Machine Translation and Sequence-to-sequence Models

http://phontron.com/class/mtandseq2seq2017/

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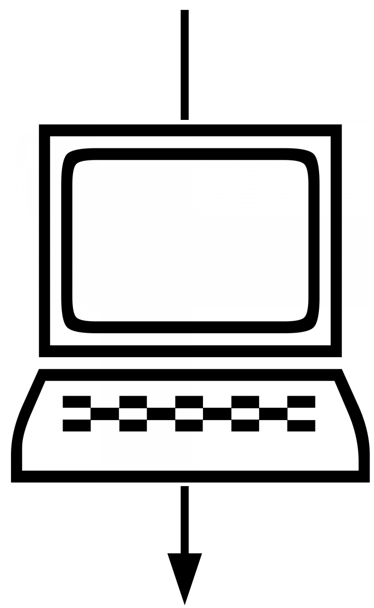
CS 11-731

What is Machine Translation?

kare wa ringo wo tabeta .



He ate an apple .

What are Sequence-to-sequence Models?

Sequence-to-sequence Models

Machine translation:

kare wa ringo wo tabeta → he ate an apple

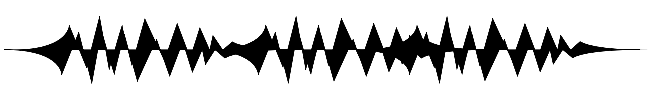
Tagging:

he ate an apple → PRN VBD DET PP

Dialog:

he ate an apple → good, he needs to slim down

Speech Recognition:

 → he ate an apple

And just about anything...:

1010000111101 → 00011010001101

Why MT as a Representative?

Useful!

KUSHINIKIZA! Google Translate SAVES BABY in Irish roadside birth

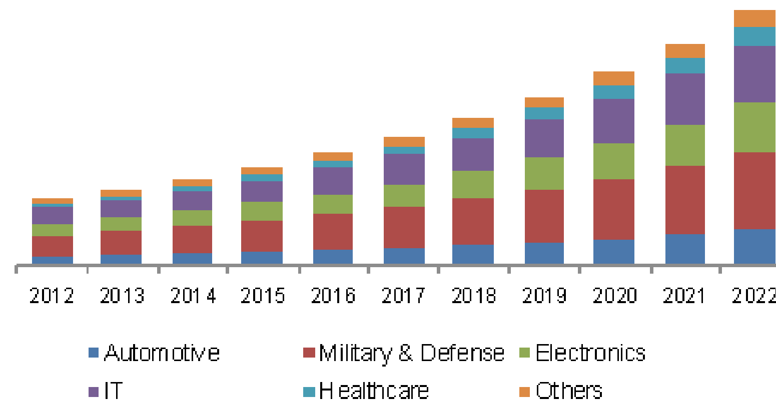
Do no evil? We literally save lives now

13 Feb 2015 at 12:01, John Leyden 8

Quick-thinking Irish paramedics turned to Google Translate to communicate with a pregnant woman who spoke Swahili, allowing her to safely give birth.

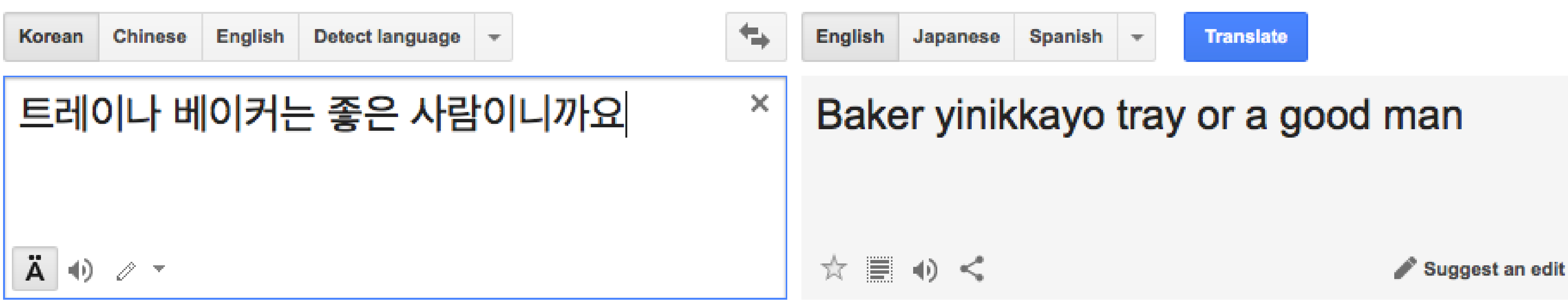
Source: The Register

Global MT Market Expected To Reach $983.3 Million by 2022



Source: Grand View Research

Imperfect...



MT and Machine Learning

Big Data! Billions of words for major languages

… but little for others

Well-defined, Difficult Problem!

Use for algorithms, math, etc.

Algorithms Widely Applicable!

MT and Linguistics

트레이나 베이커는 좋은 사람이니까요

Baker yinikkayo tray or a good man

Trina Baker is a good person

Morphology! 이니까요 is a variant of 이다 (to be)

Syntax! should keep subject together

Semantics! "Trina" is probably not a man...

… and so much more!

Class Organization

Class Format

- **Before class:**
  - Read the assigned material
  - Ask questions via web (piazza/email)
- **In class:**
  - Take a small quiz about material
  - Discussion/questions
  - Pseudo-code walk
  - Programming (TAs/Instructor will supervise)

Assignments

- **Assignment 1:** Create a neural sequence-to-sequence modeling system. Turn in code to run it, and a short 1-2 page report.
- **Assignment 2:** Create a symbolic sequence-to-sequence modeling system. Similarly turn in code/report.
- **Final project:** Come up with an interesting new idea and test it.

Assignment Instructions

- Bring your computer to every class and make a Github account.
- We recommend you implement in the following libraries:
    - DyNet: for neural networks (C++ or Python)
    - OpenFST: for transducers, if you use them (C++)
    - pyfst: for transducers in Python
- It is OK to work in small groups up to 3, particularly for the final project. If you do so, please use a shared git repository and commit the code that you write, and in reports note who did what part of the project.

Class Grading

- **Short quizzes:** 20%
- **Assignment 1:** 20%
- **Assignment 2:** 20%
- **Final Project:** 40%

Class Plan

1. Introduction (Today): 1 class
2. Language Models: 4 classes
3. Neural MT: 2 classes
3. Evaluation/Data: 2 classes — #1 Due
4. Symbolic MT: 4 classes
5. Algorithms: 2 classes — #2 Due
7. Advanced Topics: 11 classes
8. Final Project Discussion: 2 classes — Project Due

Guest Lectures

- Bob Frederking:
  Knowledge-based Translation
- LP Morency:
  Something Multi-modal

(Date TBD)

Statistical Machine Translation

Statistical Machine Translation

F = *kare wa ringo wo tabeta .*

E = He ate an apple .

Probability model: $P(E|F;\Theta)$

Parameters

Problems in SMT

- **Modeling:** How do we define $P(E|F;\Theta)$?
- **Learning:** How do we learn Θ?
- **Search:** Given F, how do we find the highest scoring translation?

$$E' = \text{argmax}_E \, P(E|F;\Theta)$$

- **Evaluation:** Given E' and a human reference E, how do we determine how good E' is?

Part 1: Neural Models

Language Models 1: n-gram Language Models

Given multiple candidates, which is most likely as an English sentence?

E_1 = he ate an apple
E_2 = he ate an apples
E_3 = he insulted an apple
E_4 = preliminary orange orange

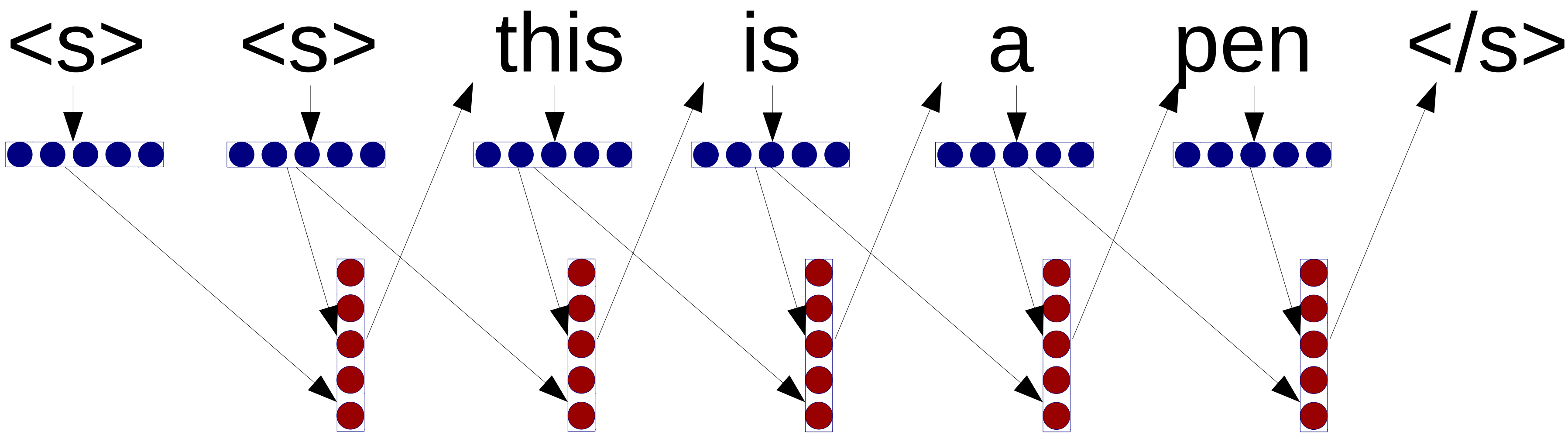
- Definition of language modeling
- Count-based n-gram language models
- Evaluating language models
- **Implement:** n-gram language model

Language Models 2: Log-linear Language Models

$$
\begin{array}{l} \text{a} \\ \text{the} \\ \text{talk} \\ \text{gift} \\ \text{hat} \\ \ldots \end{array}
\quad
\boldsymbol{b} = \begin{pmatrix} 3.0 \\ 2.5 \\ -0.2 \\ 0.1 \\ 1.2 \\ \ldots \end{pmatrix}
\quad
\boldsymbol{w}_{1,a} = \begin{pmatrix} -6.0 \\ -5.1 \\ 0.2 \\ 0.1 \\ 0.6 \\ \ldots \end{pmatrix}
\quad
\boldsymbol{w}_{2,\text{giving}} = \begin{pmatrix} -0.2 \\ -0.3 \\ 1.0 \\ 2.0 \\ -1.2 \\ \ldots \end{pmatrix}
\quad
\boldsymbol{s} = \begin{pmatrix} -3.2 \\ -2.9 \\ 1.0 \\ 2.2 \\ 0.6 \\ \ldots \end{pmatrix}
$$

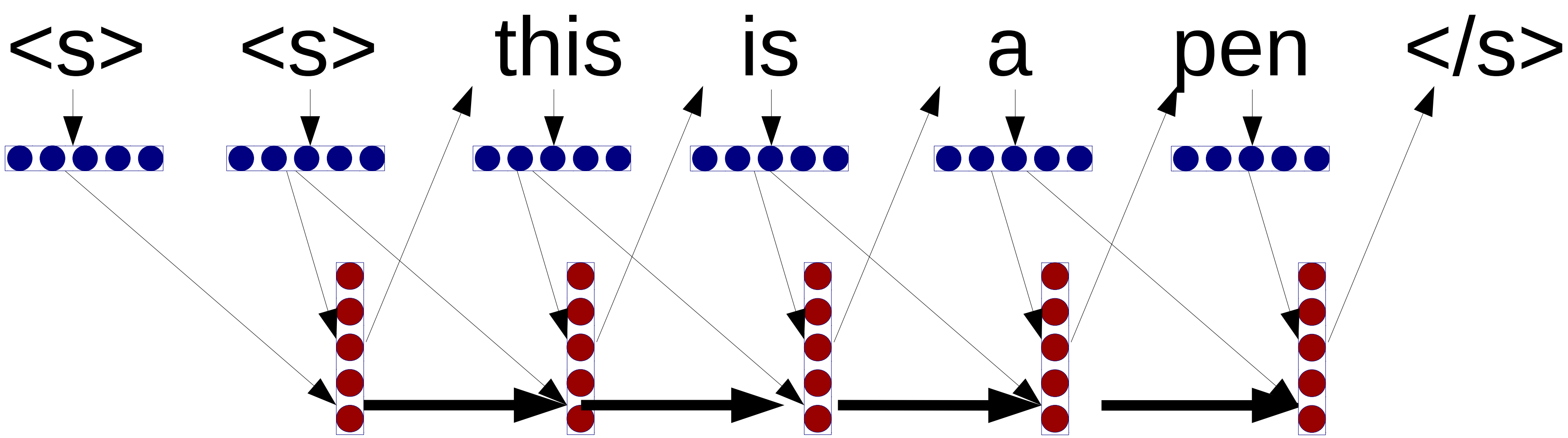
- Log-linear language models
- Stochastic gradient descent
- Features for language modeling
- **Implement:** Log-linear language model

Language Models 3: Neural Networks and Feed-forward LMs



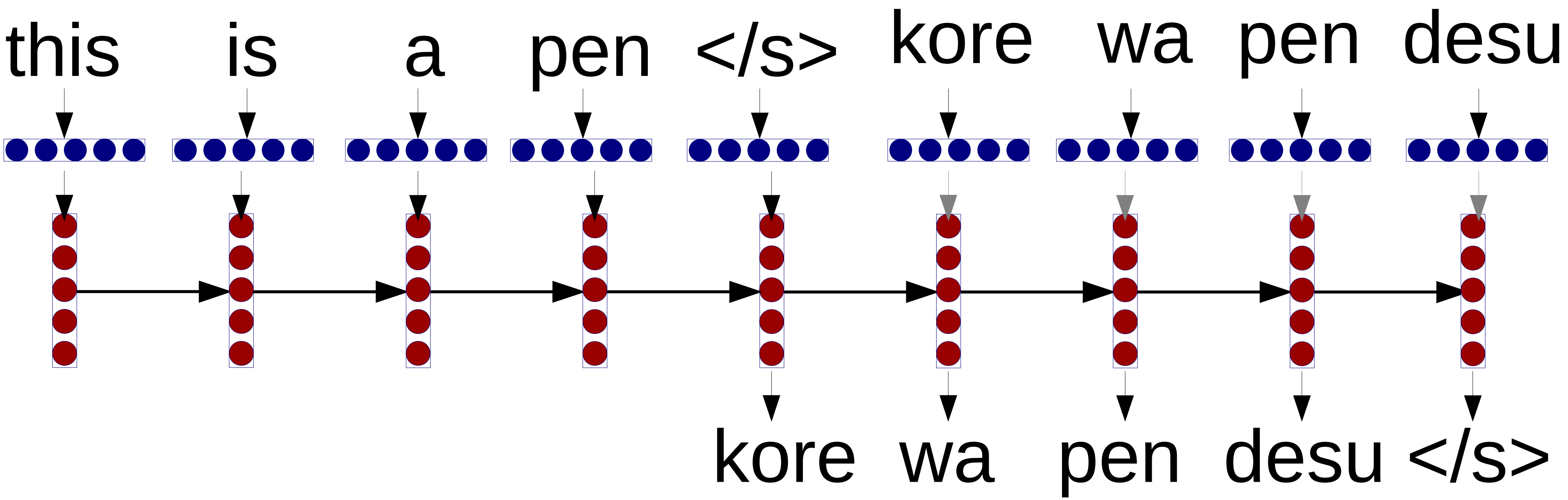
- Neural networks and back-propagation
- Feed-forward neural language models
- Mini-batch training
- **Implement:** Feed-forward LM

Language Models 4: Recurrent LMs



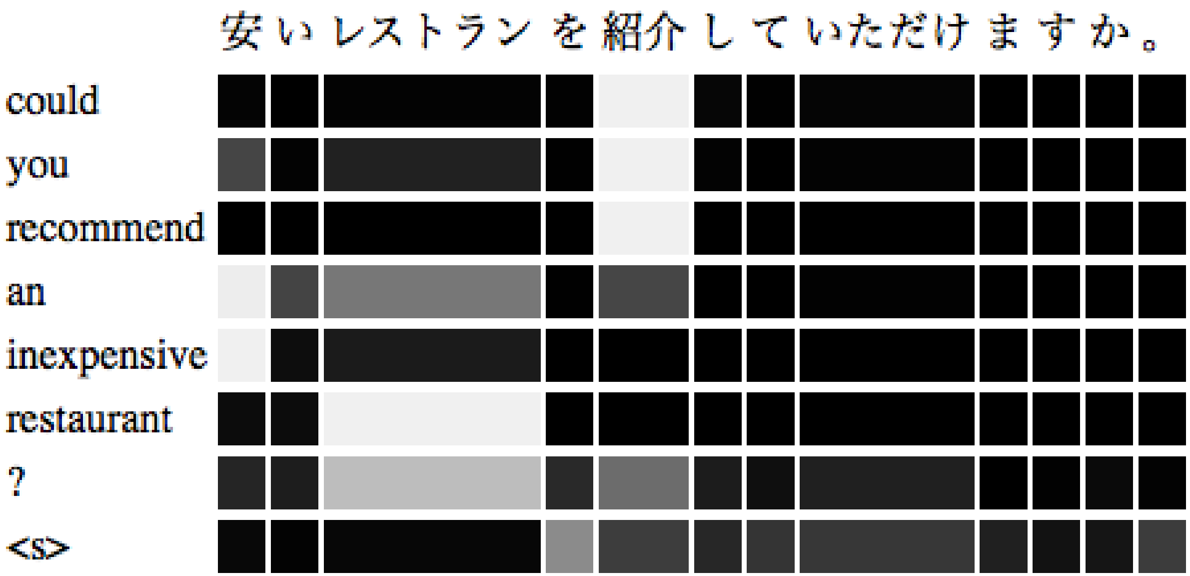
- Recurrent neural networks
- Vanishing Gradient and LSTMs/GRUs
- Regularization and dropout
- **Implement:** Recurrent neural network LM

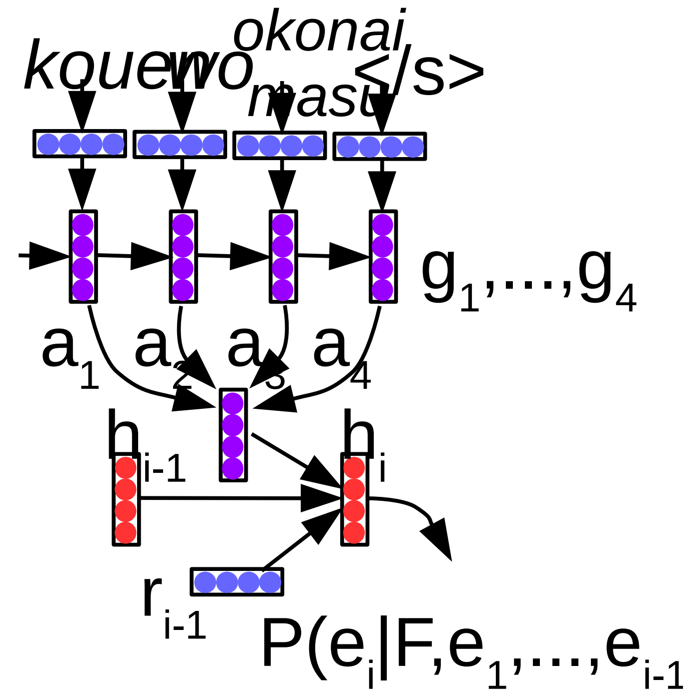
Neural MT 1: Encoder-decoder Models



- Encoder-decoder Models
- Searching for hypotheses
- Mini-batched training
- **Implement:** Encoder-decoder model

Neural MT 2: Attentional Models





- Attention in its various varieties
- Unknown word replacement
- Attention improvements, coverage models
- **Implement:** Attentional model

Data and Evaluation

Creating Data

毎日jp

ホーム ニュース オピニオン スポーツ エンタメ 地域 特集・連載 ENG

オピニオン 社説 余録 解説 コラム

トップ > オピニオン > 記事

[PR] 休肝日が気になる40代男性が始めた健康法！しじみ習慣／無料サンプル

+1 0 ツイート 23 おすすめ 15 チェック 記事を印刷 文字サ

社説:超高齢社会　「肩車型」の常識を疑え

毎日新聞　2012年05月05日　02時30分

長寿はおめでたいことなのに、高齢化となると悲観論をもって語られることが多い。現役世代

続けているせいでもある。現役4人が高齢者1人を背負う「騎馬戦型」から、現役1人が高齢者1

車型」になると言われたら誰しも不安になるだろう。たしかに人口比率はそのようになる。

だからこそ先進国最低レベルの国民負担率（税と保険の負担）をもう少し引き上げるべきだ

「肩車型」説は登場したはずだったが、野田佳彦首相らの言い方がまずいのだろうか、逆に社会

The Mainichi

[PR] ４０歳からの「しじみ習慣」休肝日が気になるあなたに！／無料サンプル

+1 0 ツイート 0 おすすめ チェック 記事を印刷 文字サイズ 小 中 大

Editorial: Aging society does not necessarily spell doom

Longevity is something to be celebrated, but when it comes to the aging of Japanese society, it is often discussed in a pessimistic tone.

One reason for this is the continuing decline in people of working age. Learning that our society is shifting from one in which four working people financially support one senior citizen, to another in which each working person must support one senior citizen -- a so-called "piggyback" setup -- would make anyone anxious. And indeed, that is exactly what is happening.

- Preprocessing
- Document harvesting and crowdsourcing
- Other tasks: dialog, captioning
- **Implement:** Find/preprocess data

Evaluation

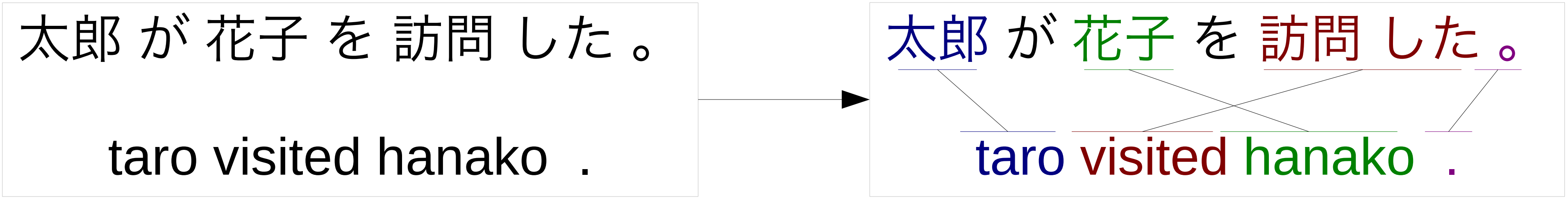
taro ga hanako wo otozureta

	Taro visited Hanako	the Taro visited the Hanako	Hanako visited Taro
Adequate?	○	○	X
Fluent?	○	X	○
Better?	B, C	C	

- Human evaluation
- Automatic evaluation
- Significance tests and meta-evaluation
- **Implement:** BLEU and measure correlation

Symbolic Translation Models

Symbolic Methods 1: IBM Models



- The IBM/HMM models
- The EM algorithm
- Finding word alignments
- **Implement:** Word alignment

Symbolic Methods 2: Monotonic Symbolic Models

he ate an apple

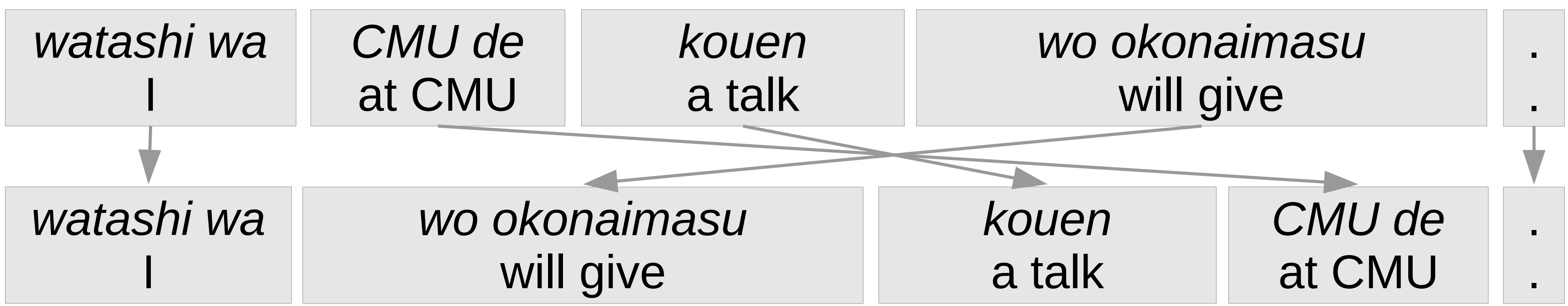
↓

PRN VBD DET PP

- Models for sequence transduction
- The Viterbi algorithm
- Weighted finite-state transducers
- **Implement:** A part-of-speech tagger

Symbolic Methods 3: Phrase-based MT

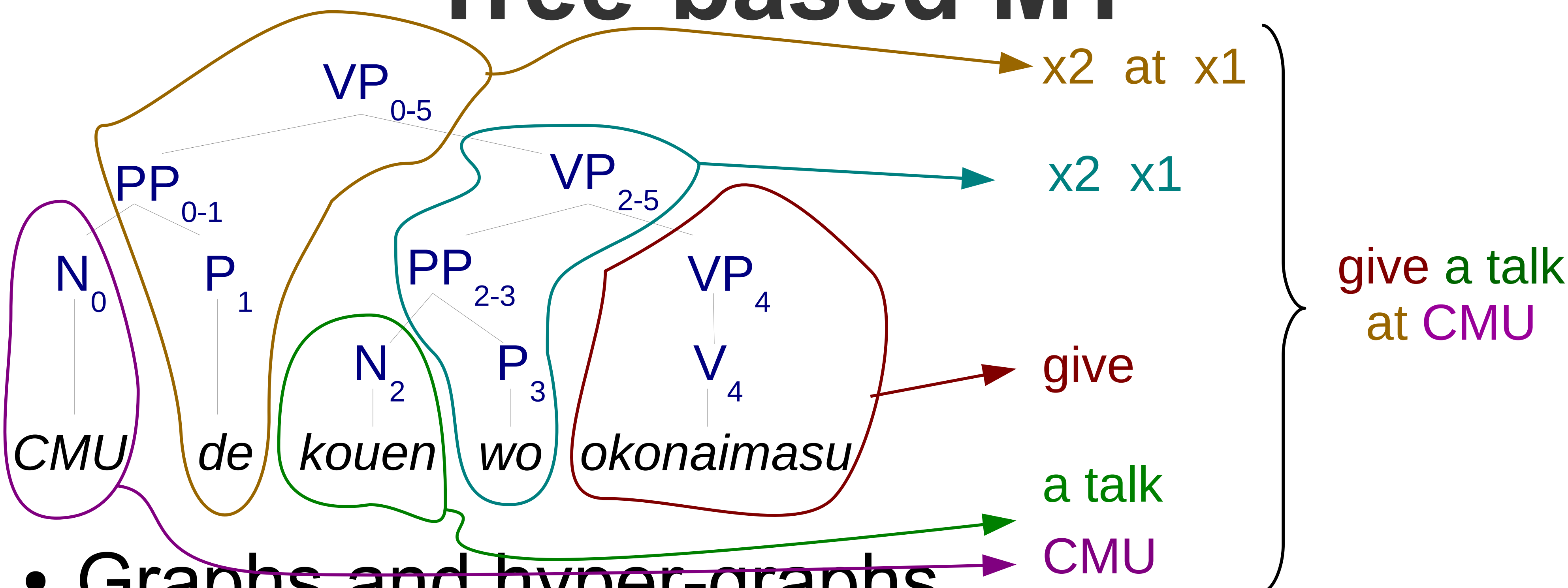
F = *watashi wa CMU de kouen wo okonaimasu .*



E = I will give a talk at CMU .

- Phrase extraction and scoring
- Reordering models
- Phrase-based decoding
- **Implement:** Phrase extraction or decoding

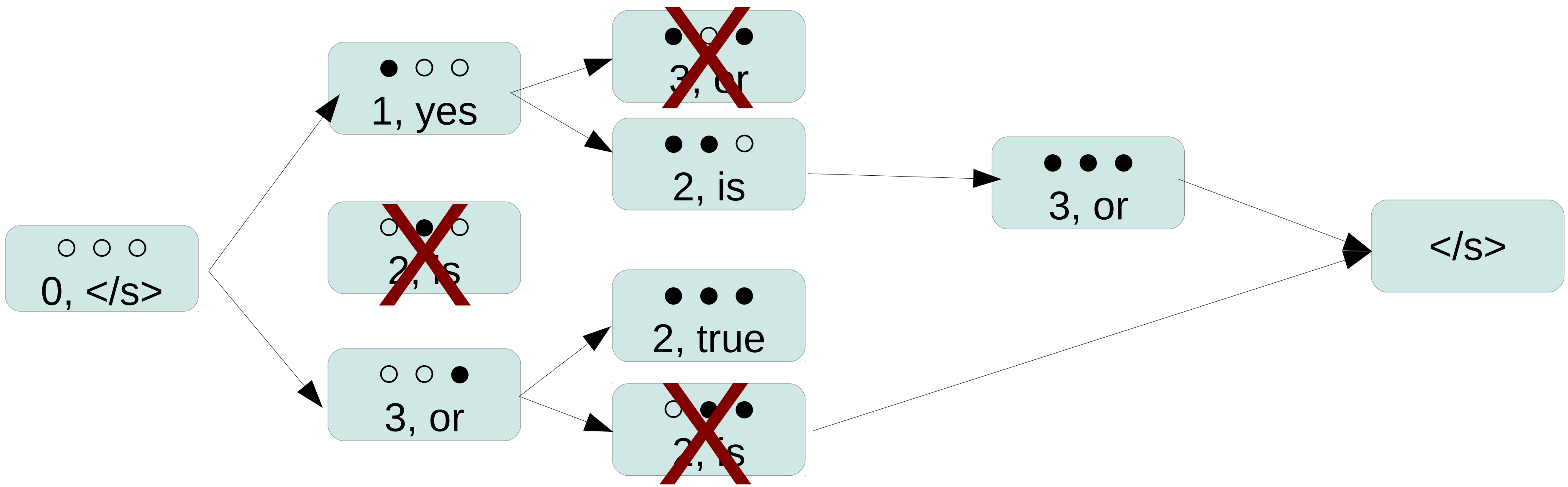
Symbolic Methods 4: Tree-based MT



- Graphs and hyper-graphs
- Synchronous context free grammars
- Tree substitution grammars
- **Implement:** Search over hyper-graphs

Algorithms

Algorithms 1: Search



- Beam search and cube pruning
- Hypothesis recombination
- Future costs, A* search
- **Implement:** Beam search

Algorithms 2: Parameter Optimization

Highest ○

	LM	TM	RM	
○ Taro visited Hanako	0.2*-4	0.3*-3	0.5*-1	-2.2
X the Taro visited the Hanako	0.2*-5	0.3*-4	0.5*-1	-2.7
X Hanako visited Taro	0.2*-2	0.3*-3	0.5*-2	-2.3

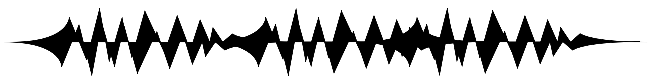
- Loss functions
- Deciding the hypothesis space
- Optimization criteria
- **Implement:** Optimization of NMT or PBMT

Advanced Topics

Other Sequence-to-sequence Tasks

he ate an apple → PRN VBD DET PP

he ate an apple → good, he needs to slim down

 → he ate an apple

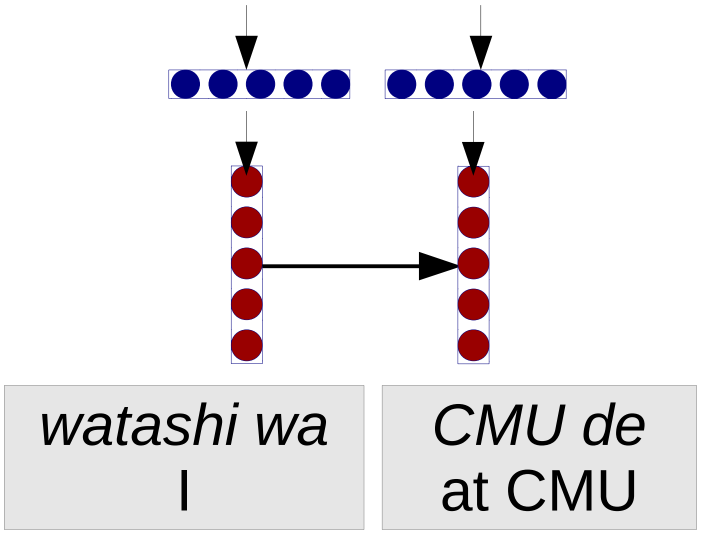
- Case studies about task-specific models
  - Consistency constraints in tagging
  - Diversity objectives in dialog
  - Dynamic programming in speech
- **Implement:** Try models on other tasks

Ensembling/System Combination

Model 1 + Model 2

- Ensembles and distillation
- Post-hoc hypothesis combination
- Reranking
- **Implement:** Ensembled decoding

Hybrid Neural-symbolic Models



- Symbolic models with neural components
- Neural models with symbolic components
- **Implement:** Implement lexicons in NMT or neural feature functions

Multi-lingual and Multi-task Learning

hello

こんにちは

hola

- Learning for multiple tasks
- Learning for multiple languages
- **Implement:** Implement a multi-lingual neural system

Subword Models

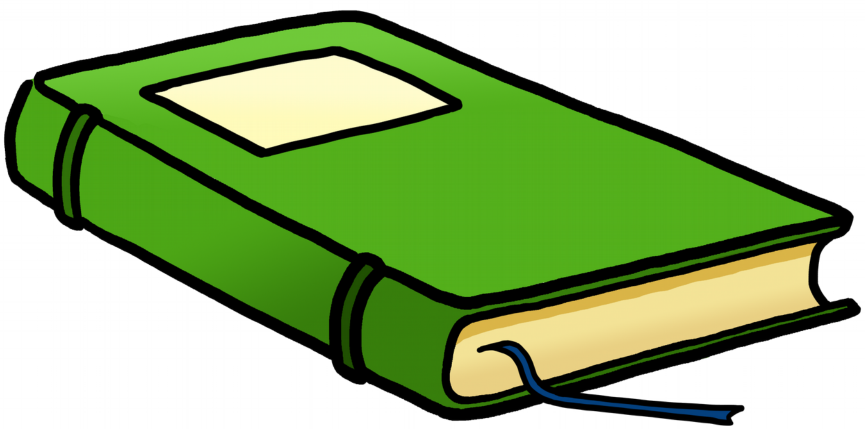
reconstructed

↓

re+ construct+ ed

- Character models
- Subword models
- Morphology models
- **Implement:** Implement subword splitting

Document Level Models



- Document level modeling
- Document level evaluation
- Stream decoding
- **Implement:** Document level measures

For Next Class

Homework

- Read n-gram language modeling materials
- Get software working on your machine (doing all at once may be more efficient?)
  - By Thursday 1/19: Python
  - By Tuesday 1/24: Numpy
  - By Thursday 1/26: DyNet