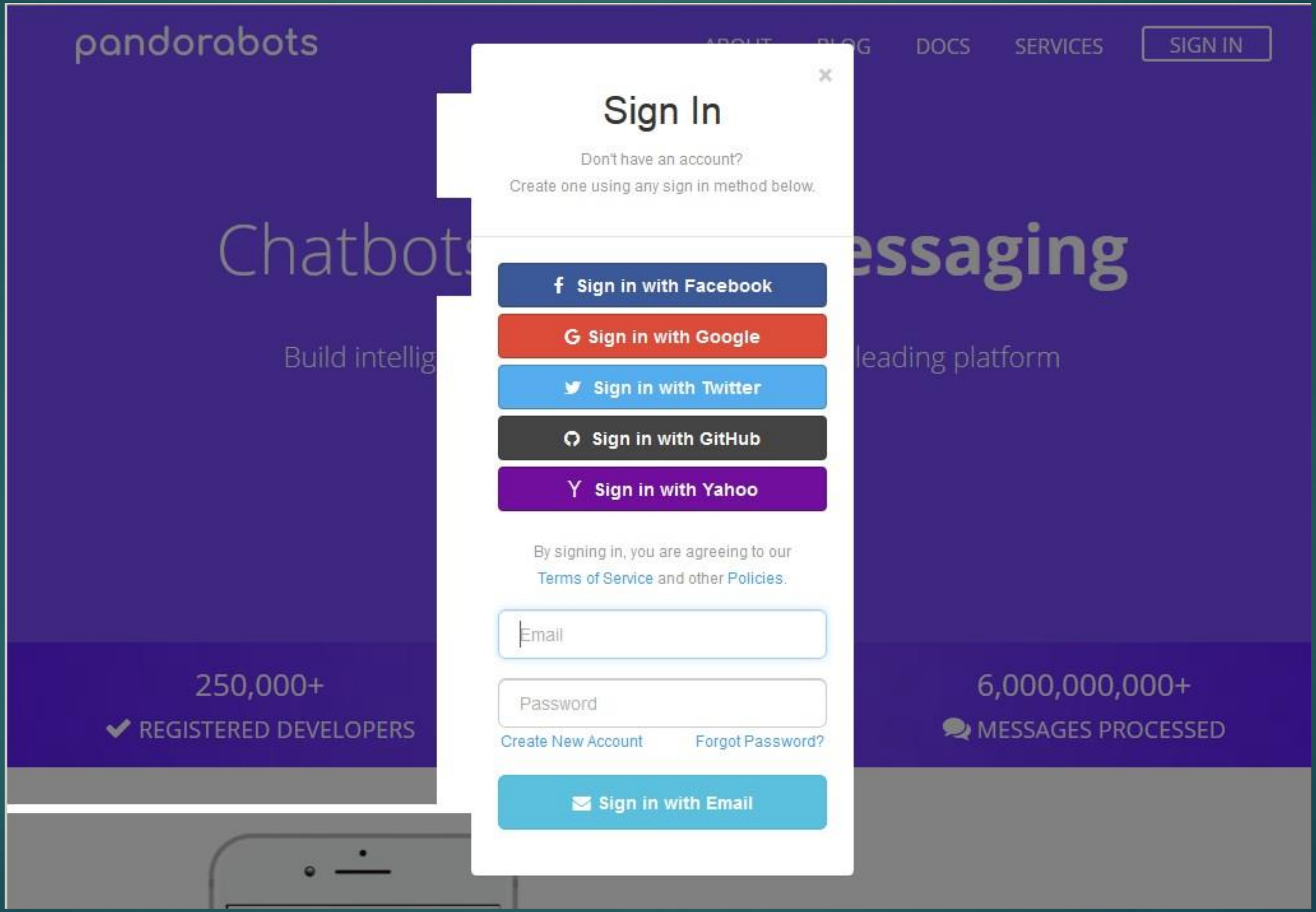
Experiment with Chatterbots

Objective – Learn about the capabilities and limitations of this approach to NLP by building our own chatterbot.

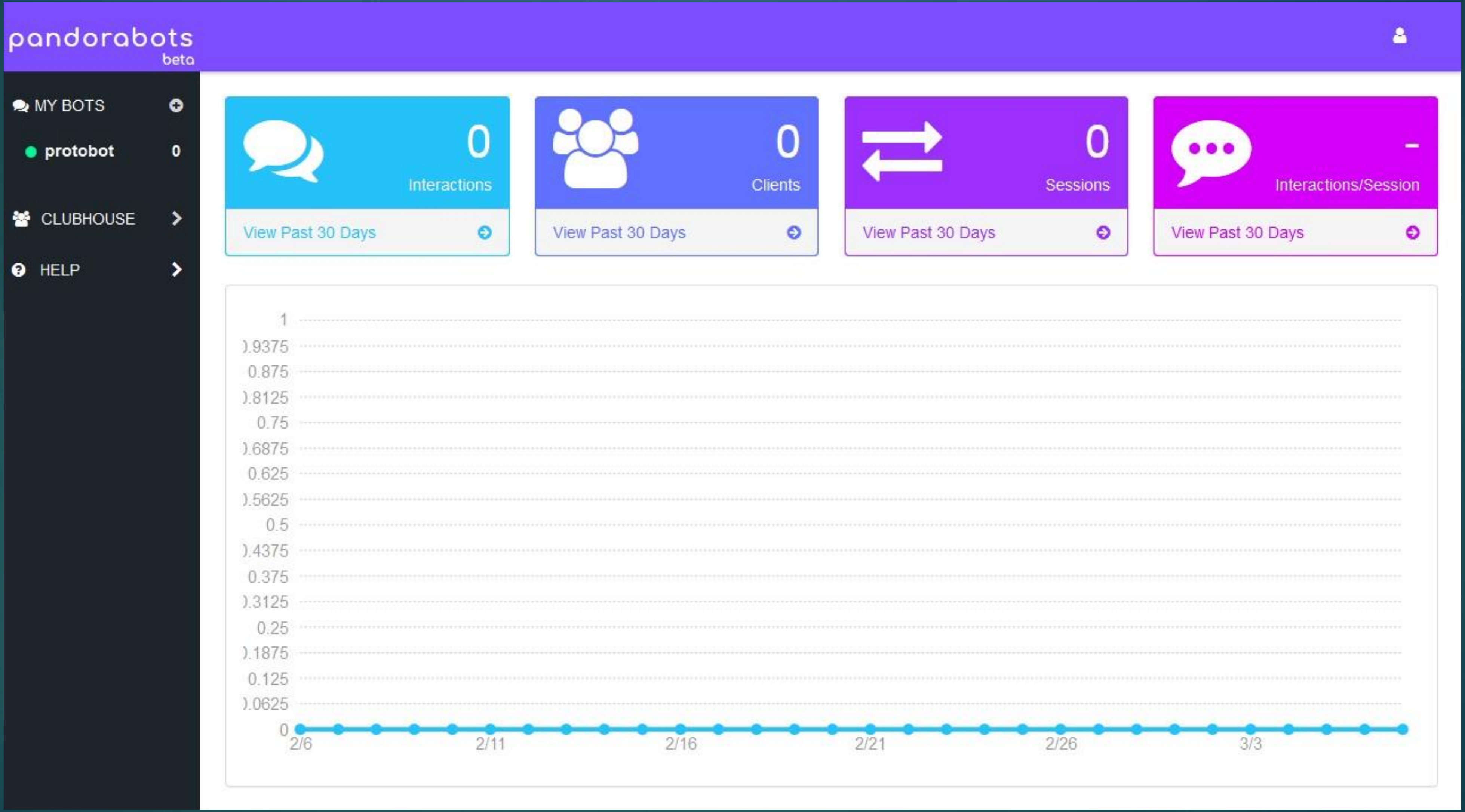
Procedure – Use Pandorabots to program a bot using AIML (Artificial Intelligence Markup Language), which is written in XML syntax.

Sign In

http://pandorabots.com

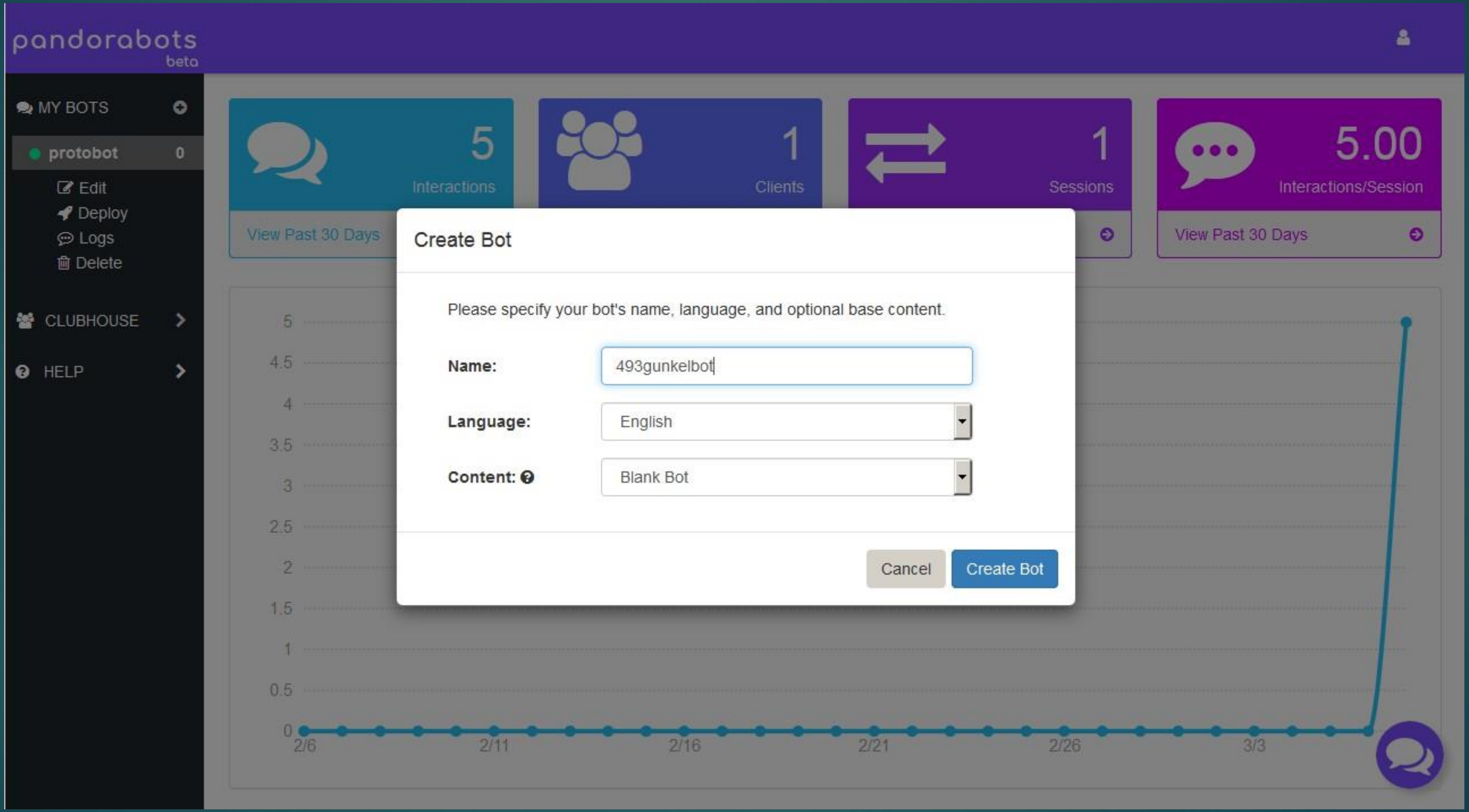


Editor

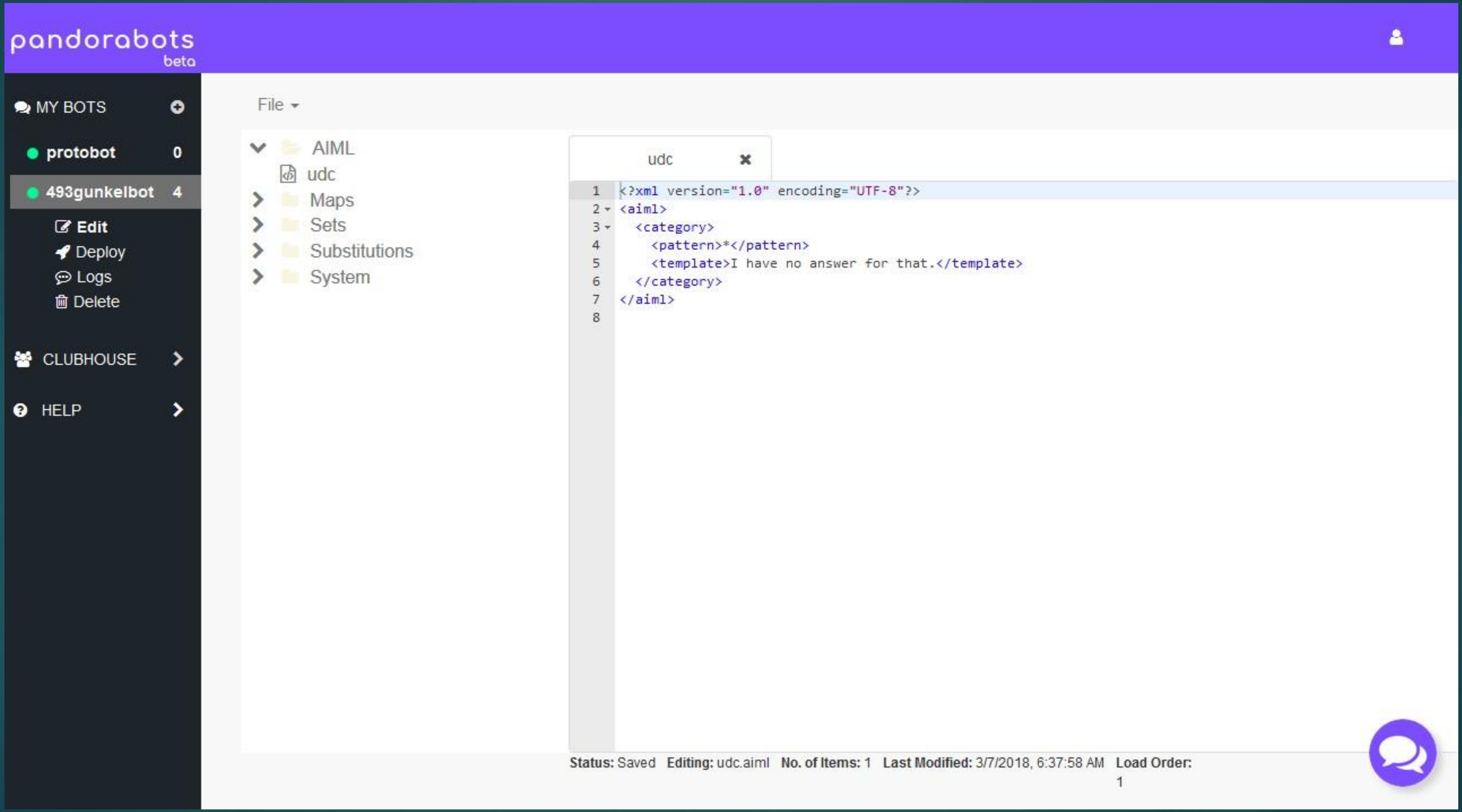

pandorabots
beta
MY BOTS
protobot
0
CLUBHOUSE
HELP
0
Interactions
View Past 30 Days
0
Clients
View Past 30 Days
0
Sessions
View Past 30 Days
-
Interactions/Session
View Past 30 Days
1
).9375
0.875
).8125
0.75
).6875
0.625
).5625
0.5
).4375
0.375
).3125
0.25
).1875
0.125
).0625
0
2/6
2/11
2/16
2/21
2/26
3/3

Create New Bot

493 + Last Name + bot



Files – Write AIML



Writing AIML

XML Primer

AIML is an extension of a language called XML.

It is written using “tags” (code) and text..

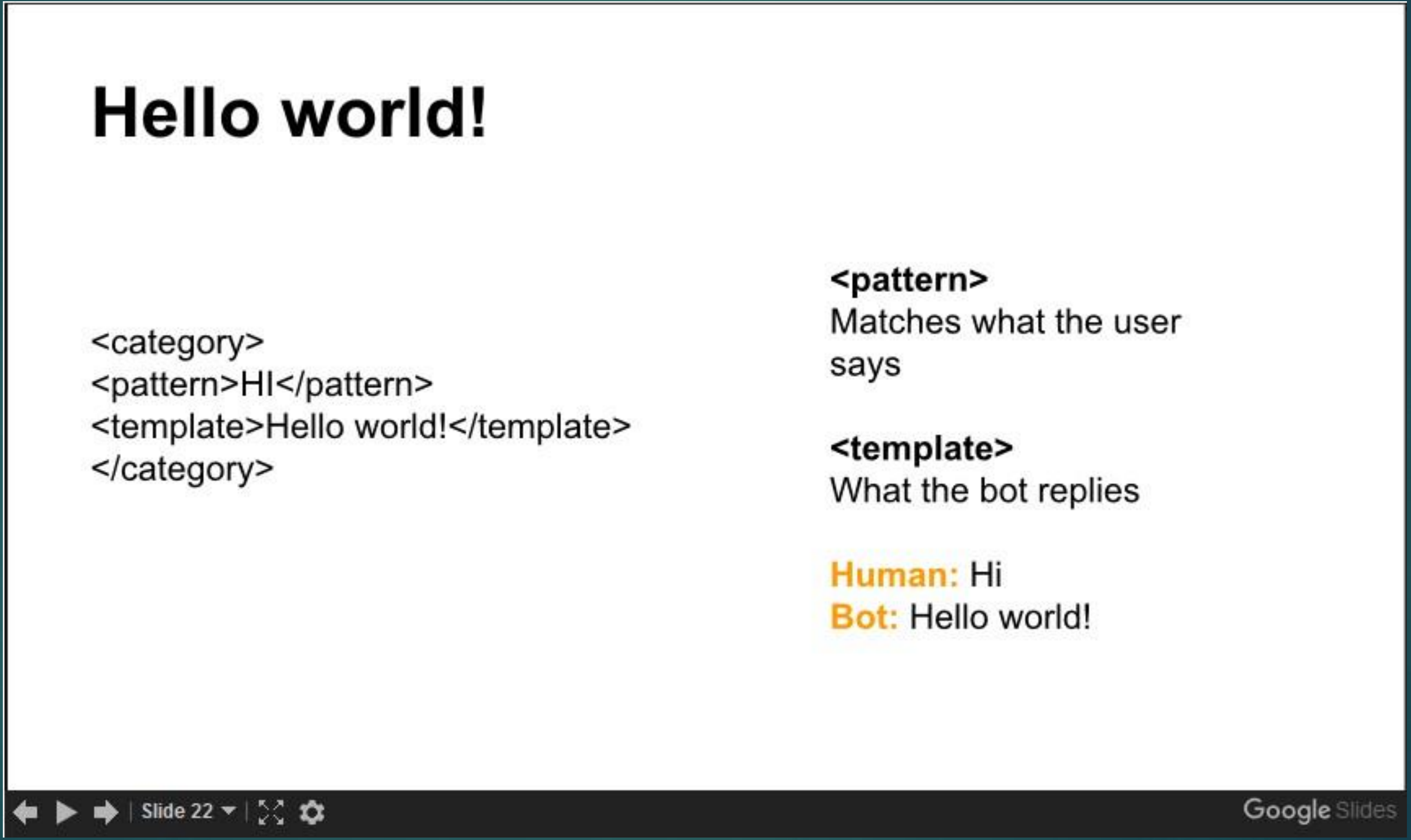
Some tags come in pairs, with some content (text and/or other tags) appearing in between:

<template>Some string goes here</template>

While others are “self-closing” and do not require a partner or an inner string:

<get name=“age” />

Writing AIML



Writing AIML

Explaining the “tags”

<category> - delineates the beginning and end of the category.

<pattern>HI</pattern> - defines a pattern that matches a certain input from the user. *AIML matching does not differentiate between capital and lowercase letters (i.e. if the client said either “hi” or “HI”, the bot would match this category. We use all caps to make the code more readable).*

<template>Hello world!</template> - defines the bot’s response to the matched pattern. Capital letters do matter in the template!

</category> - marks the end of the category

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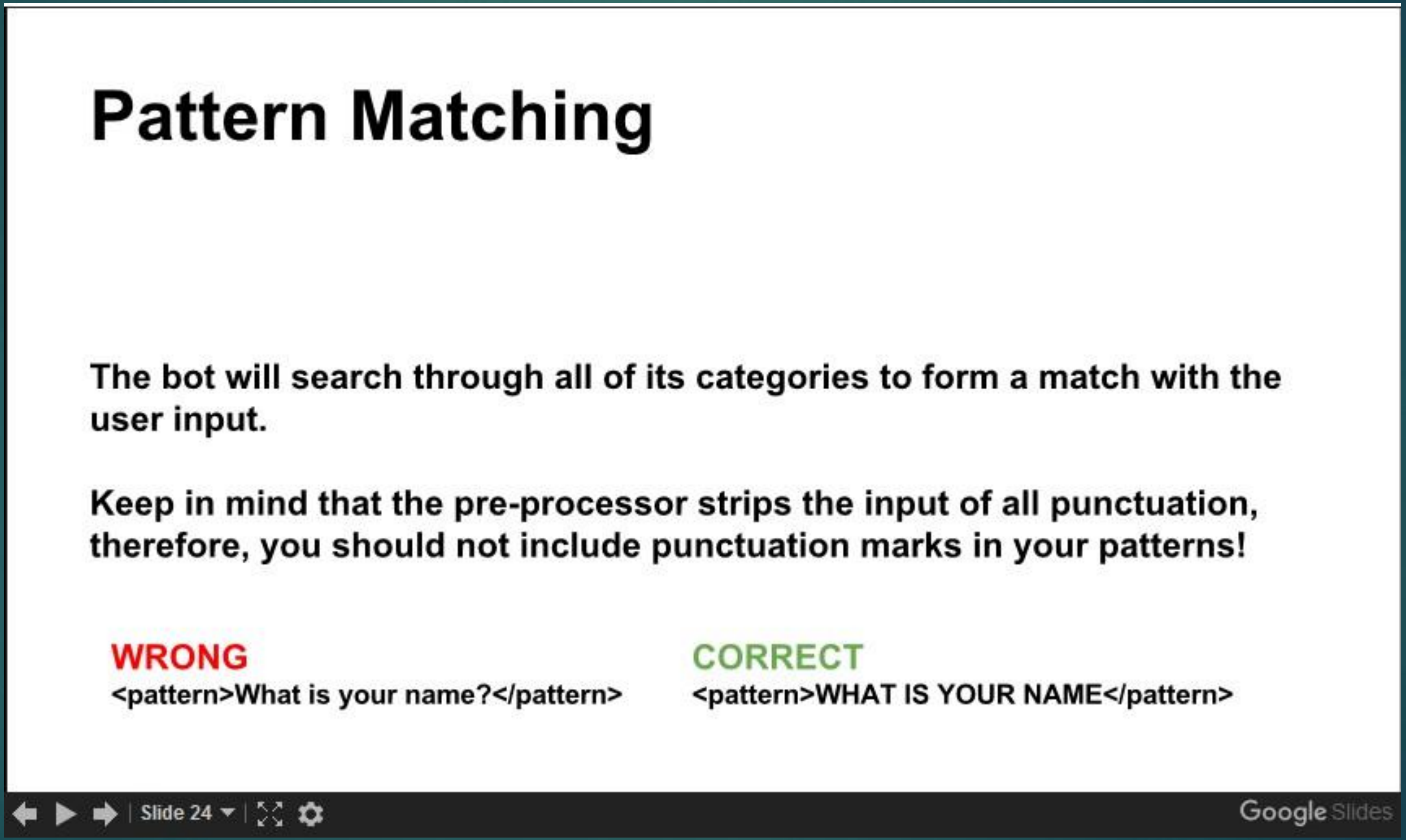
Writing AIML



Writing AIML

Ultimate Default Category (UDC)

What if the user input does not match any of the patterns you have defined?

The Ultimate Default Category (UDC) is used by the bot to provide an answer if no other suitable category can be matched.

```
<category>
<pattern>*</pattern>
<template>I have no answer for that.</template>
</category>
```

Writing AIML

Randomized responses

You can use the <random> tag to provide many different responses for the same input pattern. This is especially useful in the UDC because it can hide the fact that your bot is relying on a default answer.

```
<category>
<pattern>*</pattern>
<template>
<random>
<li>What was that?</li>
<li>I don't understand</li>
<li>Can you say that more clearly?</li>
</random>
</template>
</category>
```

Each time this category is matched, the bot will pick one of the list elements (<li>) at random as its response.

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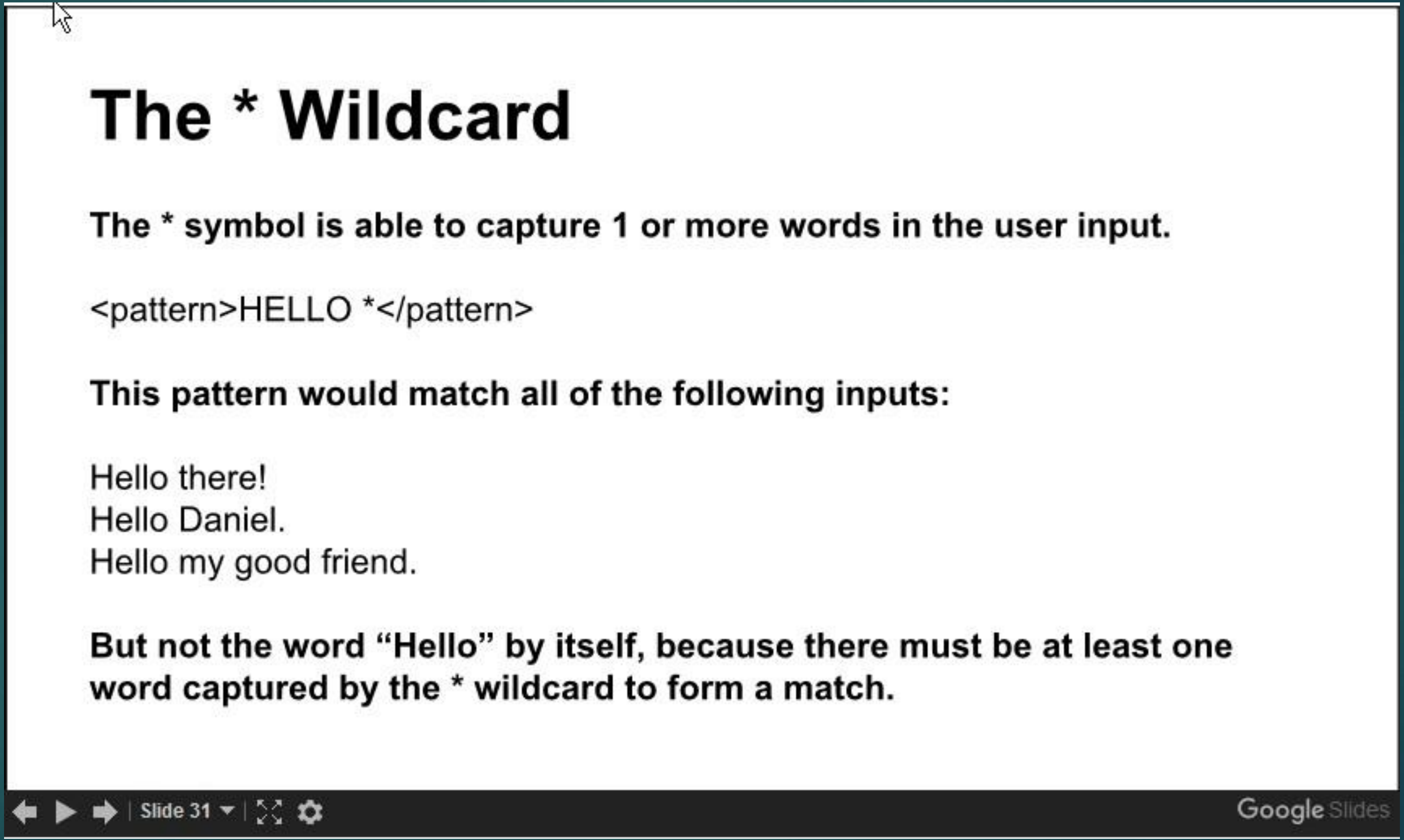
Wildcards *


The * Wildcard
The * symbol is able to capture 1 or more words in the user input.
<pattern>HELLO *</pattern>
This pattern would match all of the following inputs:
Hello there!
Hello Daniel.
Hello my good friend.
But not the word “Hello” by itself, because there must be at least one word captured by the * wildcard to form a match.
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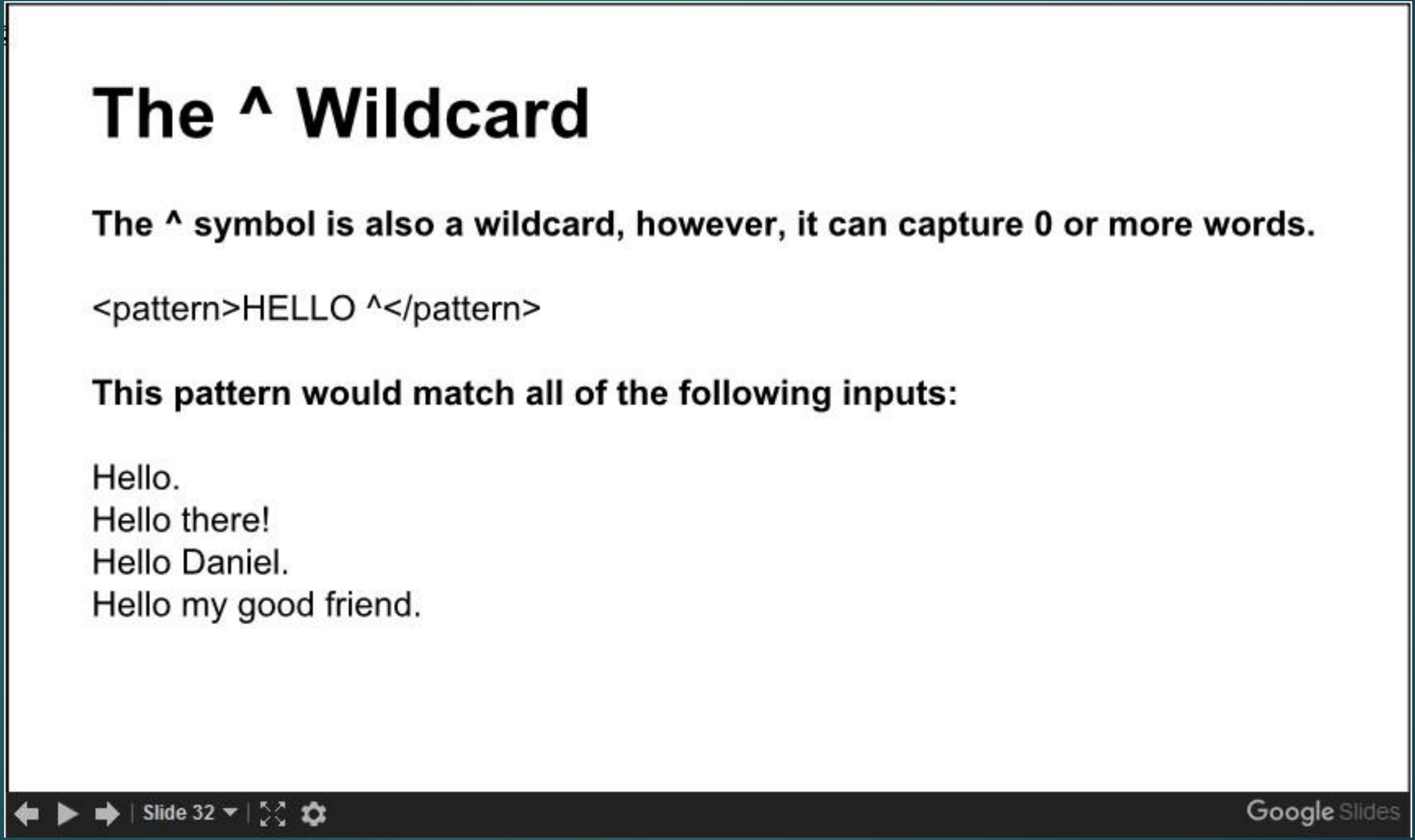
Wildcards ^


The ^ Wildcard
The ^ symbol is also a wildcard, however, it can capture 0 or more words.
<pattern>HELLO ^</pattern>
This pattern would match all of the following inputs:
Hello.
Hello there!
Hello Daniel.
Hello my good friend.
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Wildcards - <star/>

More Wildcards

You can "echo" the words captured by the wildcard from within the template by using the <star/> tag.

```
<category>
<pattern>MY NAME IS *</pattern>
<template>Hello, <star/>.</template>
</category>
```

Human: My name is Daniel
Bot: Hello, Daniel.

Wildcards - <star index="n"/>

Multiple Wildcards

You can have more than one wildcard per pattern. You can echo multiple wildcards in your pattern by using <star index="x"/>, where x corresponds to the index number (position in the sentence) of the wildcard:

```
<category>
<pattern>MY NAME IS * AND I AM * YEARS OLD</pattern>
<template>Hi <star/>. I am also <star index="2"/> years old!</template>
</category>
```

Variables

What are variables?

In programming, a variable is a symbol whose value can be changed.

AIML has variables as well. These can be used to store information about your bot, user, or anything else you would like. There are 3 types:

1. <u>Properties</u> - global constants for a bot. Can only be changed by the botmaster.

2. <u>Predicates</u> - global variables for the bot. Usually set by the client when a template is activated.

3. <u>Local variables</u> - which are just like predicates, except their scope is limited to one category.

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Variables – Predicate

Setting Predicates

Using a predicate variable, you can write a category that will store the name of the client. This category will store the client's name under a predicate called "name":

```
<category>
<pattern>MY NAME IS *</pattern>
<template>Nice to meet you, <set name="name"><star/></set></template>
</category>
```

Note how the use of the * wildcard and <star/> allows us to write a single category that will capture any name!

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Variables – Predicate

Recalling Predicates

Once you have set a predicate, it can be recalled elsewhere in your AIML.

```
<category>
<pattern>WHAT IS MY NAME</pattern>
<template>Your name is <get name="name"/>.</template>
</category>
```

If you have set the predicate using the category on the previous page, this will now recall the value of the predicate called "name".

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Variables – Predicate

Predicates (altogether)

The categories you have just written would enable a conversation like the one below:

Human: My name is Daniel.
Bot: Nice to meet you, Daniel.

Human: What is my name?
Bot: Your name is Daniel.

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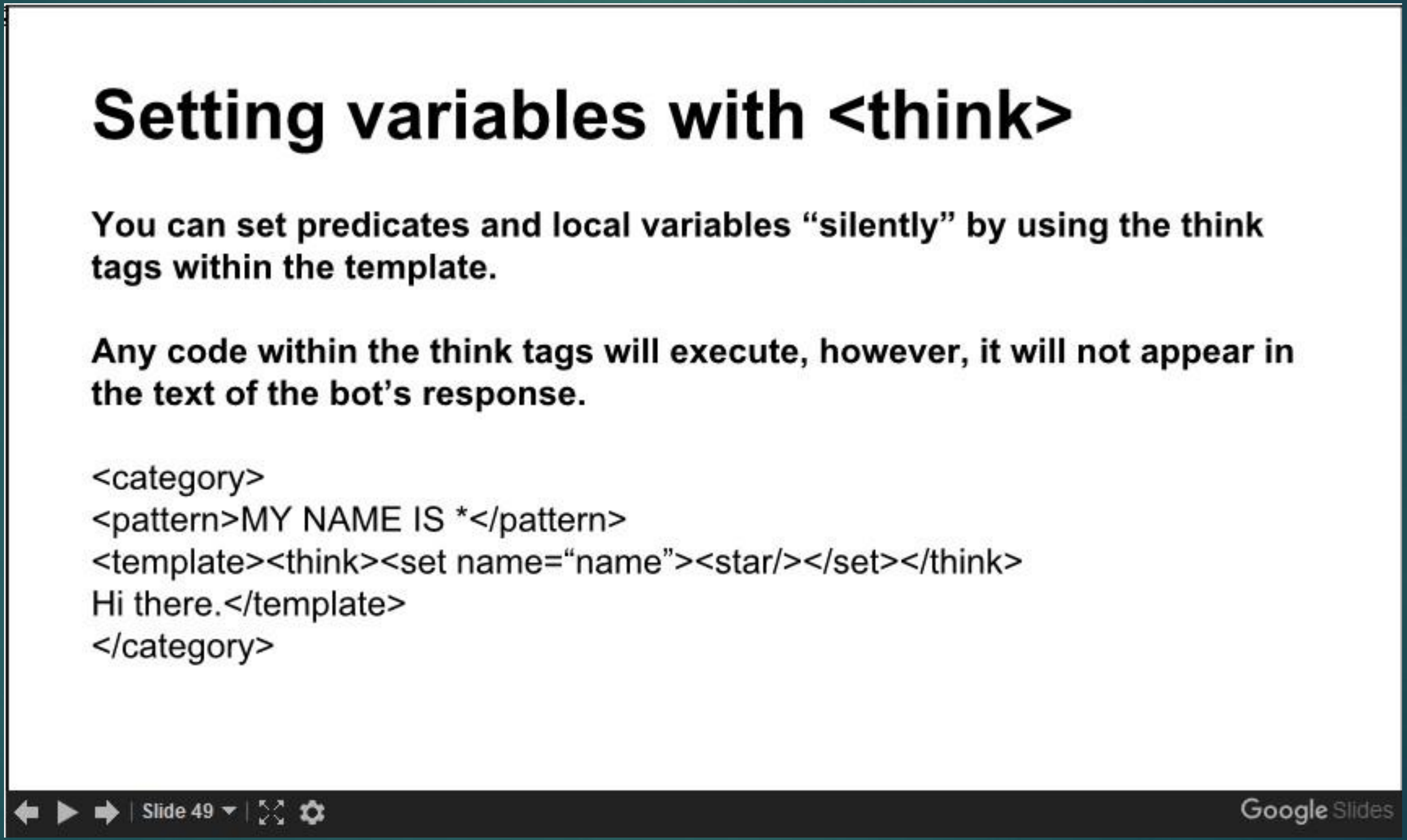
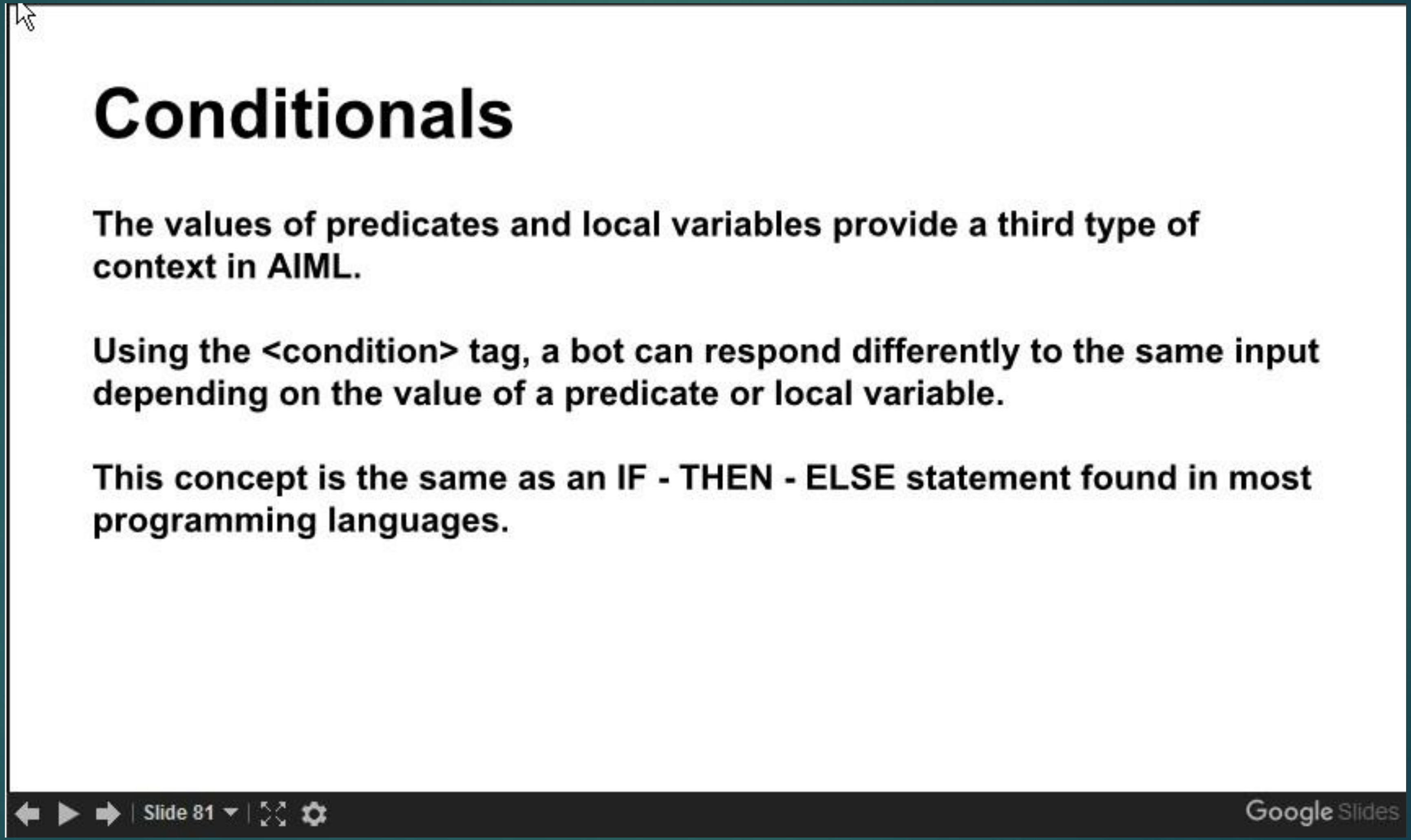
Variables – <think>



Conditionals



Conditionals

Conditionals: Test Case I

Consider the following:

Human: Today is Monday.
Bot: The start of the work week!
Human: Today is Tuesday.
Bot: Tuesday already?
Human: Today is Wednesday.
Bot: Humpday, we're halfway to the weekend!

The bot answers differently depending on what day it is.

Using the <condition> tag, we can enable this conversation with a single category!

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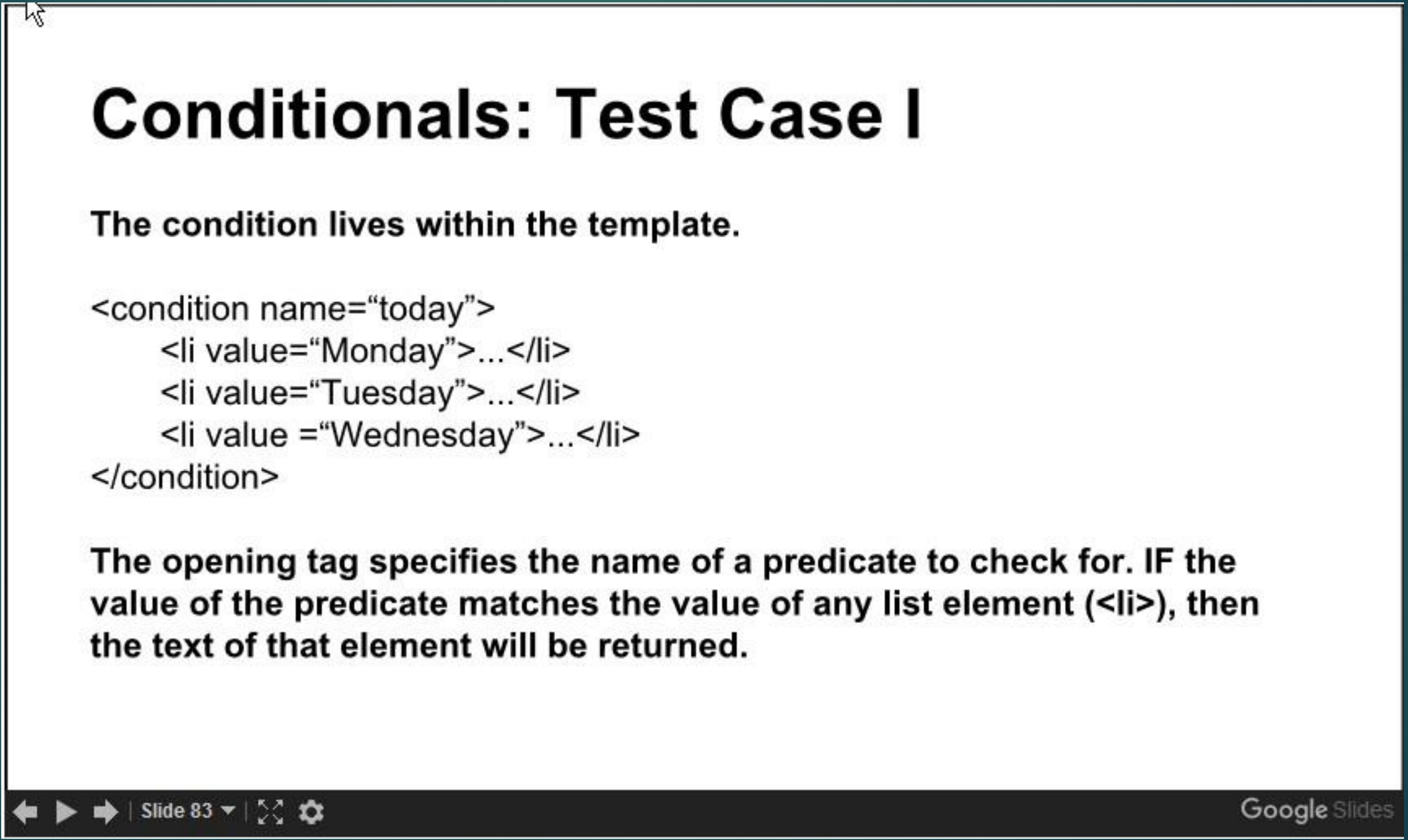
Conditionals



Conditionals

Conditionals: Test Case I

Altogether, the category for our test case would look like this:

```
<category>
<pattern>TODAY IS *</pattern>
<template>
<think><set name="today"> <star/></set></think>
<condition name="today">
<li value="Monday">Ah. The start of a new week.</li>
<li value="Tuesday">Tuesday already?</li>
<li value="Wednesday>Humpday, halfway to the weekend!</li>
...
<li>That isn't the name of a day!</li>
</condition>
</template>
</category>
```

The final list element (the one without a value attribute) will be returned if the none of the other conditions are met.

Conditionals

Conditionals: Test Case II

You can also use conditionals to check the status of a predicate, i.e. whether or not it has been set.

```
<category>
<pattern>WHAT IS MY NAME</pattern>
<template>
<condition name=“name”>
<li value=“*”>Your name is <get name=“name”></li>
<li>You haven’t told me your name yet!</li>
</condition>
</template>
</category>
```

If the “name” predicate has been set to anything (denoted by the asterisk), the first list element will return, otherwise the second.