COMPUTER SCIENCE
UNIVERSITY OF MARYLAND

# Machine Translation History & Evaluation

## CMSC 470

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# Today's topics
# Machine Translation

- Context: Historical Background

- Machine Translation Evaluation

# 1947

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

Warren Weaver

# 1950s-1960s

- 1954 Georgetown-IBM experiment
  - 250 words, 6 grammar rules
- 1966 ALPAC report
  - Skeptical in research progress
  - Led to decreased US government funding for MT

# Rule based systems

- Approach
  - Build dictionaries
  - Write transformation rules
  - Refine, refine, refine
- Meteo system for weather forecasts (1976)
- Systran (1968), …

```
"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"
```

# 1988

## A Statistical Approach to Machine Translation

Peter F. Brown, John Cocke, Stephen A. Della Pietra, Vincent J. Della Pietra, Fredrick Jelinek, John D. Lafferty, Robert L. Mercer, and Paul S. Roossin

IBM
Thomas J. Watson Research Center
Yorktown Heights, NY

In this paper, we present a statistical approach to machine translation. We describe the application of our approach to translation from French to English and give preliminary results.

## The COLING Paper Review

The validity of statistical (information theoretic) approach to MT has indeed been recognized, as the authors mention, by Weaver as early as 1949. And was universally recognized as mistaken by 1950. (cf. Hutchins, MT: Past, Present, Future, Ellis Horwood, 1986, pp. 30ff. and references therein) The crude force of computers is not science. The paper is simply beyond the scope of COLING.

More about the IBM story: [20 years of bitext workshop]

# Exercise: Learn Centauri/Arcturan translation from examples [Knight, 1997]

Your assignment, translate this to Arcturan: farok crrrok hihok yorok clok kantok ok-yurp

1a. ok-voon ororok sprok .
1b. at-voon bichat dat .

2a. ok-drubel ok-voon anok plok sprok .
2b. at-drubel at-voon pippat rrat dat .

3a. erok sprok izok hihok ghirok .
3b. totat dat arrat vat hilat .

4a. ok-voon anok drok brok jok .
4b. at-voon krat pippat sat lat .

5a. wiwok farok izok stok .
5b. totat jjat quat cat .

6a. lalok sprok izok jok stok .
6b. wat dat krat quat cat .

7a. lalok farok ororok lalok sprok izok enemok .
7b. wat jjat bichat wat dat vat eneat .

8a. lalok brok anok plok nok .
8b. iat lat pippat rrat nnat .

9a. wiwok nok izok kantok ok-yurp .
9b. totat nnat quat oloat at-yurp .

10a. lalok mok nok yorok ghirok clok .
10b. wat nnat gat mat bat hilat .

11a. lalok nok crrrok hihok yorok zanzanok .
11b. wat nnat arrat mat zanzanat .

12a. lalok rarok nok izok hihok mok .
12b. wat nnat forat arrat vat gat .

# Challenges: word translation ambiguity

- What is the best translation?

$$\text{Sicherheit} \rightarrow \text{security } 14{,}516$$
$$\text{Sicherheit} \rightarrow \text{safety } 10{,}015$$
$$\text{Sicherheit} \rightarrow \text{certainty } 334$$

- Solution intuition: use counts in parallel corpus (aka bitext)
  - Here European Parliament corpus

# Challenges: word order

- Problem: different languages organize words in different order to express the same idea

  En: The red house

  Fr: La maison rouge

- Solution intuition: language modeling!

# Challenges: output language fluency

- What is most fluent?

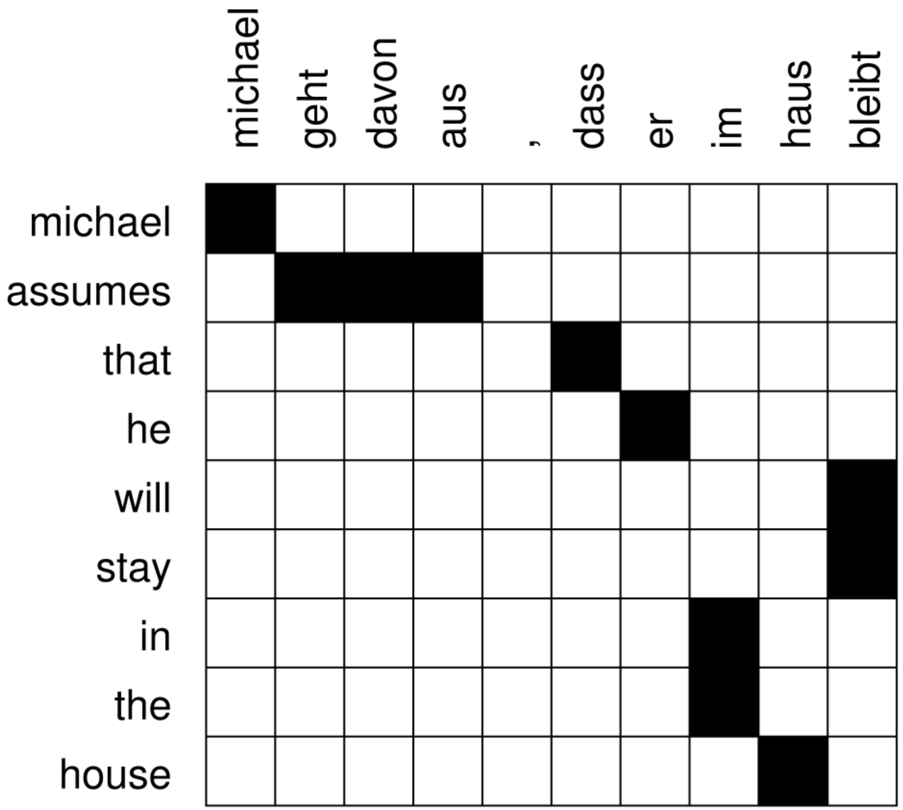
a problem for translation

a problem of translation

a problem in translation

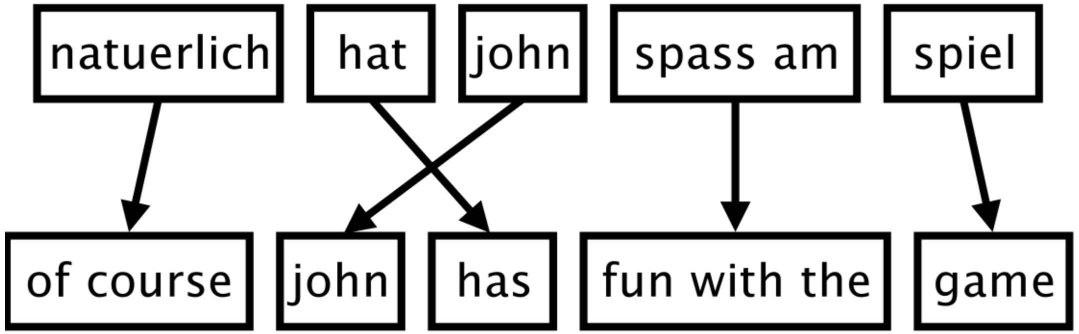
- Solution intuition: a language modeling problem!

# Word Alignment



# Phrase-based Models

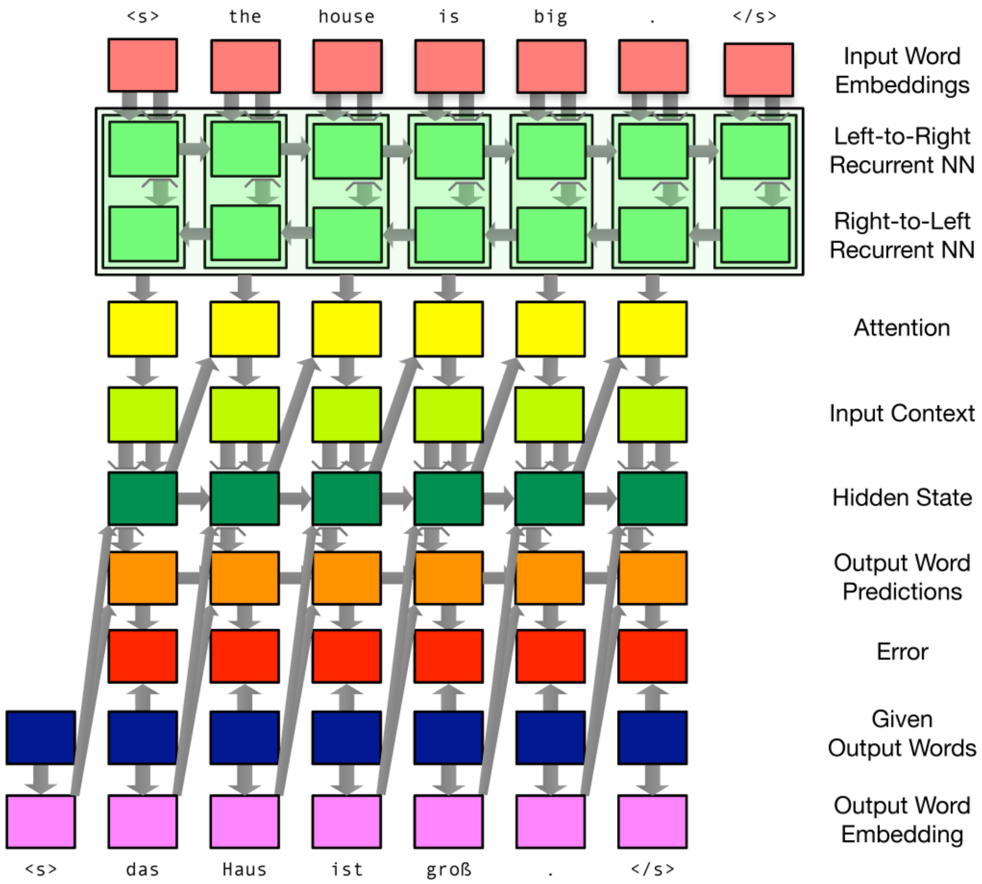
- Input segmented in phrases
- Each phrase is translated in output language
- Phrases are reordered



# Statistical Machine Translation

- 1990s: increased research
- Mid 2000s: phrase-based MT
  - (Moses, Google Translate)
- Around 2010: commercial viability
- Since mid 2010s: neural network models

# Neural MT



<s>
the
house
is
big
.
</s>
Input Word Embeddings
Left-to-Right Recurrent NN
Right-to-Left Recurrent NN
Attention
Input Context
Hidden State
Output Word Predictions
Error
Given Output Words
Output Word Embedding
<s>
das
Haus
ist
groß
.
</s>

# How Good is Machine Translation Today?

March 14 2018:

**“Microsoft reaches a historic milestone, using AI to match human performance in translating news from Chinese to English”**

https://techcrunch.com/2018/03/14/microsoft-announces-breakthrough-in-chinese-to-english-machine-translation/

But also


https://www.haaretz.com/israel-news/palestinian-arrested-over-mistranslated-good-morning-facebook-post-1.5459427

# How Good is Machine Translation Today? Output of Research Systems at WMT18

**上周，古装**剧**《美人私房菜》**临时停播，意外引发了关于国产剧收视率造假的热烈讨论。

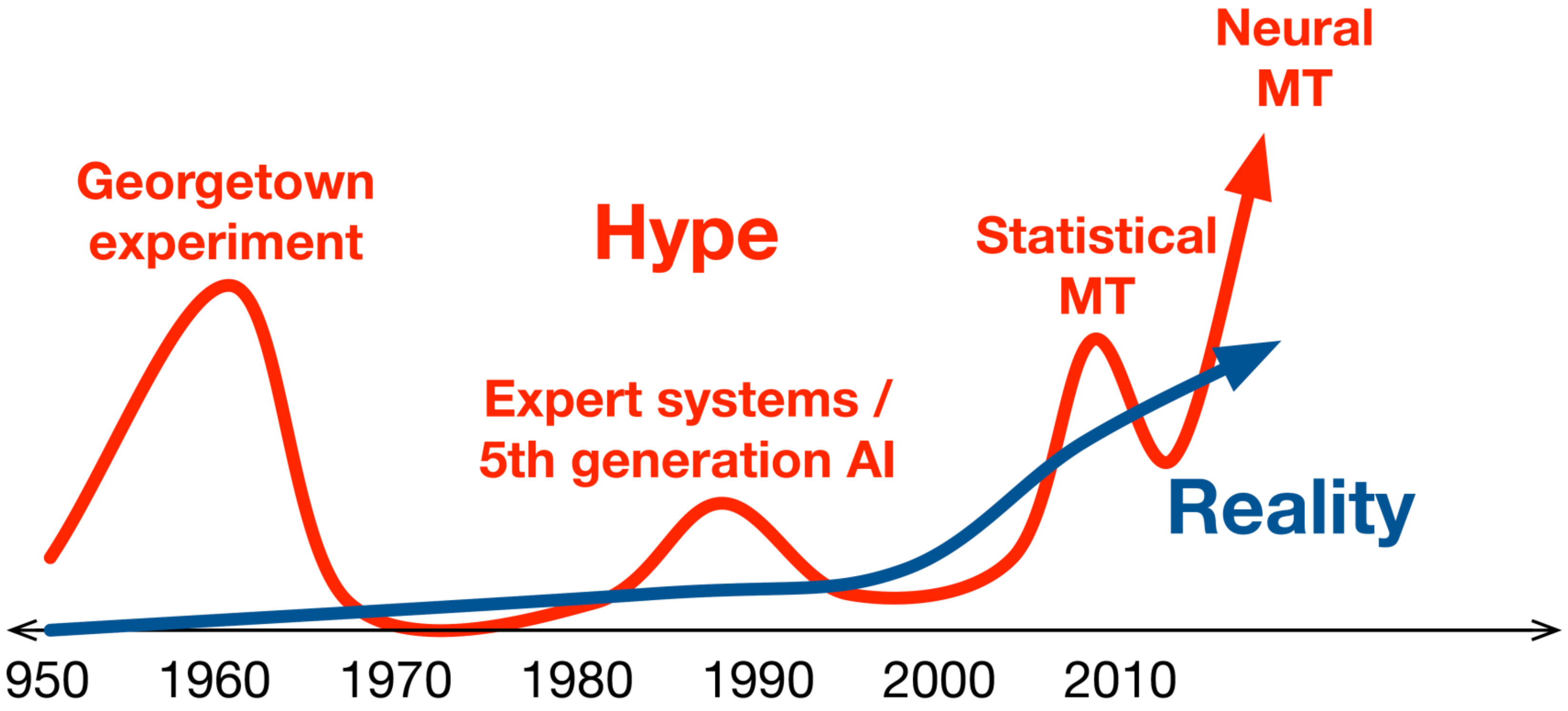
Last week, the vintage drama "Beauty private dishes" was temporarily suspended, accidentally sparking a heated discussion about the fake ratings of domestic dramas.

**民**权团体针对密苏里州发出旅**行警告**

Civil rights groups issue travel warnings against Missouri

http://matrix.statmt.org

# MT History: Hype vs. Reality



# What is MT good (enough) for?

- **Assimilation:** reader initiates translation, wants to know content
  - User is tolerant of inferior quality
  - Focus of majority of research
- **Communication:** participants in conversation don’t speak same language
  - Users can ask questions when something is unclear
  - Chat room translations, hand-held devices
  - Often combined with speech recognition
- **Dissemination:** publisher wants to make content available in other languages
  - High quality required
  - Almost exclusively done by human translators

# Today's topics
# Machine Translation

- Context: Historical Background
  - Machine Translation is an old idea, its history mirrors history of AI
  - Why is machine translation difficult?
    - Translation ambiguity
    - Word order changes across languages
  - Translation model history: rule-based -> statistical -> neural

- Machine Translation Evaluation

# How good is a translation?
# 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.

# Evaluation

- How good is a given machine translation system?
- Many different translations acceptable
- Evaluation metrics
  - Subjective judgments by human evaluators
  - Automatic evaluation metrics
  - Task-based evaluation

# Adequacy and Fluency

- Human judgment
  - Given: machine translation output
  - Given: input and/or reference translation
  - Task: assess quality of MT output
- Metrics
  - **Adequacy:** does the output convey the meaning of the input sentence? Is part of the message lost, added, or distorted?
  - **Fluency:** is the output fluent? Involves both grammatical correctness and idiomatic word choices.

# Fluency and Adequacy: Scales

| Adequacy | |
|---|---|
| 5 | all meaning |
| 4 | most meaning |
| 3 | much meaning |
| 2 | little meaning |
| 1 | none |

| Fluency | |
|---|---|
| 5 | flawless English |
| 4 | good English |
| 3 | non-native English |
| 2 | disfluent English |
| 1 | incomprehensible |

# Judge Sentence

You have already judged 14 of 3064 sentences, taking 86.4 seconds per sentence.

**Source:** les deux pays constituent plutôt un laboratoire nécessaire au fonctionnement interne de l ' ue .

**Reference:** rather , the two countries form a laboratory needed for the internal working of the eu .

| **Translation** | **Adequacy** | **Fluency** |
|---|---|---|
| both countries are rather a necessary laboratory the internal operation of the eu . | 1 2 3 4 5 (5 selected) | 1 2 3 4 5 (5 selected) |
| both countries are a necessary laboratory at internal functioning of the eu . | 1 2 3 4 5 (3 selected) | 1 2 3 4 5 (3 selected) |
| the two countries are rather a laboratory necessary for the internal workings of the eu . | 1 2 3 4 5 (4 selected) | 1 2 3 4 5 (4 selected) |
| the two countries are rather a laboratory for the internal workings of the eu . | 1 2 3 4 5 (3 selected) | 1 2 3 4 5 (5 selected) |
| the two countries are rather a necessary laboratory internal workings of the eu . | 1 2 3 4 5 (3 selected) | 1 2 3 4 5 (3 selected) |
| **Annotator:** Philipp Koehn **Task:** WMT06 French-English | | Annotate |
| Instructions | 5= All Meaning<br>4= Most Meaning<br>3= Much Meaning<br>2= Little Meaning<br>1= None | 5= Flawless English<br>4= Good English<br>3= Non-native English<br>2= Disfluent English<br>1= Incomprehensible |

# Let's try:
# rate fluency & adequacy on 1-5 scale

- Source:
  N'y aurait-il pas comme une vague hypocrisie de votre part ?
- Reference:
  Is there not an element of hypocrisy on your part?
- System1:
  Would it not as a wave of hypocrisy on your part?
- System2:
  Is there would be no hypocrisy like a wave of your hand?
- System3:
  Is there not as a wave of hypocrisy from you?

# Challenges in MT evaluation

- No single correct answer

- Human evaluators disagree

# Automatic Evaluation Metrics

- Goal: computer program that computes quality of translations
- Advantages: low cost, optimizable, consistent
- Basic strategy
  - Given: MT output
  - Given: human reference translation
  - Task: compute similarity between them

# Precision and Recall of Words

SYSTEM A: Israeli officials ~~responsibility~~ ~~of~~ airport ~~safety~~

REFERENCE: Israeli officials are responsible for airport security

Precision $$\frac{\textit{correct}}{\textit{output-length}} = \frac{3}{6} = 50\%$$

Recall $$\frac{\textit{correct}}{\textit{reference-length}} = \frac{3}{7} = 43\%$$

F-measure $$\frac{\textit{precision} \times \textit{recall}}{(\textit{precision} + \textit{recall})/2} = \frac{.5 \times .43}{(.5 + .43)/2} = 46\%$$

# Precision and Recall of Words


| Metric | System A | System B |
|---|---|---|
| precision | 50% | 100% |
| recall | 43% | 100% |
| f-measure | 46% | 100% |

flaw: no penalty for reordering

# BLEU
# Bilingual Evaluation Understudy

N-gram overlap between machine translation output and reference translation

Compute precision for n-grams of size 1 to 4

Add brevity penalty (for too short translations)

$$\text{BLEU} = \min\left(1, \frac{\textit{output-length}}{\textit{reference-length}}\right) \left(\prod_{i=1}^{4} \textit{precision}_i\right)^{\frac{1}{4}}$$

Typically computed over the entire corpus, not single sentences

# Multiple Reference Translations

To account for variability, use multiple reference translations

- n-grams may match in any of the references
- closest reference length used

Example

SYSTEM: Israeli officials | responsibility of | airport | safety

2-GRAM MATCH | 2-GRAM MATCH | 1-GRAM

REFERENCES:

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

# BLEU examples

SYSTEM A: Israeli officials responsibility of airport safety
2-GRAM MATCH (Israeli officials) 1-GRAM MATCH (airport)

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security Israeli officials are responsible
2-GRAM MATCH (airport security) 4-GRAM MATCH (Israeli officials are responsible)

| **Metric** | **System A** | **System B** |
|---|---|---|
| precision (1gram) | 3/6 | 6/6 |
| precision (2gram) | 1/5 | 4/5 |
| precision (3gram) | 0/4 | 2/4 |
| precision (4gram) | 0/3 | 1/3 |
| brevity penalty | 6/7 | 6/7 |
| BLEU | 0% | 52% |

# Some metrics use more linguistic insights in matching references and hypotheses

Partial credit for matching stems

| | |
|---|---|
| SYSTEM | Jim went home |
| REFERENCE | Joe goes home |

Partial credit for matching synonyms

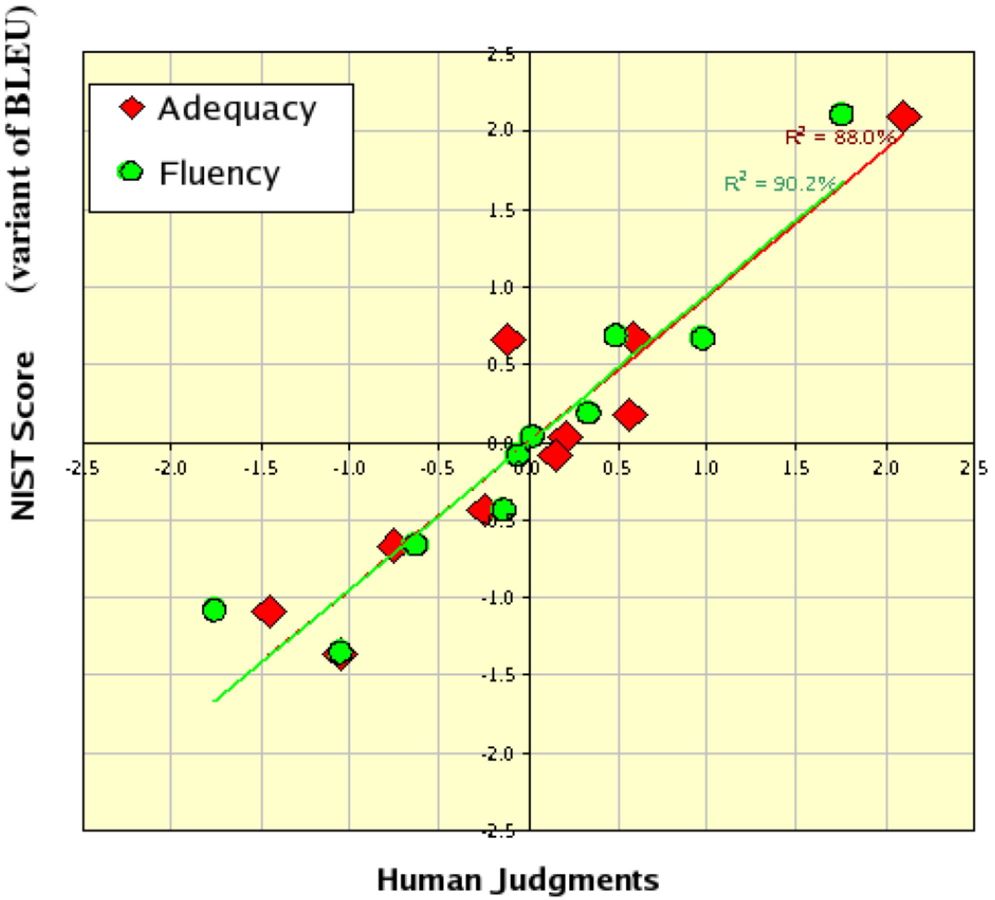
| | |
|---|---|
| SYSTEM | Jim walks home |
| REFERENCE | Joe goes home |

Use of paraphrases

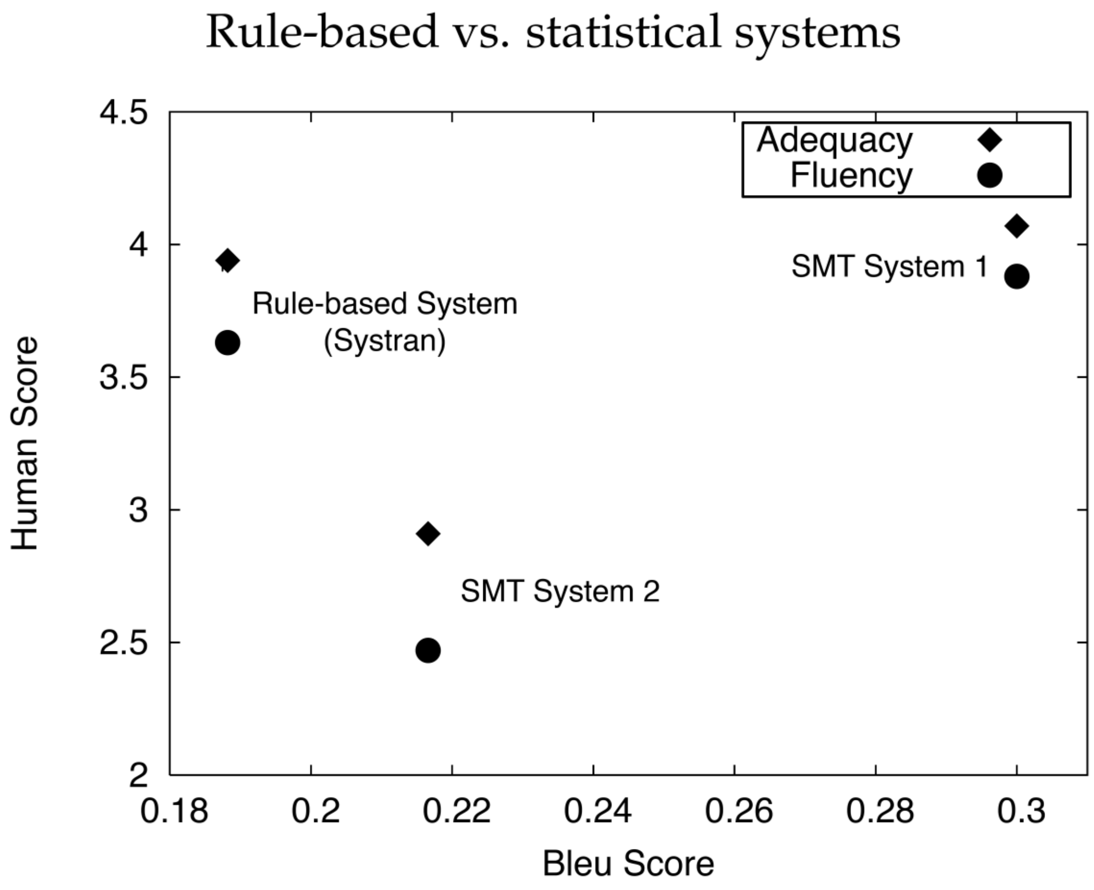
# Drawbacks of Automatic Metrics

- All words are treated as equally relevant
- Operate on local level
- Scores are meaningless (absolute value not informative)
- Human translators score low on BLEU

# Yet automatic metrics such as BLEU correlate with human judgement



# Caveats: bias toward statistical systems



# Automatic metrics

- Essential tool for system development
- Use with caution: not suited to rank systems of different types
- Still an open area of research
  - Connects with semantic analysis

# What you should know

- Context: Historical Background
  - Machine Translation is an old idea, its history mirrors history of AI
  - Why is machine translation difficult?
    - Translation ambiguity
    - Word order changes across languages
  - Translation model history: rule-based -> statistical -> neural

- Machine Translation Evaluation
  - What are adequacy and fluency
  - Pros and cons of human vs automatic evaluation
  - How to compute automatic scores: Precision/Recall and BLEU