Discussion on Bilingual Cognition in International Exchange Activities

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Outline

- International Exchange Activities
- Demands for Machine/Human Translation
- Background
- Motivation
- Methodology
- Experiments
- Conclusions

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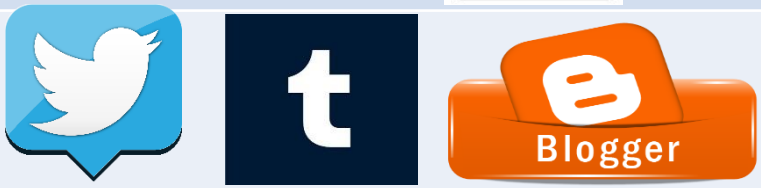
International Exchange Activities (IEAs)

How?

Weak ideas

- How could we achieve higher quality in international exchange activities?
- How about hire a multilingual human translator?
  - Money
  - Time
  - Efficiency
- How about AI?
  - Machine Translation System
    - **Quality ?**
- ....

Some efficient ways for IEAs

Different channels	Examples
Social Media Networking	
BLOGS	
Activities Sharing and Storage	
Telecommunication Options	

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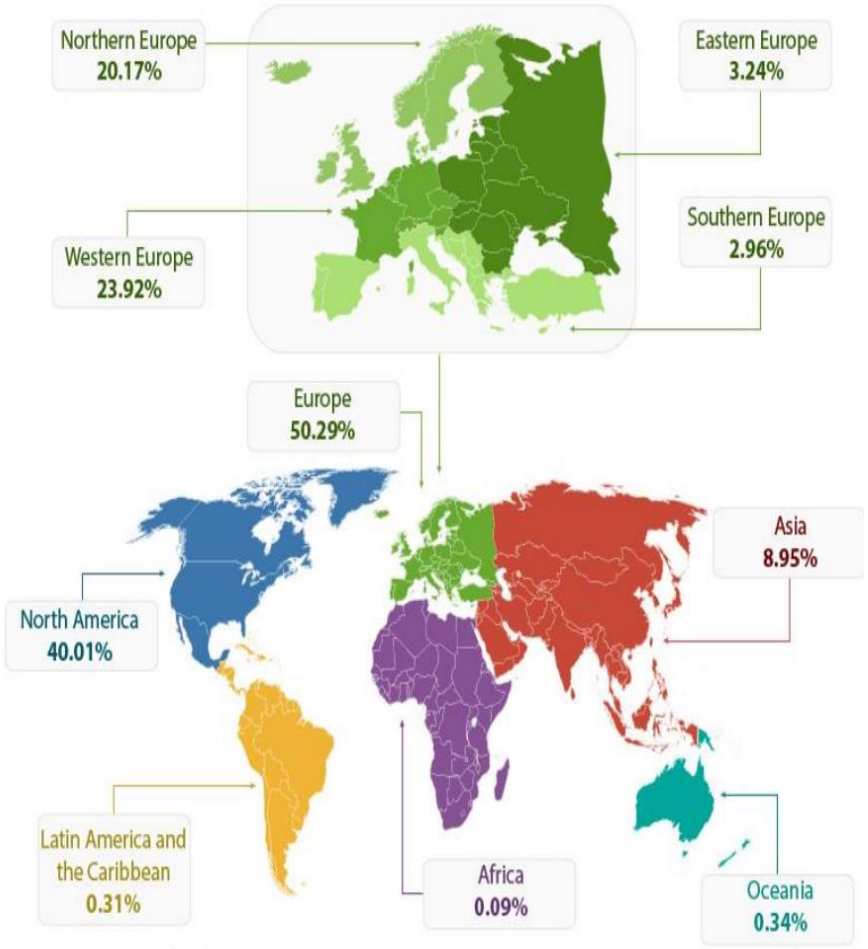
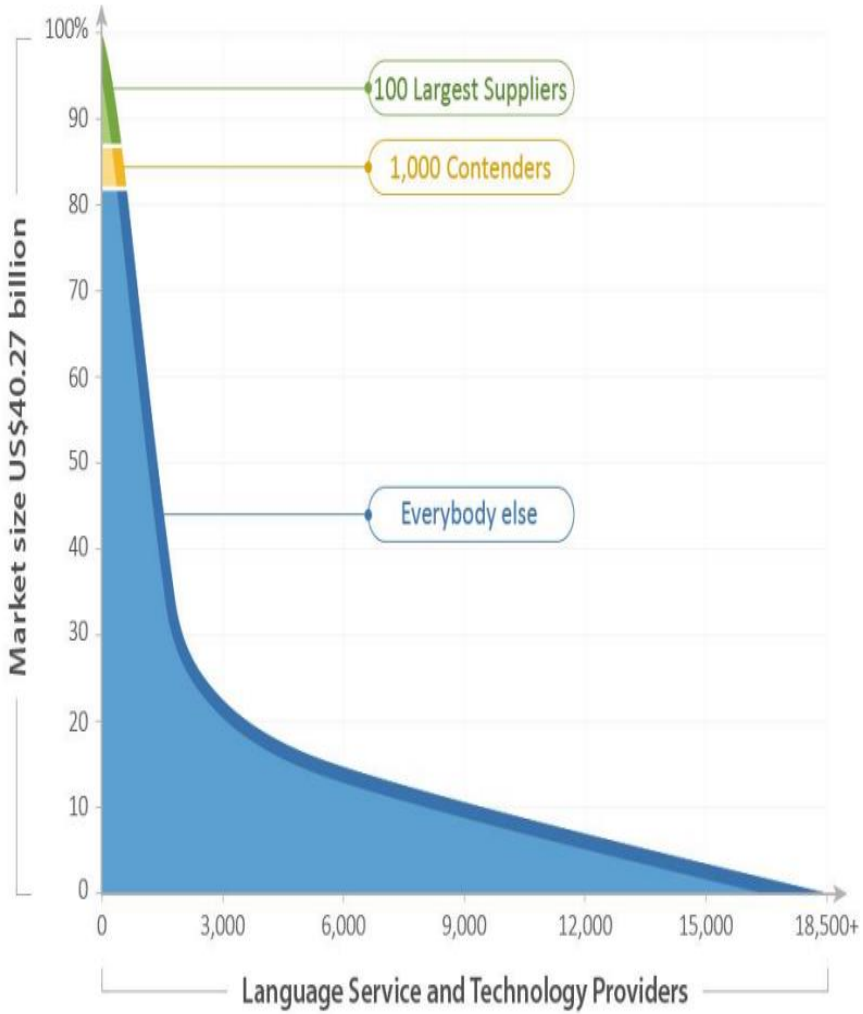
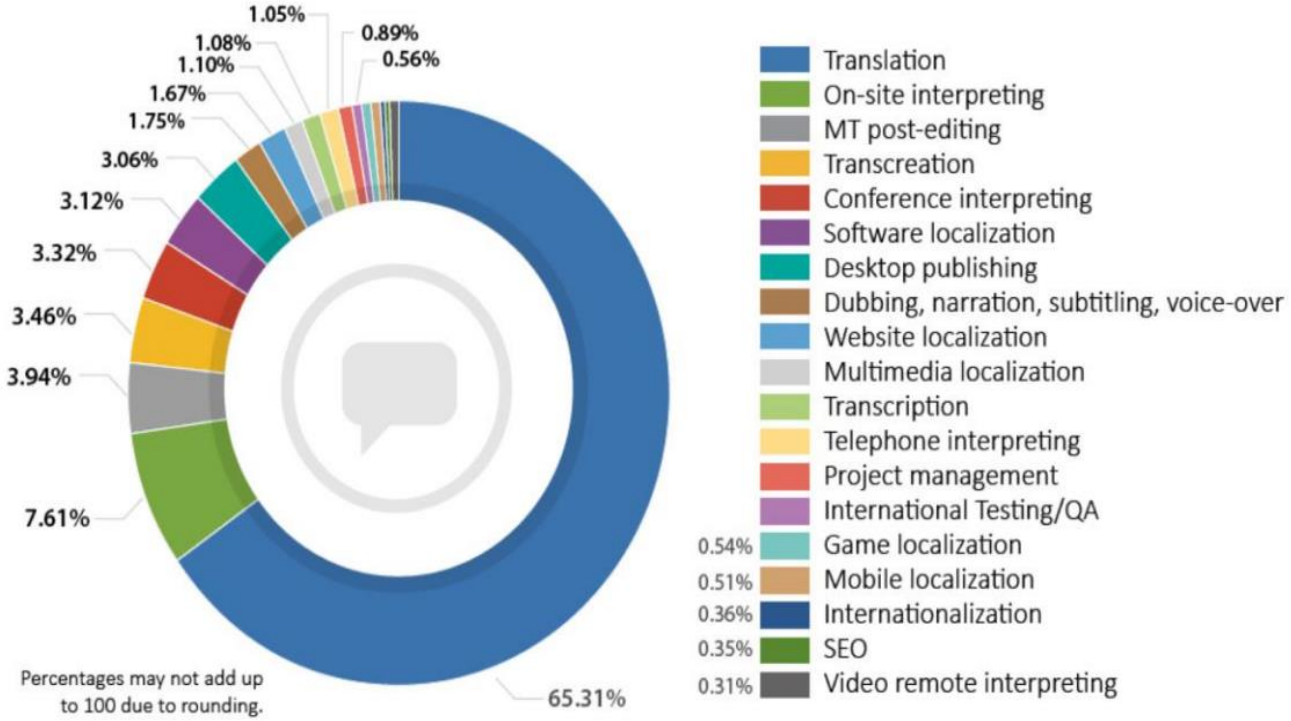
Demands for Machine/Human Translation





(Guoping Huang, Qcon2018)

Demands for Machine/Human Translation



- Human translator is the main
- Tech less than original
- MT has low percentage, but growing faster

(Guoping Huang, Qcon2018)

Demands for Machine/Human Translation

- Human translation fields

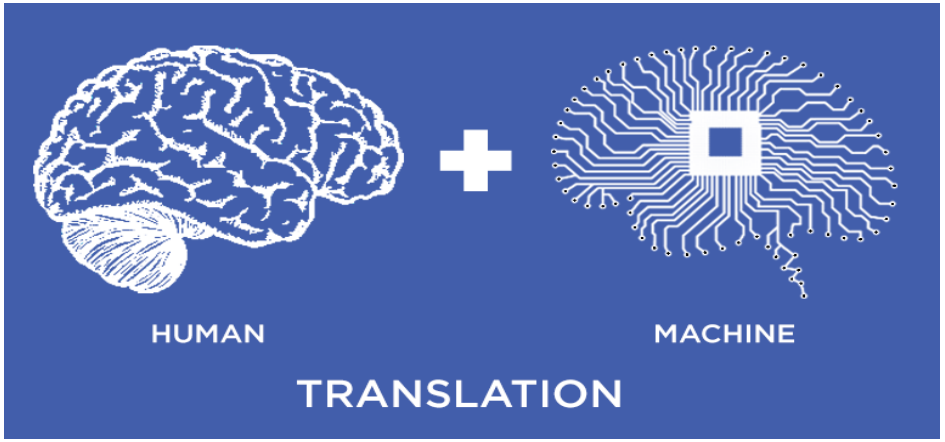
  ≈ 666 million words / day

  [Pym et al., 2012]

- Machine translation fileds

  >> 100 billion words / day

  [Turovsky, 2016]



Demand for translation for outpaces what is humanly possible to produce.

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Background

- Machine Translation (MT)
  - Statistical Phrase-based Machine Translation (SMT)
  - Neural Machine Translation (NMT)

Machine Translation (MT)

- Machine Translation: let the computer translate the human language, as well as it is a technique that uses a computer to automatically convert one natural language (Source language) to another natural language (target language).

Typical MT Systems

Demo (SMT)


1.5.245:9662/index.html
清华大学多语种翻译系统
چېڭخۇا ئۇنىۋېرسىتى كۆپ تىللىق تەرجىمە سىستېمىسى
维文
汉语
通用领域
翻译
维文
汉语
藏文
蒙文
革命先烈纪念日人民英雄敬献花篮的仪式在北京隆重举行
.ts.cn/system/2018/10/01/035399943.shtml
2018/10/01 15:37
最多可以输入500个字符
.NLP&CSS group, Tsinghua University :2011-2018 ©
Email: miradel51@126.com Tel: 13051308938 Wechat: 821777278

Demo (NMT)


多语种翻译系统
كۆپ تىللىق تەرجىمە سىستېمىسى
维吾尔语
>>
汉语
通用领域
翻译
群众组成方队，面对的是中共中央。,全国人民代表大会常务委员会,国务院；,全国政协：,中央军事委员会；,各民主党派,全国工商联及无党派爱国人士,各人民团体和各界群众,老战士,老同志和革命先烈的家属。,以中国少先队命名的九个大型花束排列。
最多可以输入500个字符

MT Parallel Corpus

他 喜欢 北京 。

He likes Beijing .

他 在 东京 居住 。

He lives in Tokyo .

日本 的 首都 是 东京 。

The capital of Japan is Tokyo .

北京 是 中国 的 首都 。

Beijing is the capital of China .

… …

他 来自 日本 。

He is from Japan .

日本 临近 中国 。

Japan is near China .

中国 是 亚洲 国家 。

China is an Asian Country .

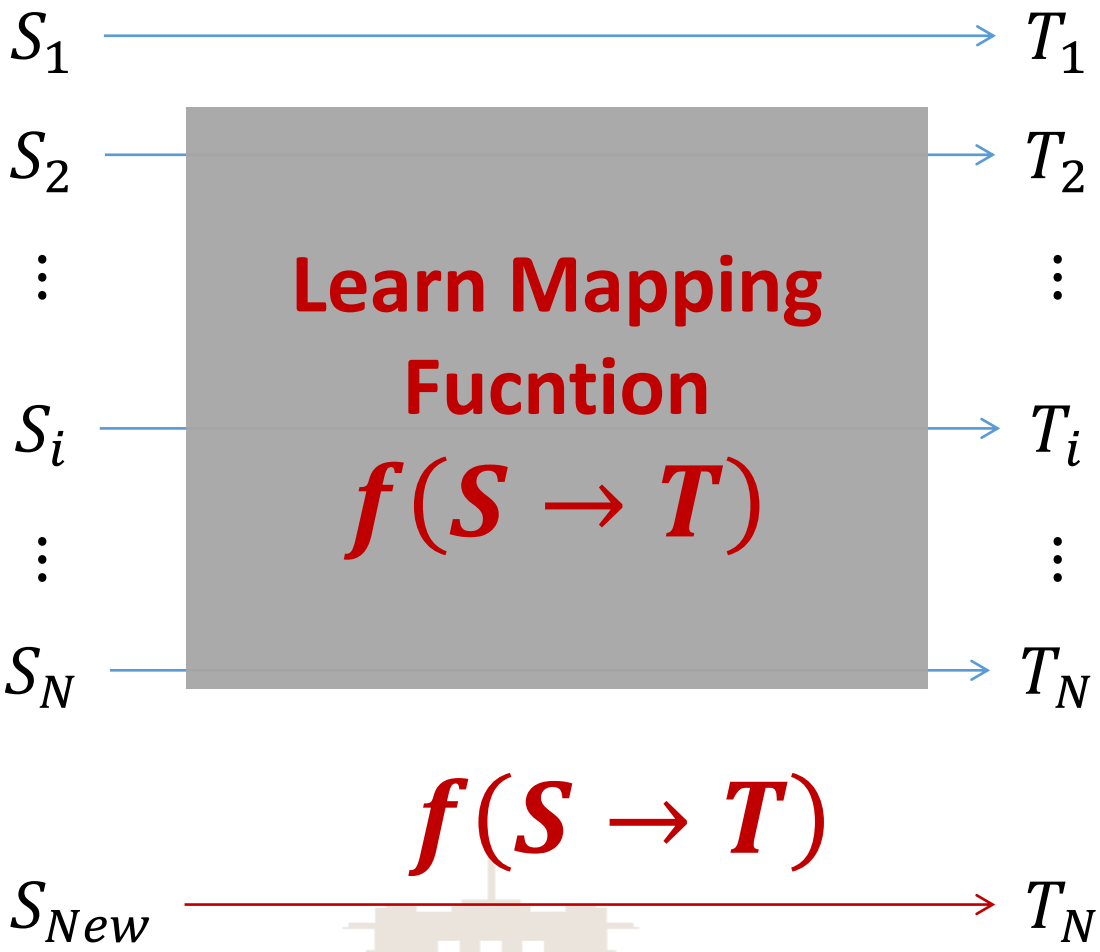
北京 位于 中国 的 北方 。

Beijing is located in the North of China .

… …

(Jiajun Zhang, CCL2018)

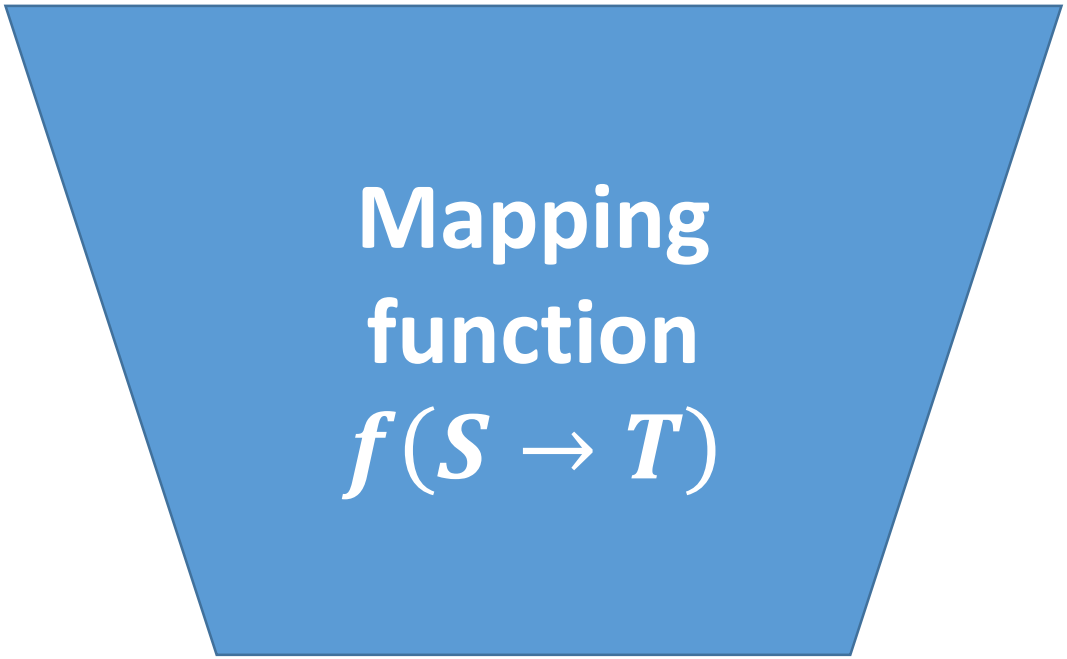
Mapping function from source to target language



(Jiajun Zhang, CCL2018)

Mapping function from source to target language

Chinese: 我 在 北京 大学 做了 报告

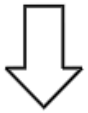


English: I gave a talk in Peking University

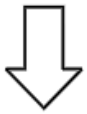
(Jiajun Zhang, CCL2018)

SMT

x 布什 与 沙龙 举行 了 会谈



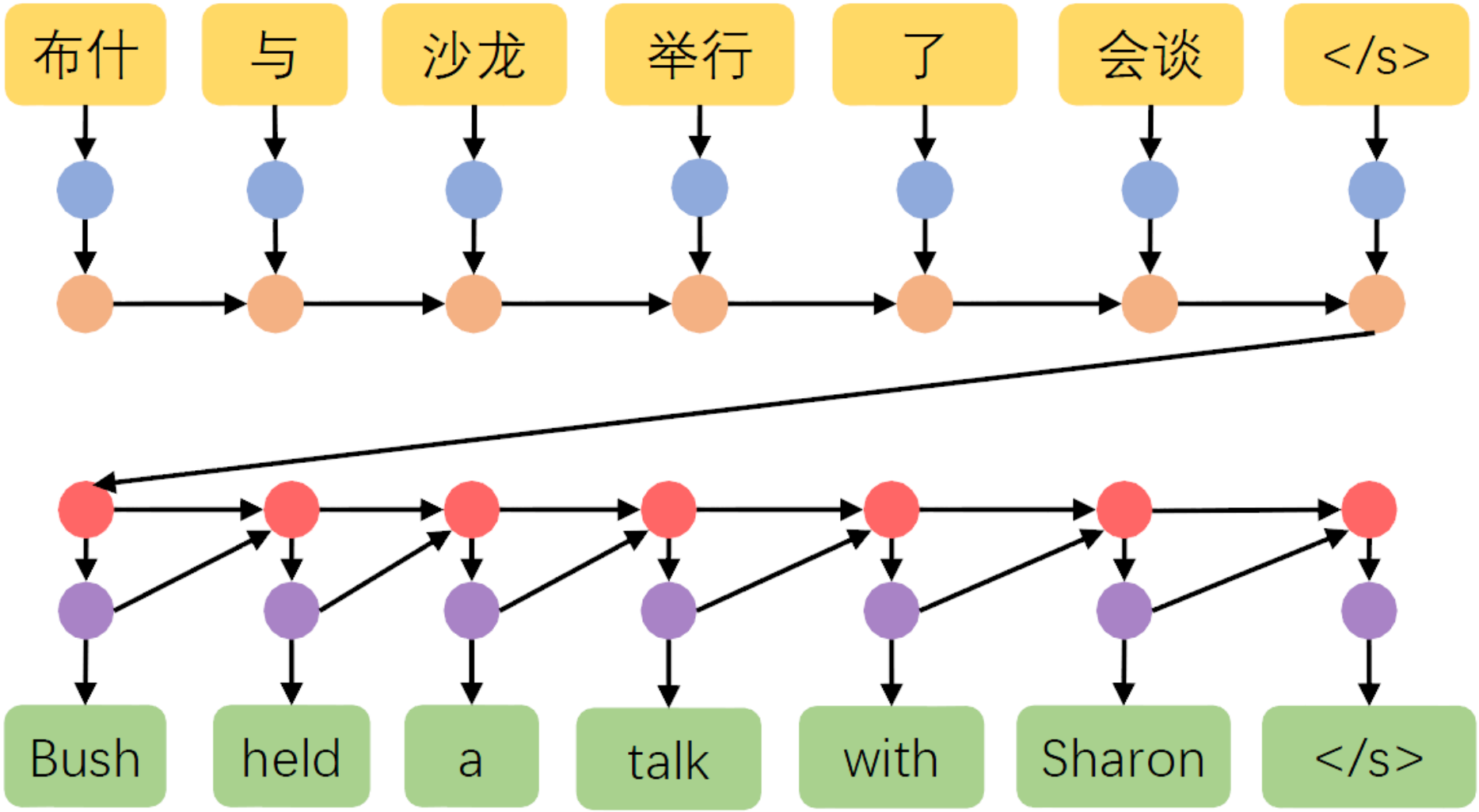
$$P(\mathbf{y}|\mathbf{x};\boldsymbol{\theta}) = \sum_{\mathbf{z}} \frac{\exp(\boldsymbol{\theta}\cdot\boldsymbol{\phi}(\mathbf{x},\mathbf{y},\mathbf{z}))}{\sum_{\mathbf{y}'}\sum_{\mathbf{z}'}\exp(\boldsymbol{\theta}\cdot\boldsymbol{\phi}(\mathbf{x},\mathbf{y}',\mathbf{z}'))}$$



y Bush held a talk with Sharon

(Och and Ney., 2002)

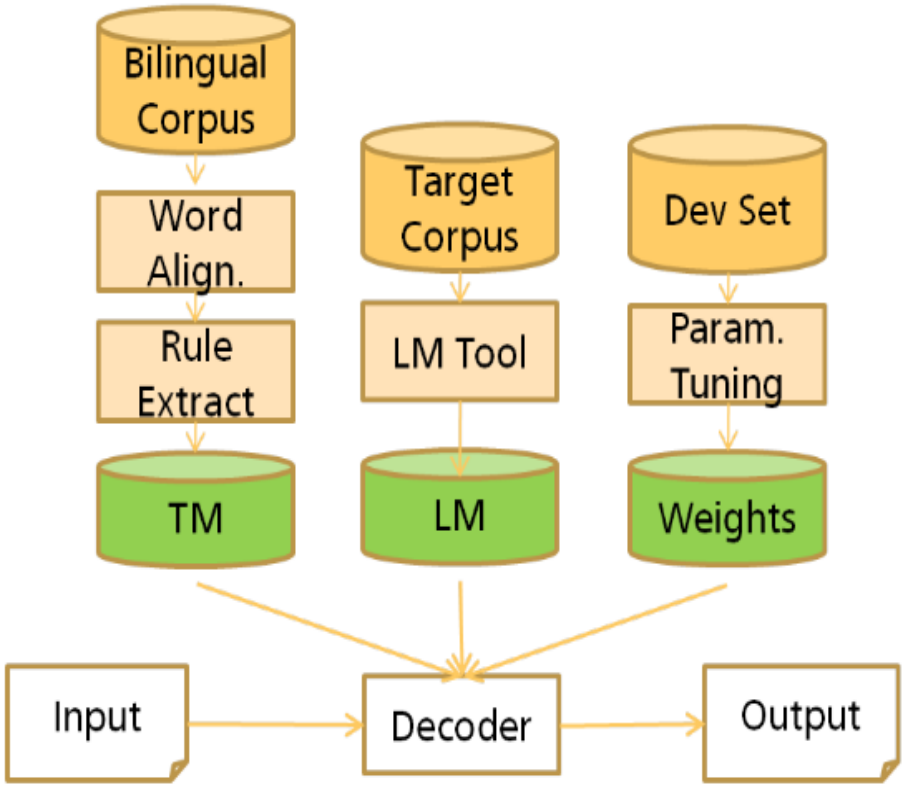
NMT



(Sutskever et al., 2014)

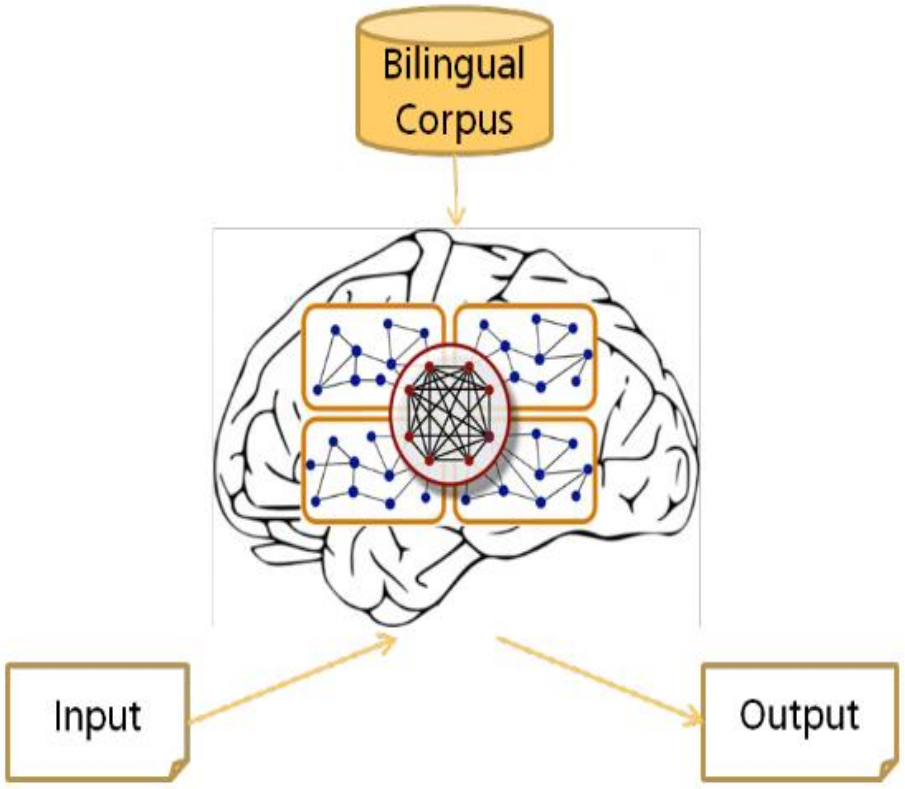
SMT && NMT

Many sub-components are tuned separately



SMT (1993 ~)

single , large neural network



NMT (2014~)

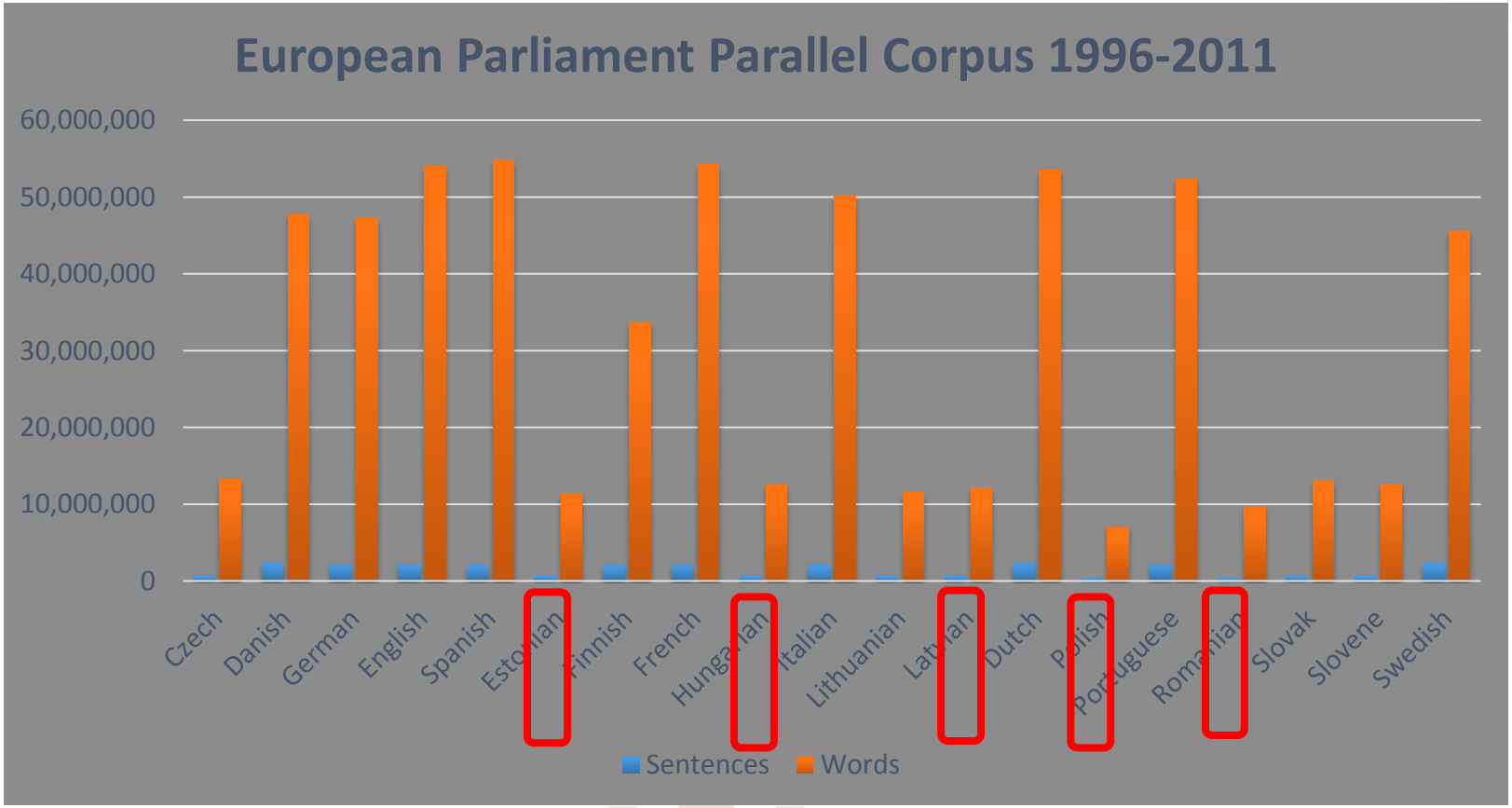
NMT

- X, Y;Raw source and target sentences.
- Given source sentences $X = x_1, \cdots, x_i, \cdots, x_I$ and target sentence Y= $y_1, \cdots, y_i, \cdots, y_I$
- Standard NMT models usually factorize the sentence-level translation probability as a product of word-level probabilities：
- $P(y|x;\theta) = \prod_{j=1}^{J} P(y_i|x, y_{<j};\theta)$
- θ is model parameters, $y_{<j}$ is partial translation.

NMT

- NMT models usually rely on an encoder-decoder scenario.
- Let $\langle X, Y \rangle = \{x^{(n)}, y^{(n)}, \}_{n=1}^{N}$ be a training corpus. The log-likelihood of the training parallel data is maximized by the standard training objective function:
- $\hat{\theta} = \underset{\theta}{\operatorname{argmax}}\{\sum_{n=1}^{N} logP(y^{(n)}|x^{(n)}; \theta)\}$
- $\hat{y} = \underset{y}{\operatorname{argmax}}\{P(y|x; \hat{\theta})\}$ $\hat{y}_j = \underset{y}{\operatorname{argmax}}\{P(y|x, \hat{y}_{<j}; \hat{\theta})\}$

Low-Resource Languages (LRLs)



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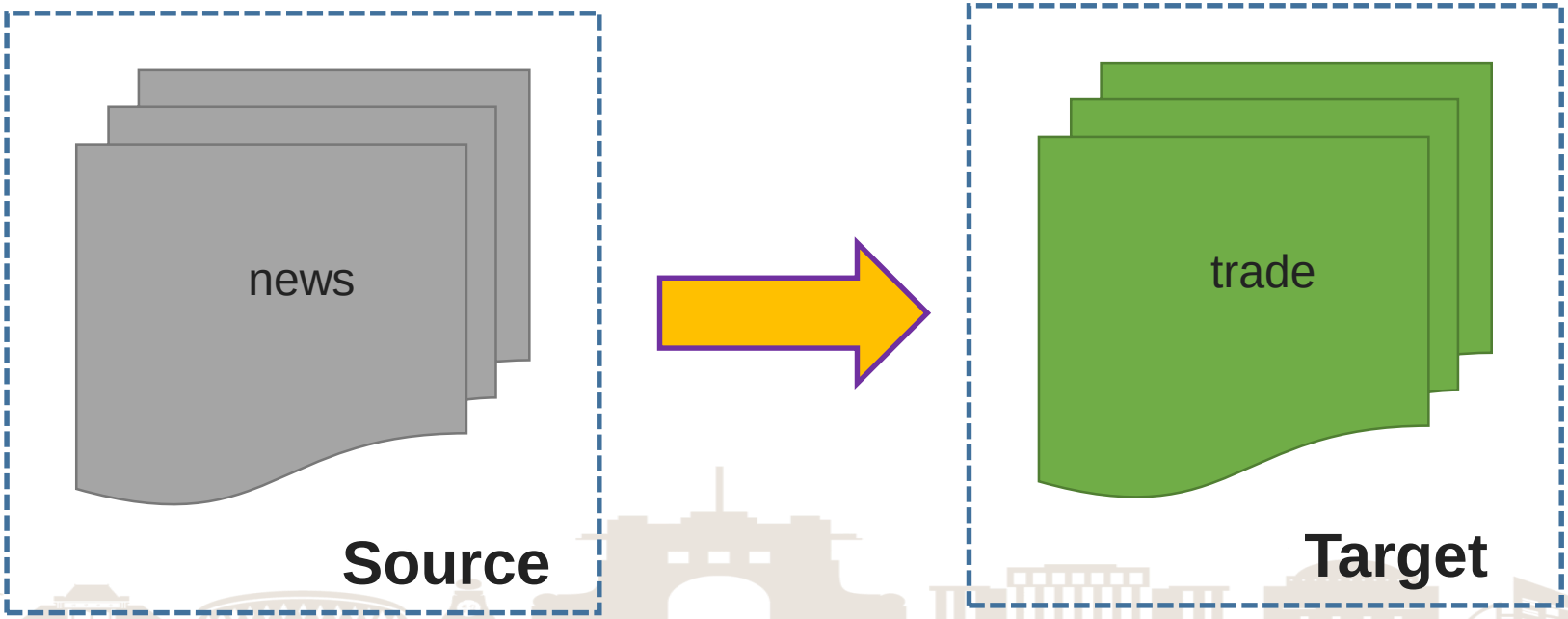
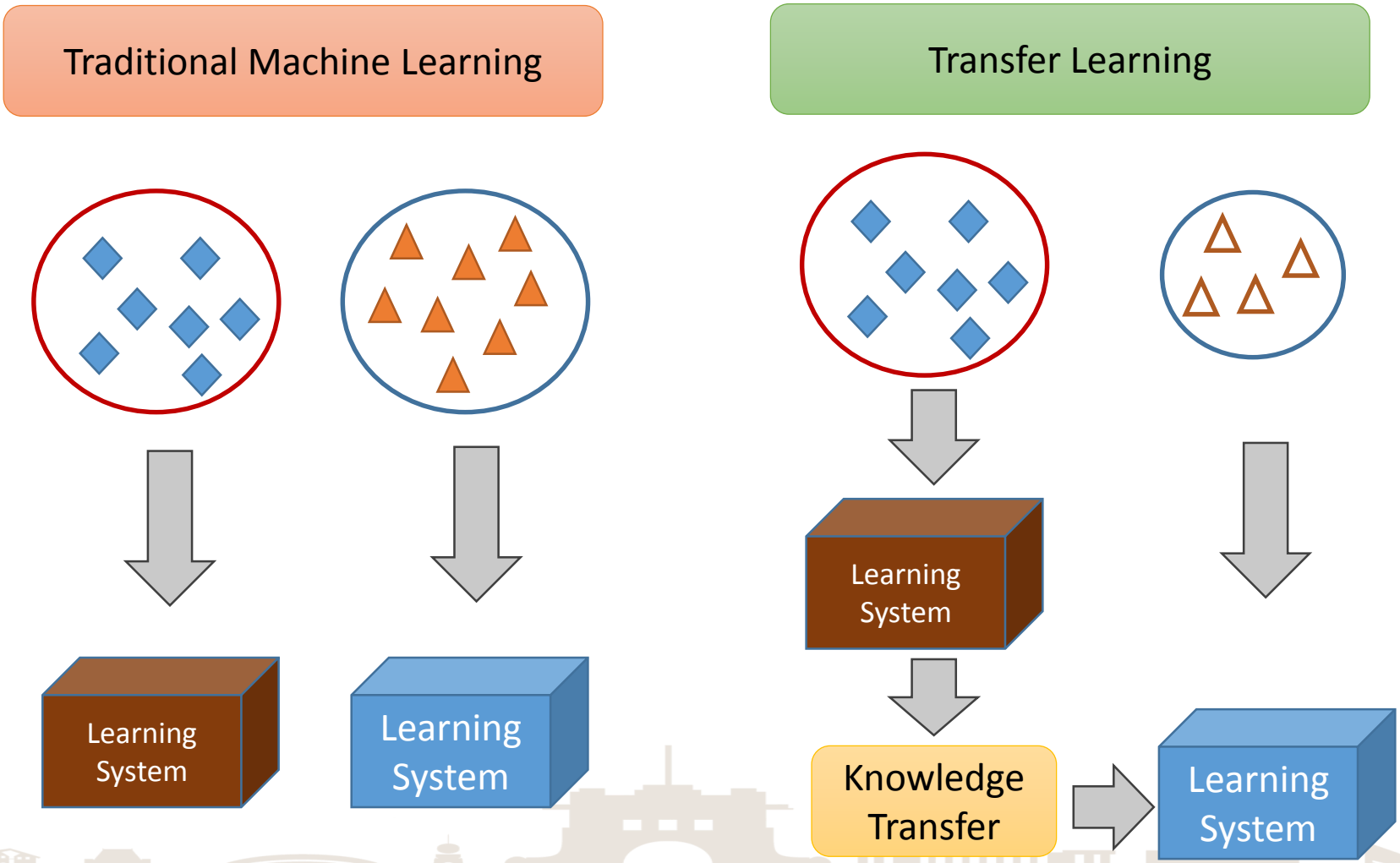
Motivation

- Transfer Learning (TL)

  This scenario arises when we aim at learning from a source data distribution a well performing model on a different (but related) target data distribution.



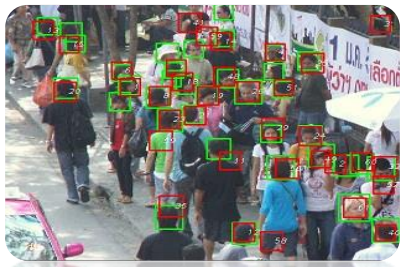
Transfer Learning



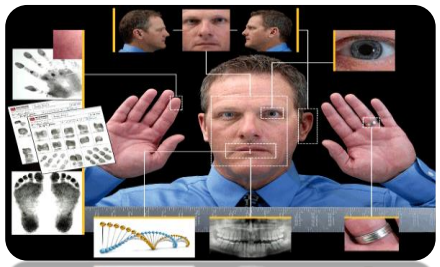
Transfer Learning

In Natural Language Processing (NLP), train a system on some language data, retune && apply it to specific different task.

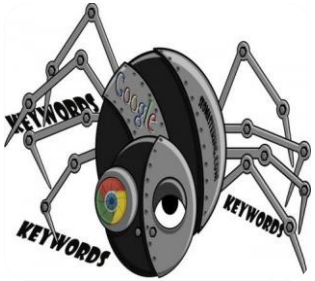
Build speech recognition system using recorded phone calls, then tune it to use as an airline reservation hotline.



CV



ER



IR

ASR

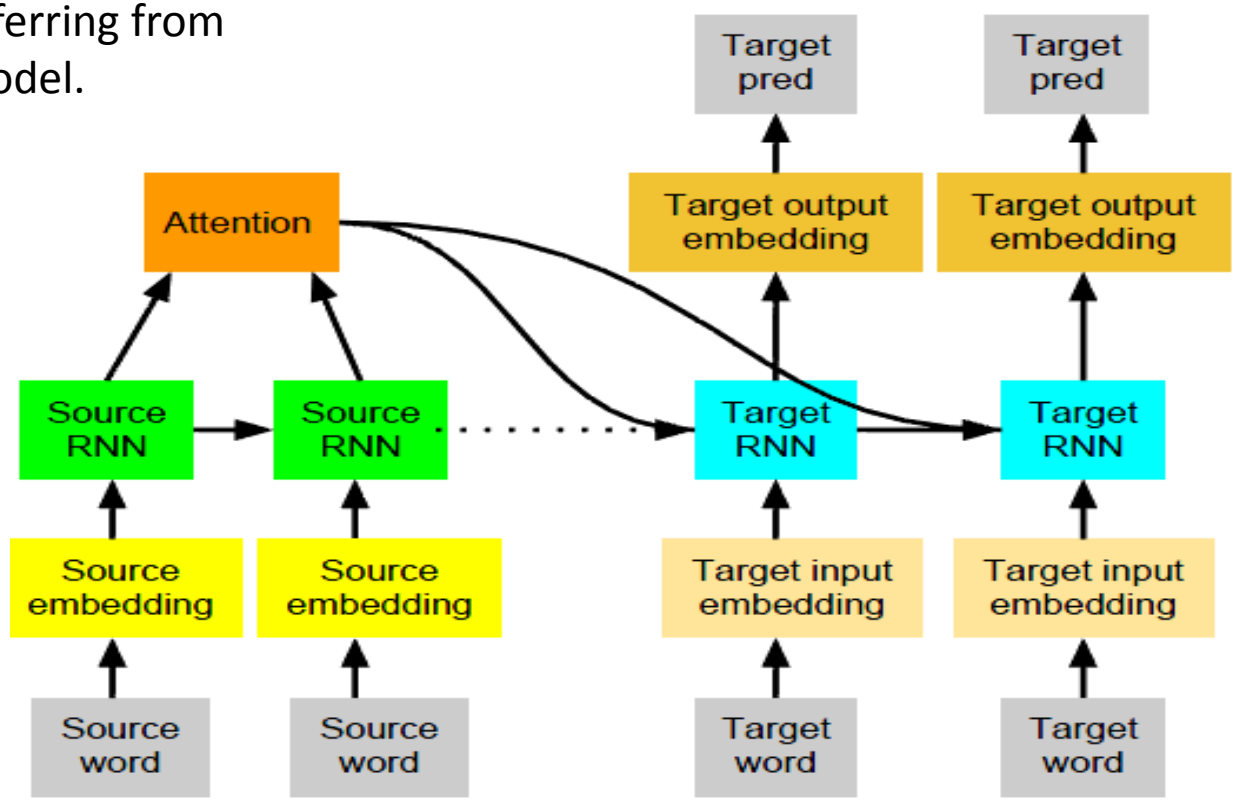
Transfer Learning

Optimal setting for transferring from **parent** model to **child** model.

Parent : Fr-En , De-En
Child: Uz-eEn

Transfer learning；
High-resource language；

Drawback:
Ignore the word sharing；



(Barret Zoph et al., 2016)

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Methodology

- We take the $L_3 \rightarrow L_2$ as parent and $L_1 \rightarrow L_2$ as child language pair. L_3 and L_1 are source languages of parent and child ,respectively, $L_2$is the target language for both.

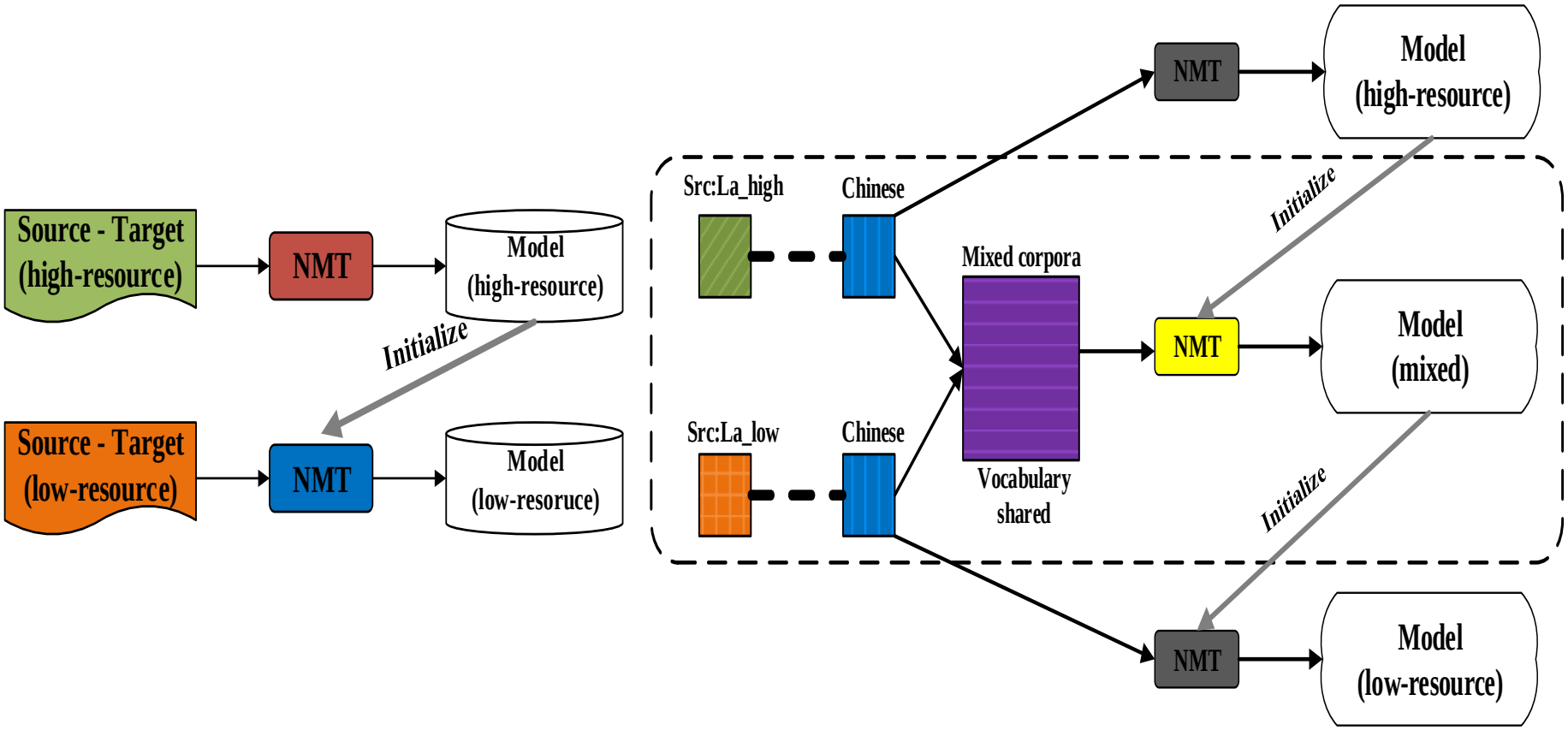
- $\theta_{L_3 \rightarrow L_2} = \{< e_{L_3}, W, e_{L_2} >\}$ while e_{L_3} and e_{L_3}source and target embedding of parent model, W is parameters.

- $\hat{\theta}_{L_3 \rightarrow L_2} = \underset{\theta_{L_3 \rightarrow L_2}}{\operatorname{argmax}}\{L(D_{L_3}, \theta_{L_3 \rightarrow L_2})\}$ train the parent model $M_{L_3 \rightarrow L_2}$

- Then fine-tune the child model $M_{L_1 \rightarrow L_2}$ with parent model $M_{L_3 \rightarrow L_2}$:

- $\theta_{L_1 \rightarrow L_2} = f(\hat{\theta}_{L_3 \rightarrow L_2})$, while f is initialization function.

Methodology



(a)

Original Transfer Learning

(b)

Mixed Transfer Learning

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Experiment

- System : DL4MT
- Parameters：
  - Dropout 0.1
  - Word Embedding 620
  - Hidden State 1000
  - Vocabulary 3w
- Other parameter we use the default parameters of DL4MT
- Preprocess
  - Clear data use NiuTrans , Chinese segmenter use THULAC

Experiment

Experiment data is available here and here.

Lnaugae	Family	Group	Branch	Order	Unit	Inflection
Arabic (Ar)	Hamito-Semitic	Semitic	South	VSO	Word	High
Farsi (Fa)	Indo-European	Indic	West	SOV	Word	Moderate
Urdu (Ur)		Iranian	Iranian	SOV	Word	Moderate
Chinese (Ch)	Sino-Tibetan	Chinese	Sinitic	SVO	Character	Light

Lnaugaes	Train	Dev	Test	Source			Target		
				Vocab.	#Word	#CoV.[%]	Vocab.	#Word	#CoV.[%]
Ar → Ch	5.1M	2.0K	2.0K	1.0M	32.2M	88.30	0.5M	37.4M	96.80
Fa → Ch	1.4M	2.0K	1.0K	0.2M	10.4M	96.80	0.2M	10.0M	96.80
Ur → Ch	78.0K	2.0K	1.0K	17.6K	2.6M	100.00	12.7K	2.4M	100.00

Experiment

	Arabic	Farsi	Urdu
Arabic	N/A	12.36%	8.61%
Farsi	2.51%	N/A	8.62%
Urdu	0.16%	0.78%	N/A

Method	Parent	Child	BlEU
RnnSearch	N/A	Ur → Ch	18.31
Mixed	Fa → Ch (Non-Shared)		19.73
	Ar→ Ch (Non-Shared)		20.04
	Fa → Ch (Shared)		21.69^{++}
	Ar→ Ch (Shared)		22.44^{++}

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Conclusions

- Mitigate the gap between a non-native speaker and native speaker by exploiting prepared or necessary draft
- Make full use of the combination of bilingual cognition and artificial translation system in IEAs.
- Provide some Efficient and effective channels for IEAs.
- The proposed NMT training approach for LRLs in IEAs is transparent to neural network architecture.

شكرا لك

köszönöm

شكريا

谢 谢！

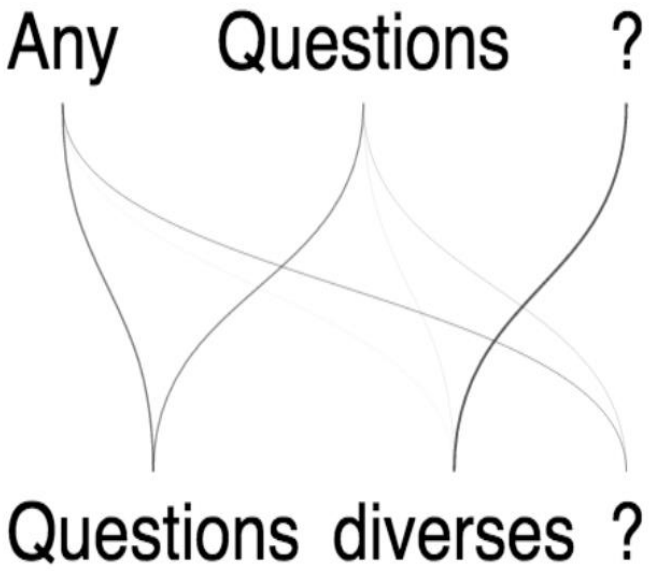
ཐུགས་རྗེ་ཆེ།

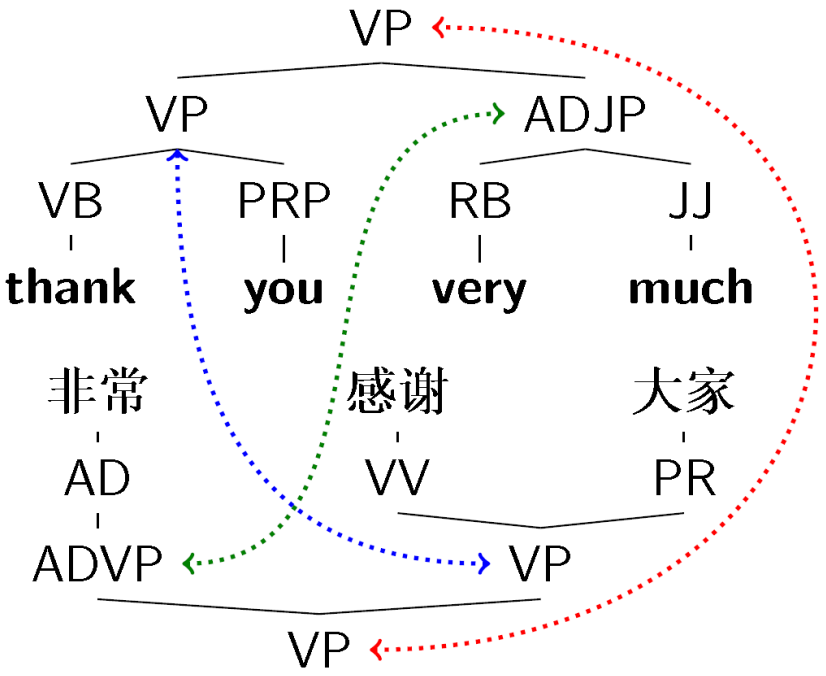
ره خمه ت!

הדות

Teşekkür

Kiitos





This inspiration comes from Dzmitry Bahdanau @ *ICLR2014* .