Machine Translation Zoo

Tree-to-tree transfer and Discriminative learning

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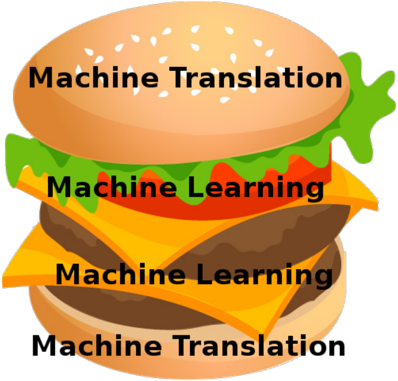
Today's Menu

1. MT Intro
   - Taxonomy
   - Hybrids
2. Online Learning
   - Perceptron
   - Structured Prediction
3. Guided Learning
4. Back to MT
   - Easy-First Decoding in MT
   - Guided Learning in MT



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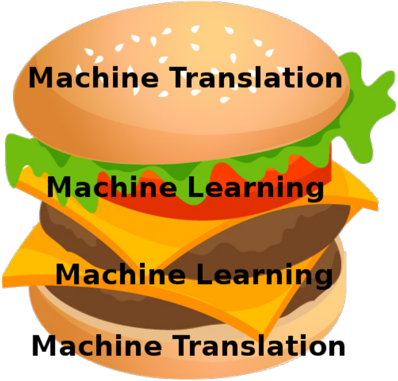
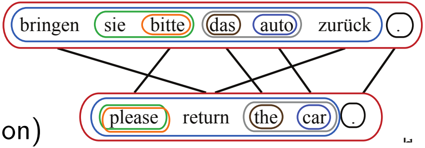


Phrase-based MT (Moses)



Training

- word-alignment
  (GIZA++ & symmetrization)
- phrase extraction
- tune parameters (MERT)

Decoding

- get all matching *rules*
- find one *derivation*
  with a maximum score (beam search)

TectoMT

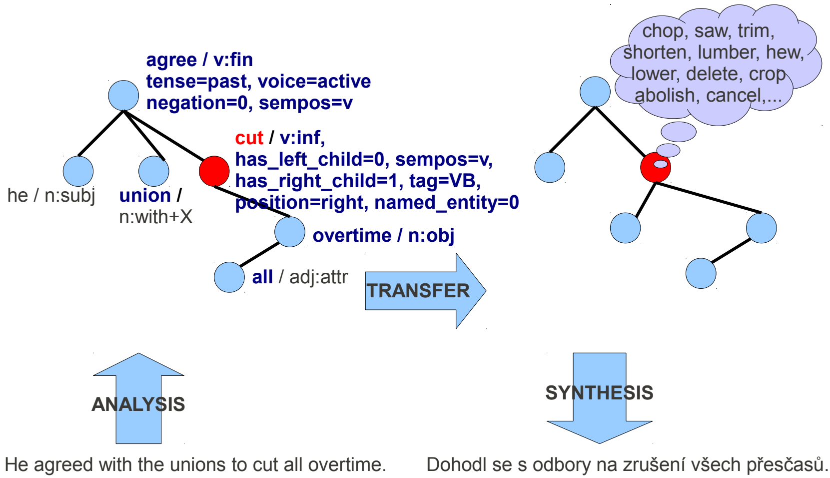
Training

- analyze CzEng to t-layer
- t-node alignment
- learn one MaxEnt model for each source lemma and formeme

Decoding

- get all translation variants for each lemma and formeme
- find a labeling with a maximum score (HMTM)

TectoMT – MaxEnt Model



Machine Translation Taxonomy

- Level of transfer:
- Base translation unit (BTU):

- Extract more segmentations in training?
- Try (search) more segmentations in decoding?
- Use more segmentations in the output translation?
- What is the context X in $P(BTU_{target} | BTU_{source}, X)$?

Machine Translation Taxonomy

- Level of transfer: surface
- Base translation unit (BTU):
  word
- Extract more segmentations in training? no
- Try (search) more segmentations in decoding? no
- Use more segmentations in the output translation? no
- What is the context X in $P(BTU_{target}|BTU_{source}, X)$?
  Considering just Translation Model: nothing

(Brown et al., 1993)
word-based

Machine Translation Taxonomy

- Level of transfer: surface
- Base translation unit (BTU):
  word, phrase
- Extract more segmentations in training? yes
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(Brown et al., 1993)
word-based

(Koehn et al., 2003)
phrase-based

Machine Translation Taxonomy

- Level of transfer: surface
- Base translation unit (BTU):
  word, phrase, phrase with gaps
- Extract more segmentations in training? yes
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  Considering just Translation Model: nothing

IBM

(Brown et al., 1993)
word-based

(Koehn et al., 2003)
phrase-based

(Chiang, 2005)
hierarchical

Machine Translation Taxonomy

- Level of transfer: surface, shallow syntax
- Base translation unit (BTU):
  word, phrase, phrase with gaps, treelet
- Extract more segmentations in training? no
- Try (search) more segmentations in decoding? no
- Use more segmentations in the output translation? no
- What is the context X in $P(BTU_{target}|BTU_{source}, X)$?
  Considering just Translation Model: neighboring treelets

Microsoft Research
(Quirk and Menezes, 2006)
dep. treelet to string

IBM
(Brown et al., 1993)
word-based

(Koehn et al., 2003)
phrase-based

(Chiang, 2005)
hierarchical

Machine Translation Taxonomy

- Level of transfer: surface, shallow syntax, tectogrammatical
- Base translation unit (BTU):
  word, phrase, phrase with gaps, treelet, node
- Extract more segmentations in training? no
- Try (search) more segmentations in decoding? no
- Use more segmentations in the output translation? no
- What is the context X in $P(BTU_{target}|BTU_{source}, X)$?
  Considering just Translation Model: neighboring nodes

Microsoft Research

(Quirk and Menezes, 2006)
dep. treelet to string

(Mareček et al., 2010)
TectoMT

(Koehn et al., 2003)
phrase-based

(Chiang, 2005)
hierarchical

IBM

(Brown et al., 1993)
word-based

Machine Translation Taxonomy

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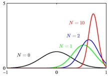


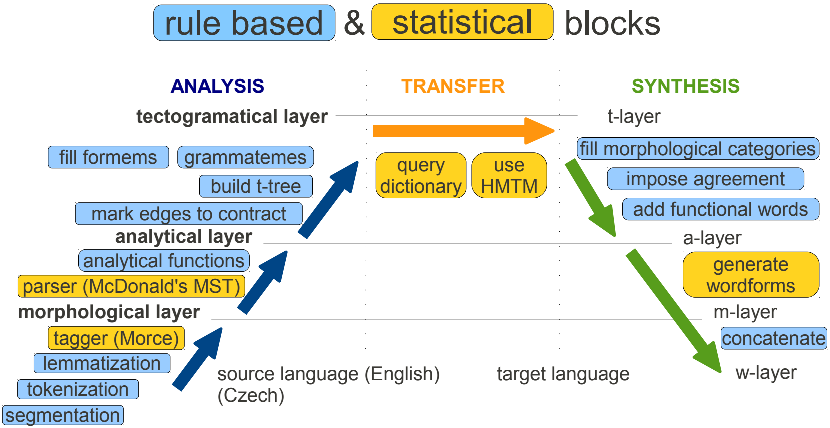
IBM

(Brown et al., 1993)
word-based

(Arun, 2011)
Monte Carlo

Hybrids: TectoMoses

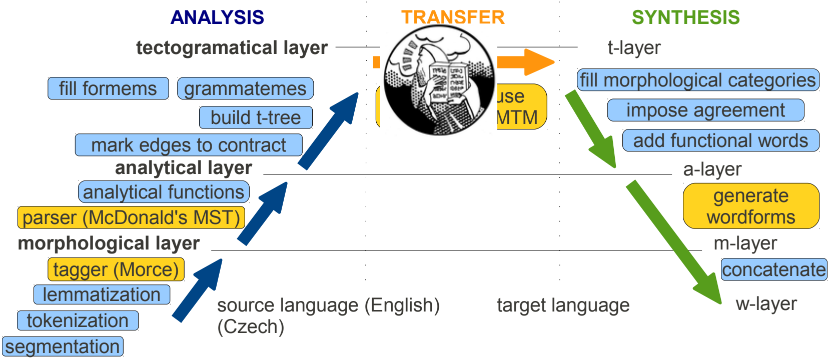
Linearize source t-trees (two factors: lemma and formeme), translate with Moses, project dependencies and use TectoMT synthesis.



Hybrids: TectoMoses

Linearize source t-trees (two factors: lemma and formeme), translate with Moses, project dependencies and use TectoMT synthesis.

rule based & statistical blocks



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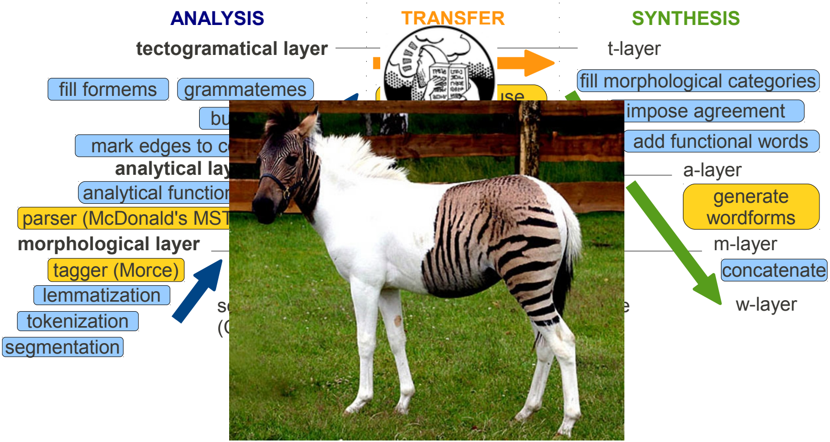

Hybrids: PhraseFix

Done for WMT 2013 by Petra Galuščáková:

- Post-edit TectoMT output using Moses
- trained on cs-tectomt → cs-reference (whole CzEng).
- How to post-edit only when confident?
  - filter phrase table
  - add "confidence" feature for MERT
  - improve alignment (monolingual)
  - boost phrase table (e.g. with identities)

Future work:

- use also source (English) sentences ⇒ multi-source translation
- project only content words (using TectoMT)
- factored translation with non-synchronous (overlapping) factors

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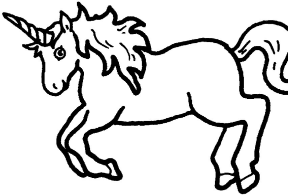

Even More Hybrids: DepFix, AddToTrain, Chimera

DepFix (Rosa et al., 2012)

- post-edit SMT using syntactic analysis and rules
- exploit also the source sentences, robust parsing

AddToTrain (Bojar, Galuščáková)

- translate monolingual news (or WMT devsets) with TectoMT
- add this to Moses parallel training data

Chimera

- post-edit AddToTrain output with DepFix
- sent to WMT 2013 in attempt to beat Google

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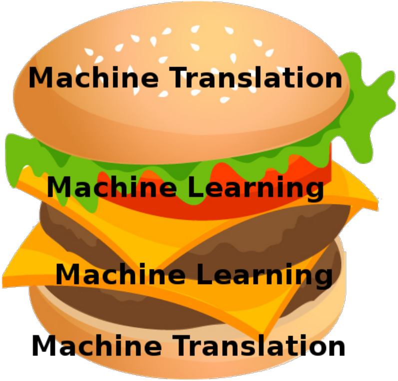

General Algorithm for Online Learning

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
  $y_{pred} :=$ prediction$(\mathbf{w}, \mathbf{x})$
  $\mathbf{w}$ += update$(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

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initialize all weights to zero

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initialize all weights to zero
for each instance (observation)

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initialize all weights to zero
for each instance (observation)
1. get its features $\mathbf{x}$

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  $\mathbf{w}$ += update$(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

initialize all weights to zero
for each instance (observation)

1. get its features $\mathbf{x}$
2. do the prediction y_{pred}

General Algorithm for Online Learning

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  $y_{pred} :=$ prediction$(\mathbf{w}, \mathbf{x})$
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Output: $\mathbf{w}$

initialize all weights to zero
for each instance (observation)

1. get its features $\mathbf{x}$
2. do the prediction y_{pred}
3. get the correct label y_{gold}

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1. get its features $\mathbf{x}$
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Definition: conservative online learning

no error $\Rightarrow$ no update
i.e., if $y_{pred} = y_{gold}$ then update$(\mathbf{x}, y_{gold}, y_{pred}) = 0$

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while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
    $y_{pred} :=$ prediction$(\mathbf{w}, \mathbf{x})$
    $\mathbf{w}$ += update$(\mathbf{x}, y_{gold}, y_{pred})$
    //prediction$(\mathbf{w}, \mathbf{x}) = y_{gold}$
Output: $\mathbf{w}$

initialize all weights to zero
for each instance (observation)

1. get its features $\mathbf{x}$
2. do the prediction y_{pred}
3. get the correct label y_{gold}
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Definition: conservative online learning

no error $\Rightarrow$ no update
i.e., if $y_{pred} = y_{gold}$ then update$(\mathbf{x}, y_{gold}, y_{pred}) = 0$

Definition: aggressive online learning

after the update, the instance would be classified correctly

Perceptron

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
  $y_{pred} := \text{prediction}(\mathbf{w}, \mathbf{x})$
  $\mathbf{w} \mathrel{+}= \text{update}(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

Binary Perceptron

$$\text{prediction}(\mathbf{w}, \mathbf{x}) \stackrel{\text{def}}{=} [\mathbf{w} \cdot \mathbf{x} > 0]$$

$$\text{update}(\mathbf{x}, y_{gold}, y_{pred}) \stackrel{\text{def}}{=} \alpha(y_{gold} - y_{pred}) \cdot \mathbf{x}$$

Perceptron

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
  $y_{pred} := \text{prediction}(\mathbf{w}, \mathbf{x})$
  $\mathbf{w} \mathrel{+}= \text{update}(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

dot product (similarity score) of weights and features
$\mathbf{w} \cdot \mathbf{x} = \sum_i w_i x_i$

Binary Perceptron

$$\text{prediction}(\mathbf{w}, \mathbf{x}) \stackrel{\text{def}}{=} [\mathbf{w} \cdot \mathbf{x} > 0]$$

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Perceptron

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
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  $\mathbf{w}$ += update$(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

dot product (similarity score) of weights and features
$\mathbf{w} \cdot \mathbf{x} = \sum_i w_i x_i$

Iverson bracket

$$[P] = \begin{cases} 1 & \text{if } P \text{ is true;} \\ 0 & \text{otherwise.} \end{cases}$$

Binary Perceptron

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$$\text{prediction}(\mathbf{w}, \mathbf{x}) \stackrel{\text{def}}{=} [\mathbf{w} \cdot \mathbf{x} > 0]$$

$$\text{update}(\mathbf{x}, y_{gold}, y_{pred}) \stackrel{\text{def}}{=} \alpha(y_{gold} - y_{pred}) \cdot \mathbf{x}$$

learning rate (step size) $\alpha > 0$

Perceptron

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
  $y_{pred} := \text{prediction}(\mathbf{w}, \mathbf{x})$
  $\mathbf{w} \mathrel{+}= \text{update}(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

	Binary Perceptron	Multi-class Perceptron
$\text{prediction}(\mathbf{w}, \mathbf{x}) \stackrel{\text{def}}{=}$	$[\mathbf{w} \cdot \mathbf{x} > 0]$	$\arg\max_y \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)$
$\text{update}(\mathbf{x}, y_{gold}, y_{pred}) \stackrel{\text{def}}{=}$	$\alpha(y_{gold} - y_{pred}) \cdot \mathbf{x}$	$\alpha\left(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})\right)$

learning rate (step size) $\alpha > 0$

Perceptron

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
  $y_{pred} :=$ prediction$(\mathbf{w}, \mathbf{x})$
  $\mathbf{w}$ += update$(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

Special case:
multi-prototype features

$$\mathbf{f}(\mathbf{x}, y) \stackrel{\text{def}}{=} \begin{array}{l} [y = class_1] \cdot \mathbf{x}\,, \\ [y = class_2] \cdot \mathbf{x}\,, \\ \cdots \\ [y = class_C] \cdot \mathbf{x} \end{array}$$

	Binary Perceptron	Multi-class Perceptron
prediction$(\mathbf{w}, \mathbf{x}) \stackrel{\text{def}}{=}$	$[\mathbf{w} \cdot \mathbf{x} > 0]$	$\arg\max_y \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)$
update$(\mathbf{x}, y_{gold}, y_{pred}) \stackrel{\text{def}}{=}$	$\alpha(y_{gold} - y_{pred}) \cdot \mathbf{x}$	$\alpha\big(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})\big)$

$$\mathbf{w} := \mathbf{w} + \alpha\mathbf{f}(\mathbf{x}, y_{gold}) - \alpha\mathbf{f}(\mathbf{x}, y_{pred})$$

Perceptron

$\mathbf{w} := 0$
while $(\mathbf{x}, y_{gold}) :=$ get_new_data()
    $y_{pred} := \text{prediction}(\mathbf{w}, \mathbf{x})$
    $\mathbf{w} \mathrel{+}= \text{update}(\mathbf{x}, y_{gold}, y_{pred})$

Output: $\mathbf{w}$

General case:
any *label-dependent* features, e.g.

$$f_{101}(\mathbf{x}, y) \stackrel{\text{def}}{=} [(y{=}\text{NNP or } y{=}\text{NNPS}) \text{ and } \mathbf{x} \text{ capitalized }]$$

	Binary Perceptron	Multi-class Perceptron
$\text{prediction}(\mathbf{w}, \mathbf{x}) \stackrel{\text{def}}{=}$	$[\mathbf{w} \cdot \mathbf{x} > 0]$	$\arg\max_y \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)$
$\text{update}(\mathbf{x}, y_{gold}, y_{pred}) \stackrel{\text{def}}{=}$	$\alpha(y_{gold} - y_{pred}) \cdot \mathbf{x}$	$\alpha\big(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})\big)$

Structured Prediction

- the number of possible labels is huge
- labels $\mathbf{y}$ have a structure (graph, tree, sequence,...)
- usually can be decomposed (factorized) into subproblems
- local features
  - $f_i(\mathbf{x}, \mathbf{y}, j)$ can use whole $\mathbf{x}$, but only such y_k where k is "near" j
  - $f_{101}(\mathbf{x}, \mathbf{y}, j) \stackrel{\text{def}}{=} [\ (y_j{=}\text{NNP or } y_j{=}\text{NNPS}) \text{ and word } x_j \text{ capitalized}\ ]$
  - $f_{102}(\mathbf{x}, \mathbf{y}, j) \stackrel{\text{def}}{=} [\ y_j{=}\text{NNP and } y_{j-1}{=}\text{NNP and } |\mathbf{x}| \leq 6\ ]$
- global features
  - $F_i(\mathbf{x}, \mathbf{y}) \stackrel{\text{def}}{=} \sum_j f_i(\mathbf{x}, \mathbf{y}, j)$
  - F_{101} ... number of capitalized words with tag NNP or NNPS
  - F_{102} ... number of NNP followed by NNP
    or 0 if the sentence is longer than six words
  - We can define also features that cannot be decomposed

Structured Prediction using Online Learning

1. local approach
   - update after each local decision
   - output of previous decisions used in local features
   - e.g. Structured Perceptron (Collins, 2002)
   - $y_{pred} = \arg\max_y \sum_i w_i f_i(\mathbf{x}, y_j, y_{j-1}, \ldots)$

2. global approach
   - generate n-best list (lattice) of outputs **y** for the whole **x**
   - compute global features, do update for each **x** (sentence)
   - we are re-ranking the n-best list
   - e.g. MIRA (Crammer and Singer, 2003)
   - $\mathbf{y}_{pred} = \arg\max_{\mathbf{y}} \sum_i w_i F_i(\mathbf{x}, \mathbf{y})$

Margin-based Online Learning

Definitions

- $\textit{score}(y) = \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)$
- $\textit{margin}(y) = \textit{score}(y_{gold}) - \textit{score}(y)$
  - $\textit{margin} > 0 \Rightarrow$ no error
  - $|\textit{margin}| \sim$ confidence
- $\textit{hinge\_loss}(y) = \textit{max}(0, 1 - \textit{margin}(y))$

Online Prediction and Update

$$y_{pred} \stackrel{\text{def}}{=} \arg\max \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)$$
$$\mathbf{w} \mathrel{+}= \alpha\big(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})\big)$$

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$$\mathbf{w} \mathrel{+}= \alpha(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred}))$$

Perceptron

$$\alpha_{\text{Perc}} \stackrel{\text{def}}{=} 1 \text{ (or any fixed value } > 0)$$

Passive Aggressive (PA)

$$\alpha_{\text{PA}} \stackrel{\text{def}}{=} \frac{hinge\_loss(y_{pred})}{||\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})||^2}$$

Passive Aggressive I

$$\alpha_{\text{PA-I}} \stackrel{\text{def}}{=} min\{C, \alpha_{\text{PA}}\}$$

Passive Aggressive II

$$\alpha_{\text{PA-II}} \stackrel{\text{def}}{=} \frac{hinge\_loss(y_{pred})}{||\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})||^2 + \frac{1}{2C}}$$

Margin-based Online Learning

Definitions

Online Prediction and Update

$$y_{pred} \stackrel{\text{def}}{=} \arg\max \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)$$

$$\mathbf{w} \mathrel{+}= \alpha\left(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})\right)$$

Perceptron

$$\alpha_{\text{Perc}} \stackrel{\text{def}}{=} 1 \text{ (or any fixed value } > 0)$$

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$$\alpha_{\text{PA}} \stackrel{\text{def}}{=} \frac{hinge\_loss(y_{pred})}{||\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})||^2}$$

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Cost-sensitive Online Learning

Definitions

- $cost(y)$ = external error metric (non-negative)
  e.g. 1 - similarity of y and y_{gold}
- $hinge\_loss(y) = max\big(0, cost(y) - margin(y)\big)$

Hope and Fear

- $\mathbf{w} \mathrel{+}= \alpha\big(\mathbf{f}(\mathbf{x}, y_{gold}) - \mathbf{f}(\mathbf{x}, y_{pred})\big)$
- min-cost $y_{hope} \stackrel{\text{def}}{=} \arg\max_y -cost(y)$
- max-score $y_{fear} \stackrel{\text{def}}{=} \arg\max_y score(y)$
- cost-diminished $y_{hope} \stackrel{\text{def}}{=} \arg\max_y score(y) - cost(y)$
- cost-augmented $y_{fear} \stackrel{\text{def}}{=} \arg\max_y score(y) + cost(y)$
- max-cost $y_{fear} \stackrel{\text{def}}{=} \arg\max_y cost(y)$

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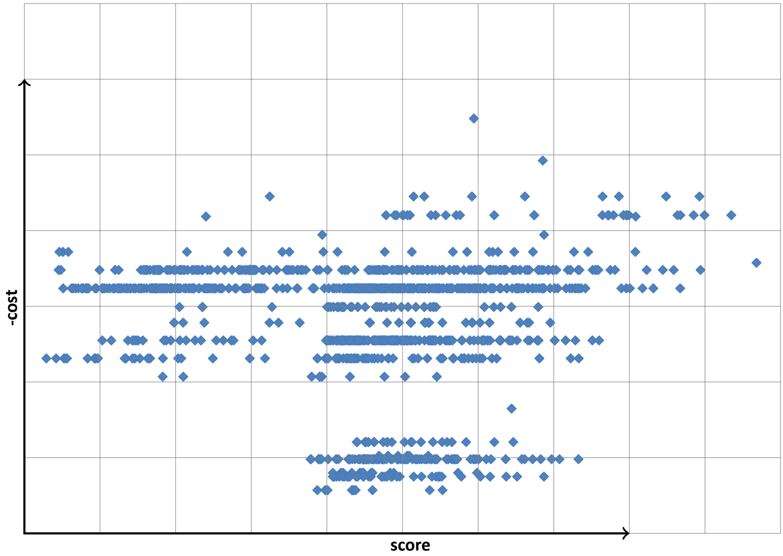
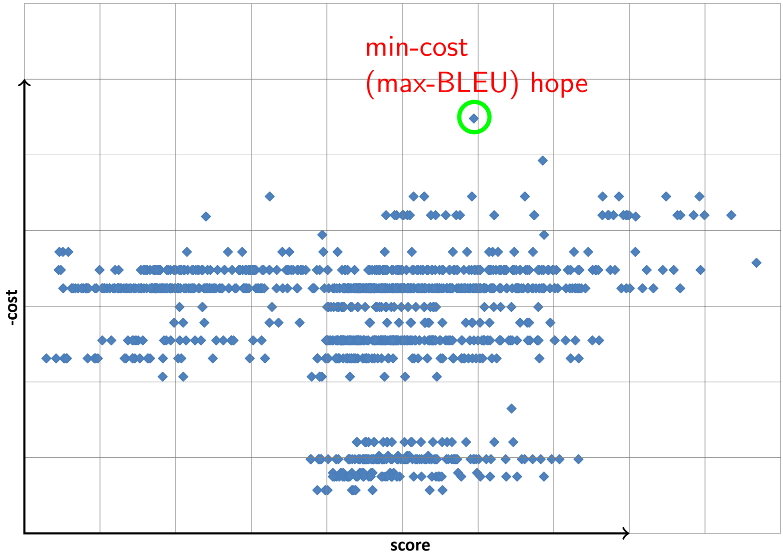
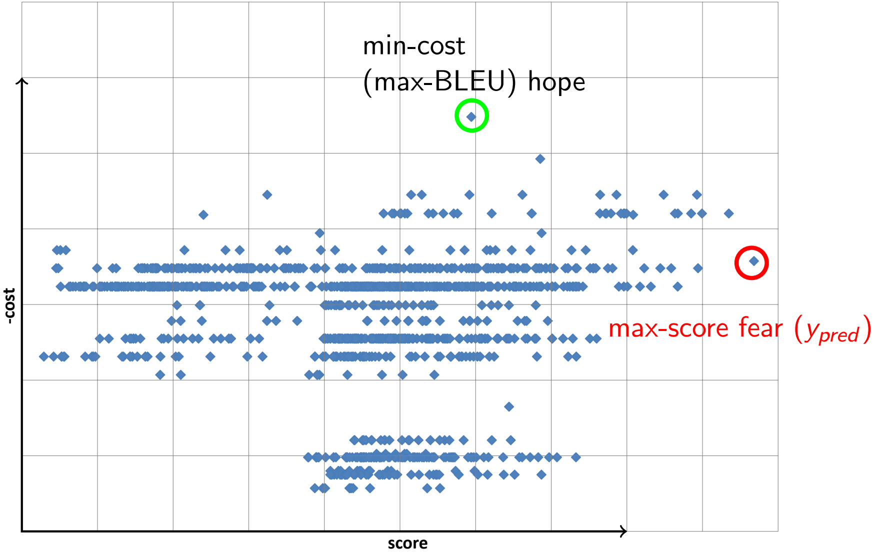
Cost-sensitive Online Learning



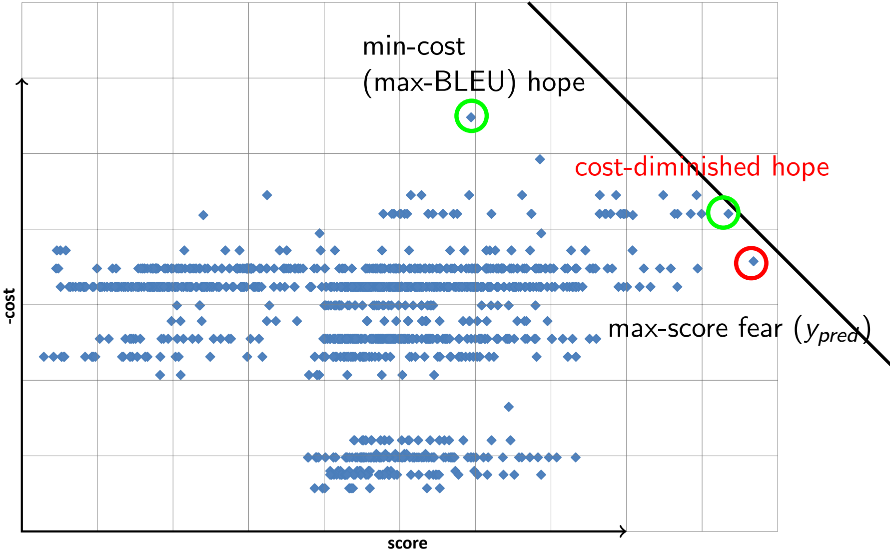
Cost-sensitive Online Learning



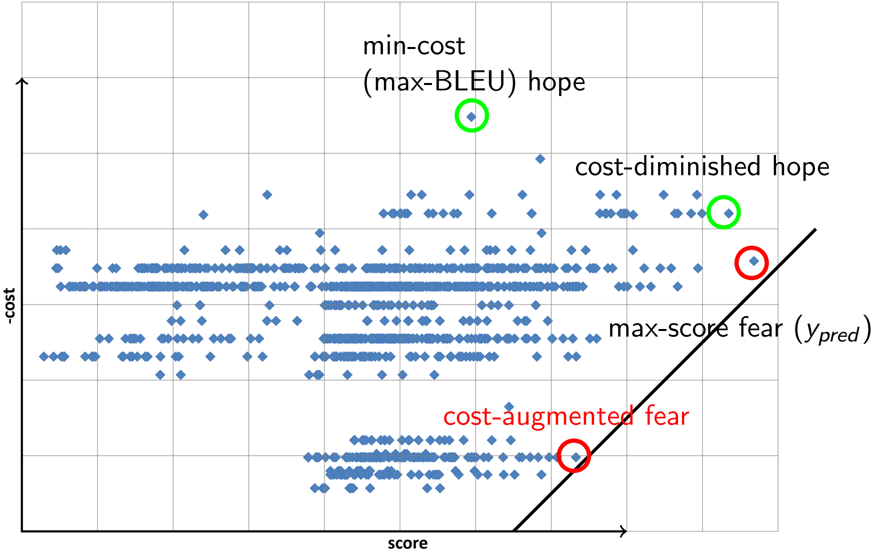
Cost-sensitive Online Learning



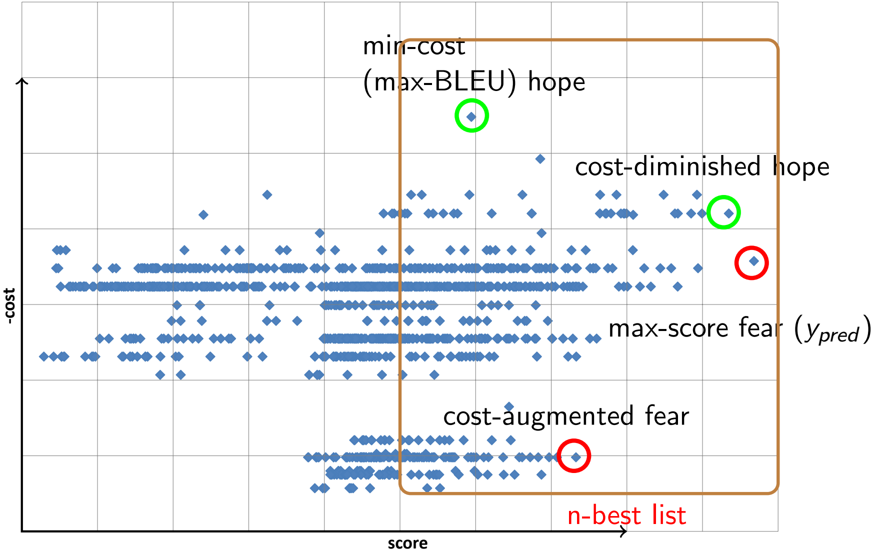
Cost-sensitive Online Learning



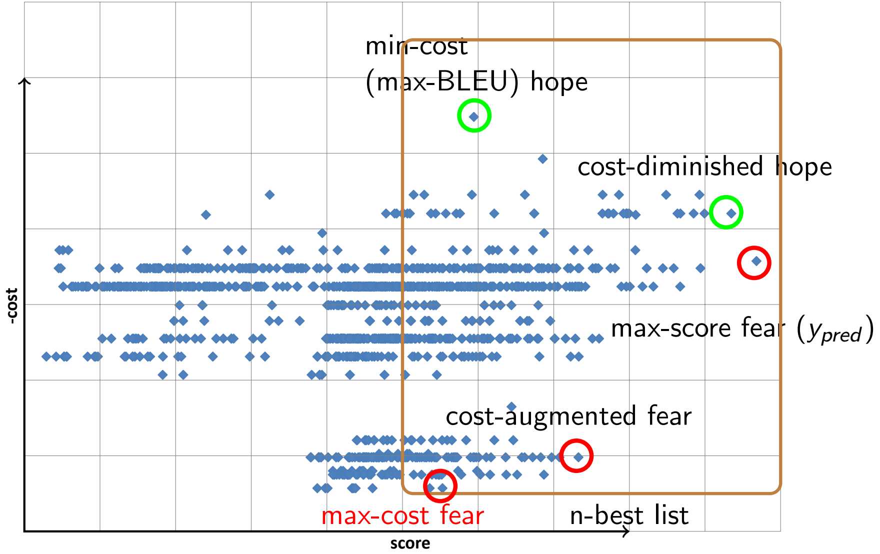
Cost-sensitive Online Learning



Cost-sensitive Online Learning



Cost-sensitive Online Learning



Application to MT

x = source sentence
y_{gold} = its reference translation

- more references sometimes available
- reference may be *unreachable*
- we score *derivations* (which include latent variables)
  one translation may have more derivations

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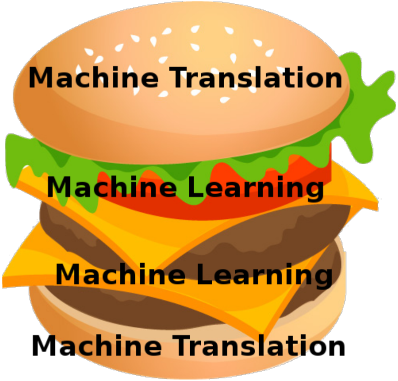
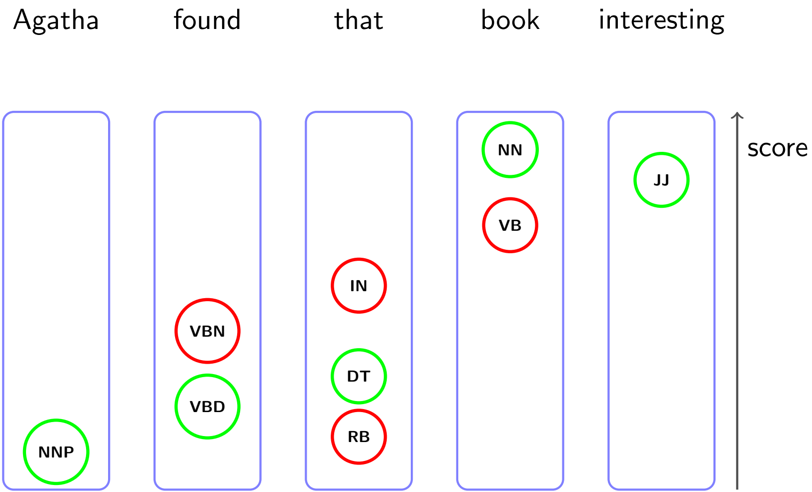
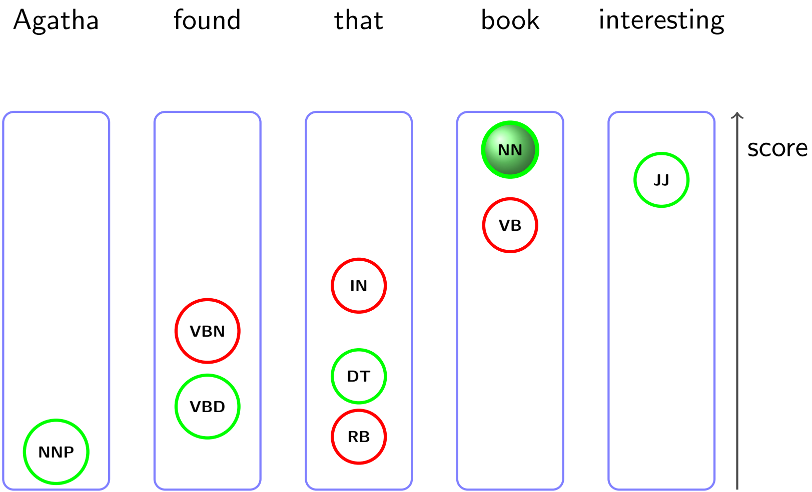


Easy-First Decoding (PoS Tagging)



(Shen, Satta and Joshi, 2007)

Easy-First Decoding (PoS Tagging)



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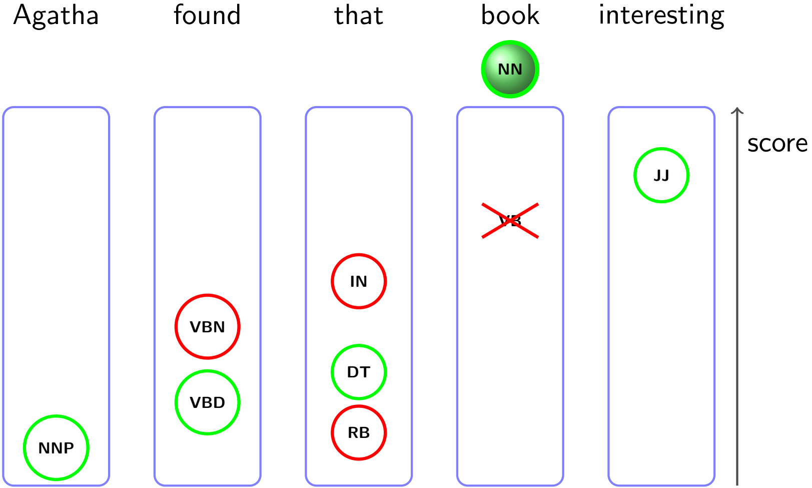

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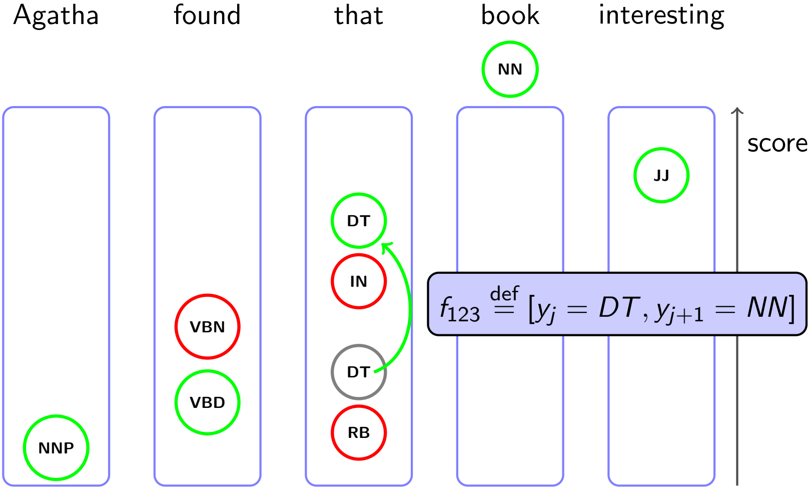
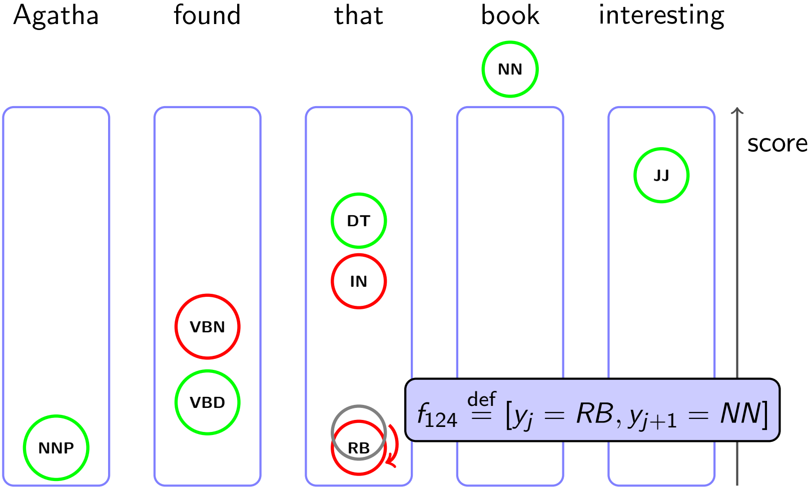


$$f_{123} \stackrel{\text{def}}{=} [y_j = DT, y_{j+1} = NN]$$

(Shen, Satta and Joshi, 2007)

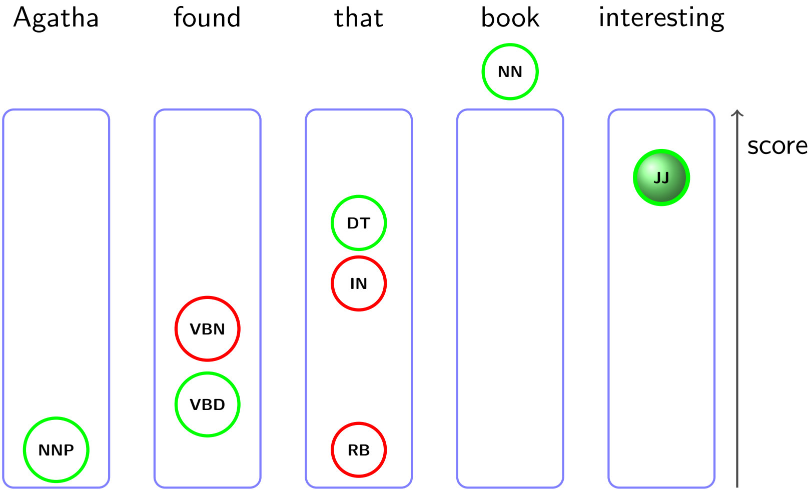
Easy-First Decoding (PoS Tagging)



$$f_{124} \stackrel{\text{def}}{=} [y_j = RB, y_{j+1} = NN]$$

(Shen, Satta and Joshi, 2007)

Easy-First Decoding (PoS Tagging)



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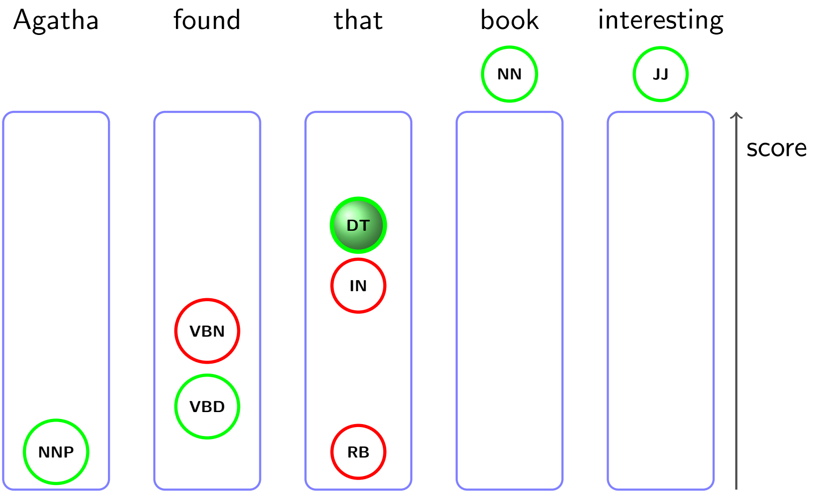

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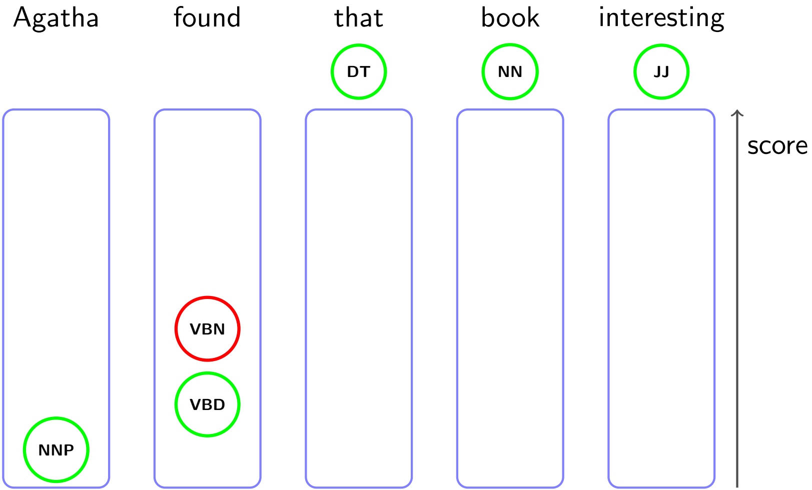

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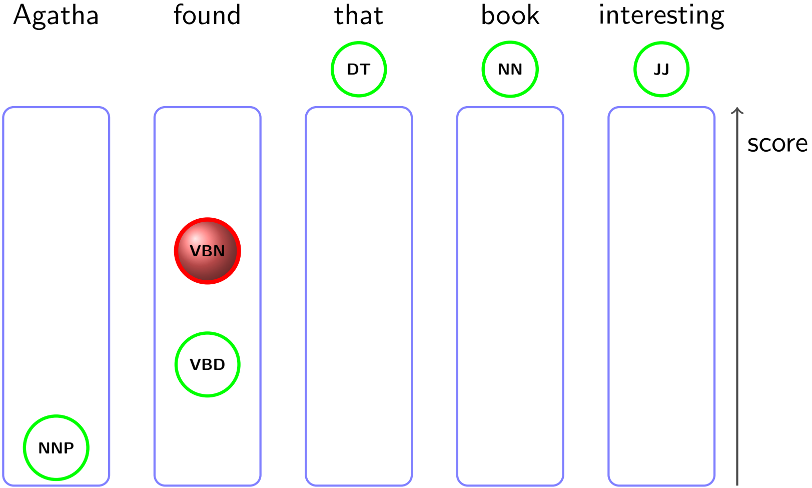
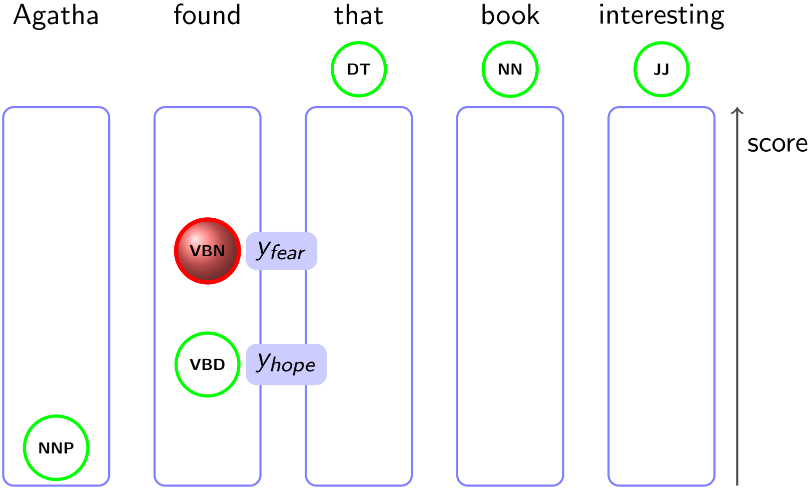
Easy-First Decoding (PoS Tagging)



(Shen, Satta and Joshi, 2007)

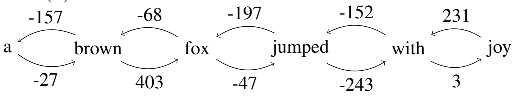
Guided Learning (PoS Tagging)



(Shen, Satta and Joshi, 2007)

Easy-First Decoding (Dependency Parsing)

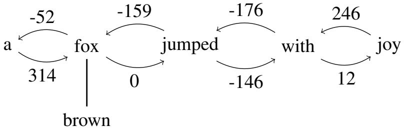
(1) ATTACHRIGHT(2)



(Goldberg and Elhadad, 2010)

Easy-First Decoding (Dependency Parsing)

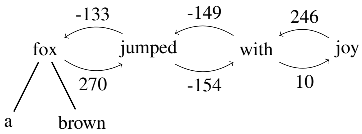
(2) ATTACHRIGHT(1)



(Goldberg and Elhadad, 2010)

Easy-First Decoding (Dependency Parsing)

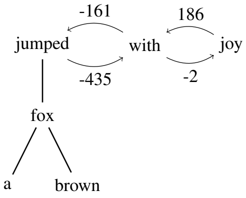
(3) ATTACHRIGHT(1)



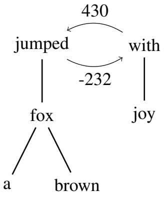
(Goldberg and Elhadad, 2010)

Easy-First Decoding (Dependency Parsing)

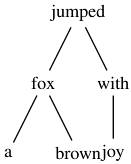
(4) ATTACHLEFT(2)



(5) ATTACHLEFT(1)



(6)



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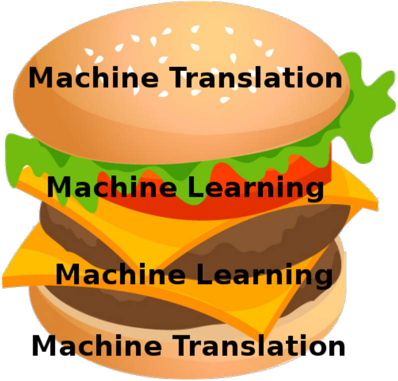
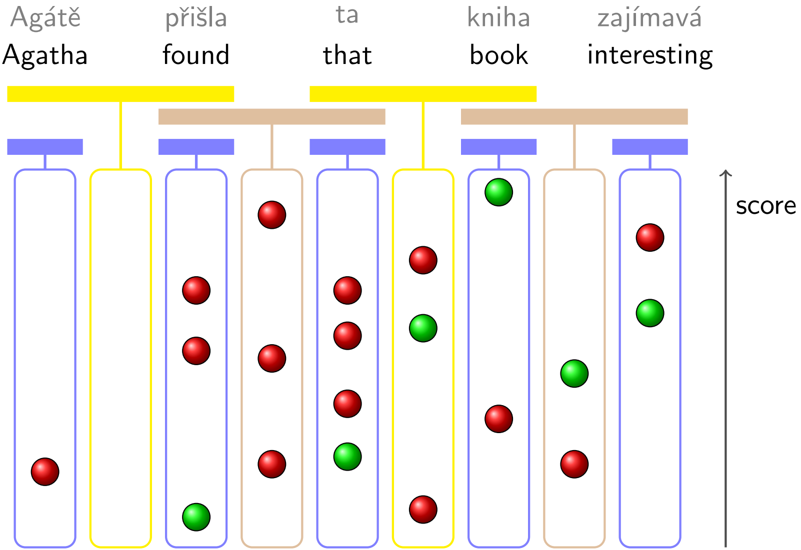


Easy-First Decoding (Phrase-Based MT)



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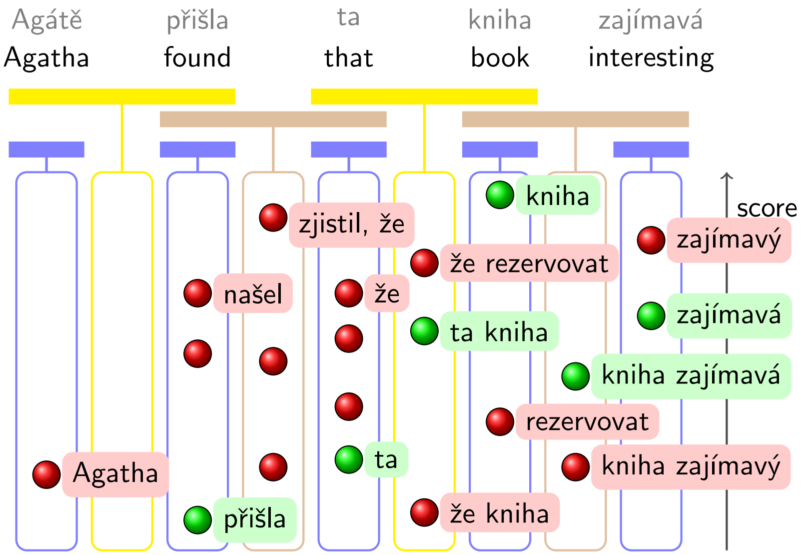

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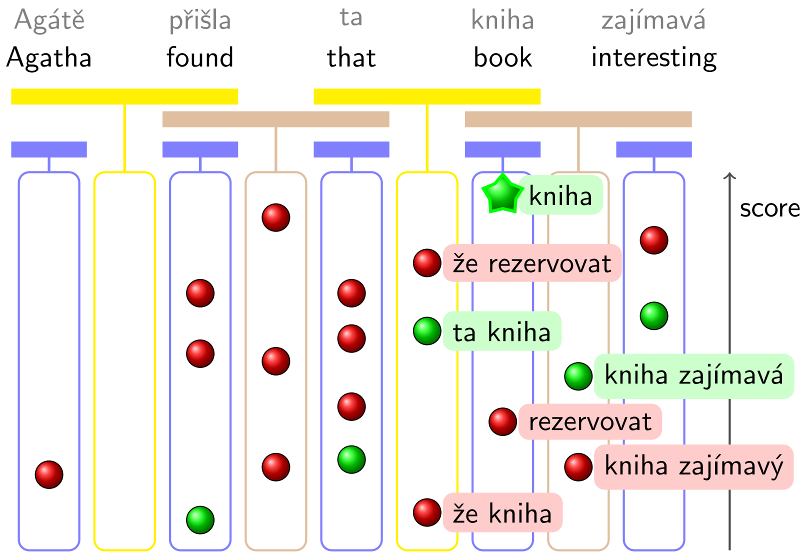

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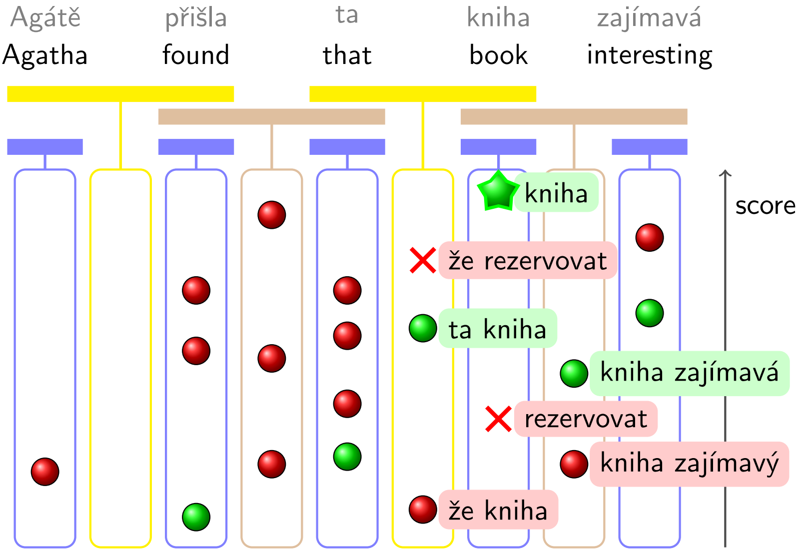

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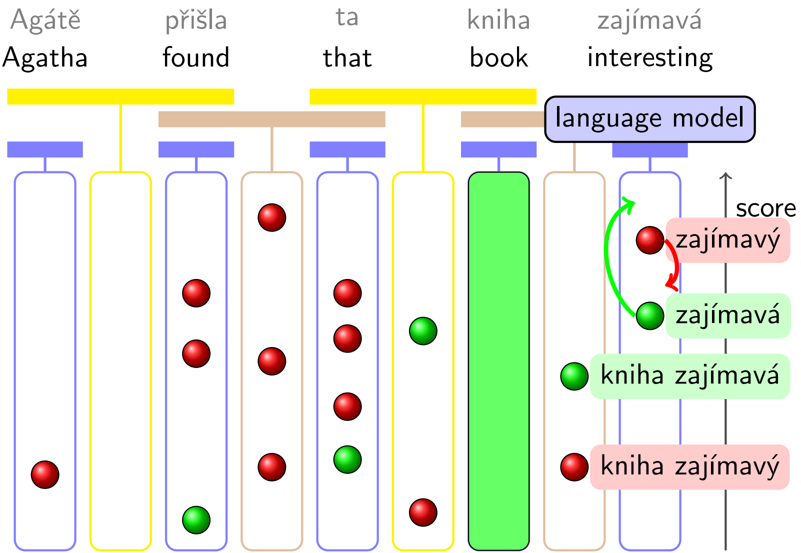

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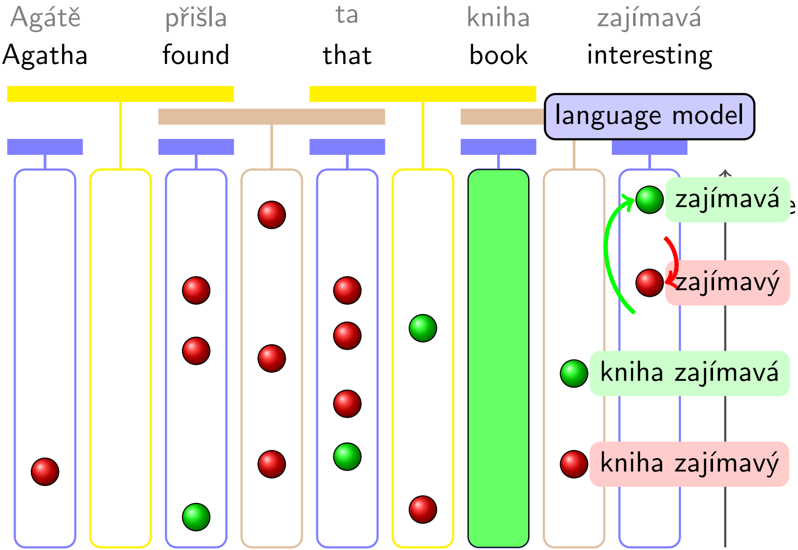

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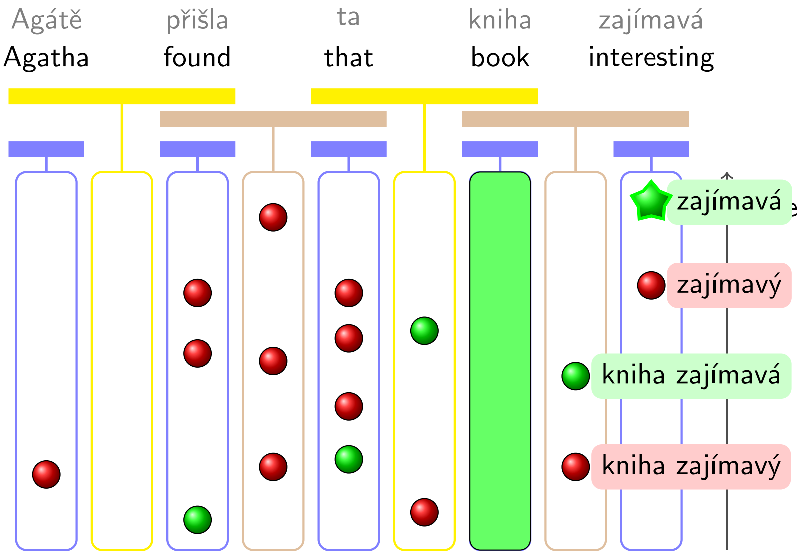

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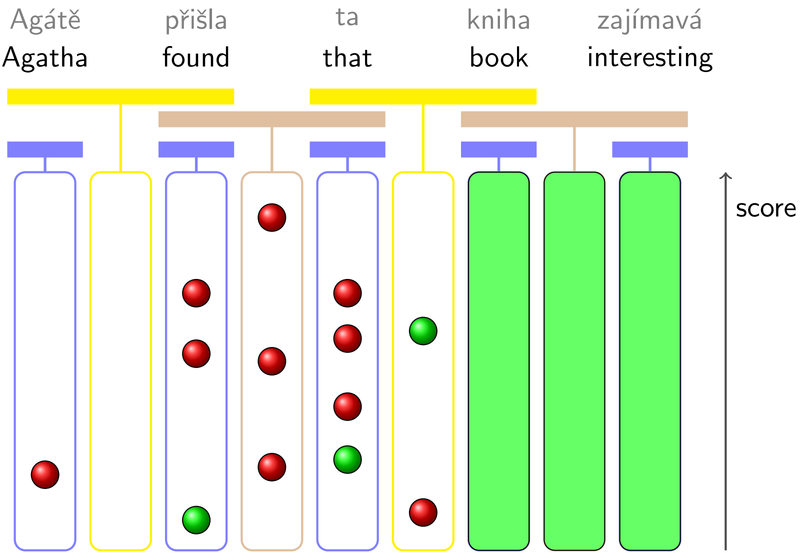

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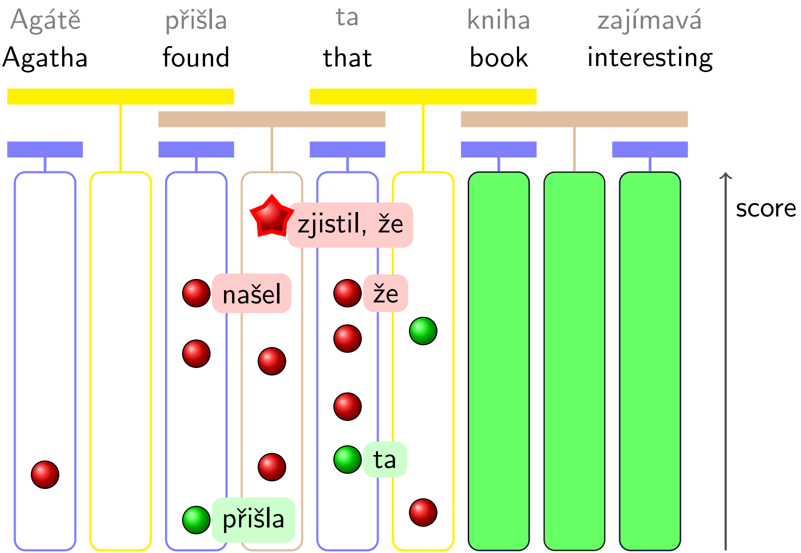

Features for Guided Learning in MT

Source Segment Features

- segment size (number of words)
- entropy $P(target|source) = -\sum_i P(src, trg_i) \cdot \log P(trg_i|src)$
- log count(source)
- source language model: log P(source)
- word identity, e.g. $f_{42} \stackrel{\text{def}}{=}$ [src=found that]
- PoS identity, e.g. $f_{43} \stackrel{\text{def}}{=}$ [src_pos=VBD IN]

Target-dependent Features

- log P(trg|src)
- target language model: log P(target | previous segment)
- log count(target)?
- identity, e.g. $f_{142} \stackrel{\text{def}}{=}$ [src=found that & trg=zjistil]

Features for Guided Learning in MT

Source Segment Features

- segment size (number of words)
- entropy $P(target|source) = -\sum_i P(src, trg_i) \cdot \log P(trg_i|src)$
- log count(source)
- source language
- word identity, e.
- PoS identity, e.g

Combinations and Quantizations

$[size(src) = 3] \cdot \log P(trg|src)$
$[size(src) = 3 \quad \& -3 < \log P(trg|src) < -2]$
etc.

Target-dependent Features

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- target language model: log P(target | previous segment)
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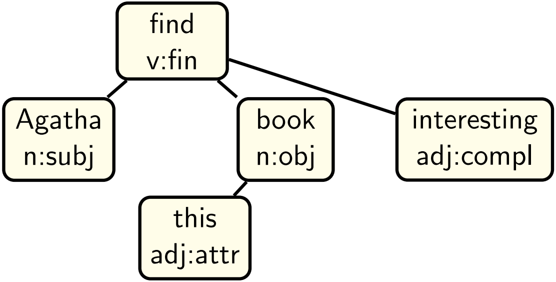
- identity, e.g. $f_{142} \stackrel{\text{def}}{=}$ [src=found that & trg=zjistil]

Application to Tecto Trees



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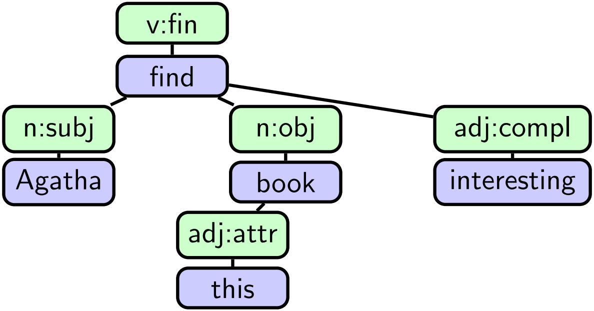
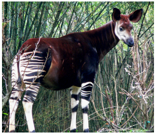
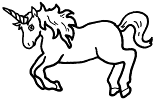
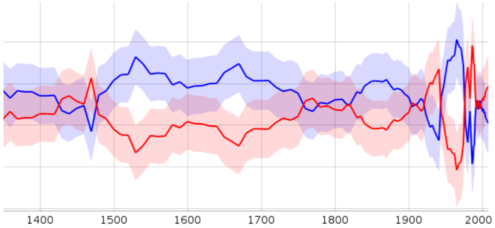


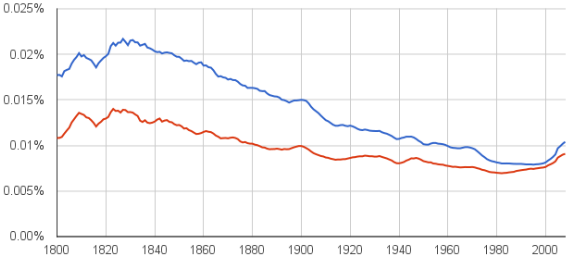
What have you seen in the Zoo





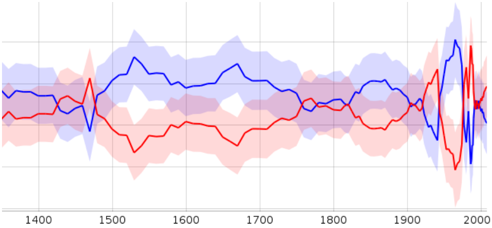
Predictions?



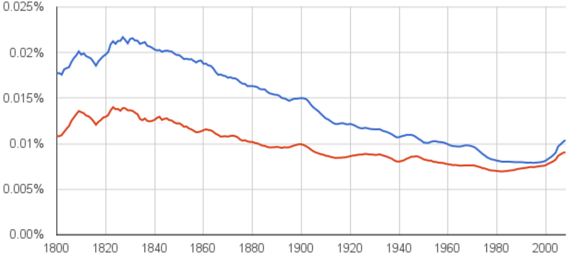


Predictions?

Hope and Fear



http://syd.korpus.cz/



http://books.google.com/ngrams/