Multi-task Learning for Multiple Languages Translation

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Background

Consider the problem of translating one source language into multiple target languages.

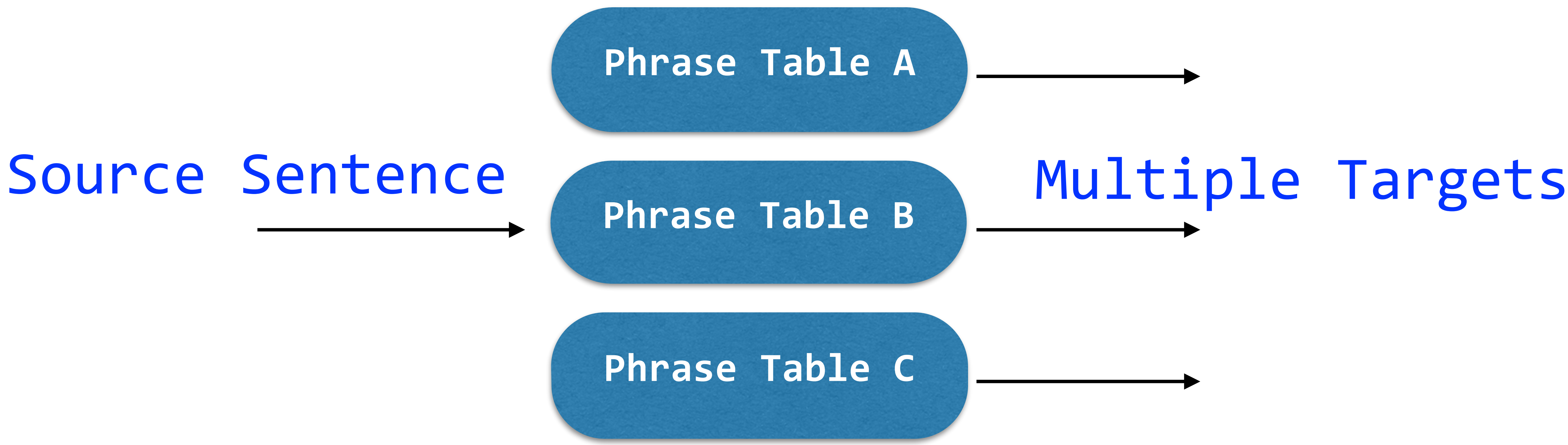
- Practical Usages :
  - Web pages translation
  - Product introduction for global scale users

  …

- Modern machine translation system solution:
  - Build up translation service in pairwise manner
  - Translation quality may not be acceptable in some directions when the size of training corpora is small

Statistical Machine Translation

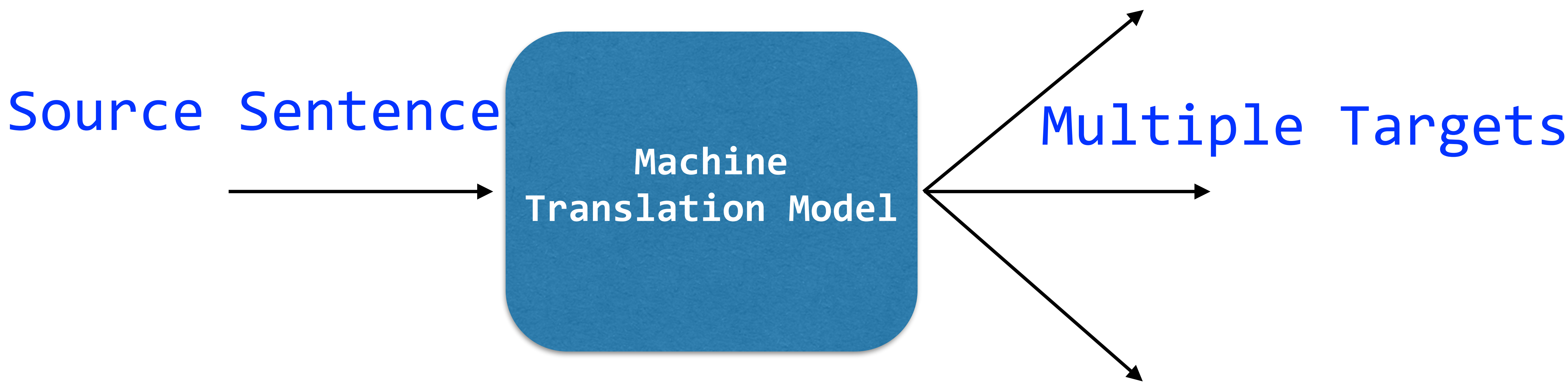
Frequently used in commercialized system



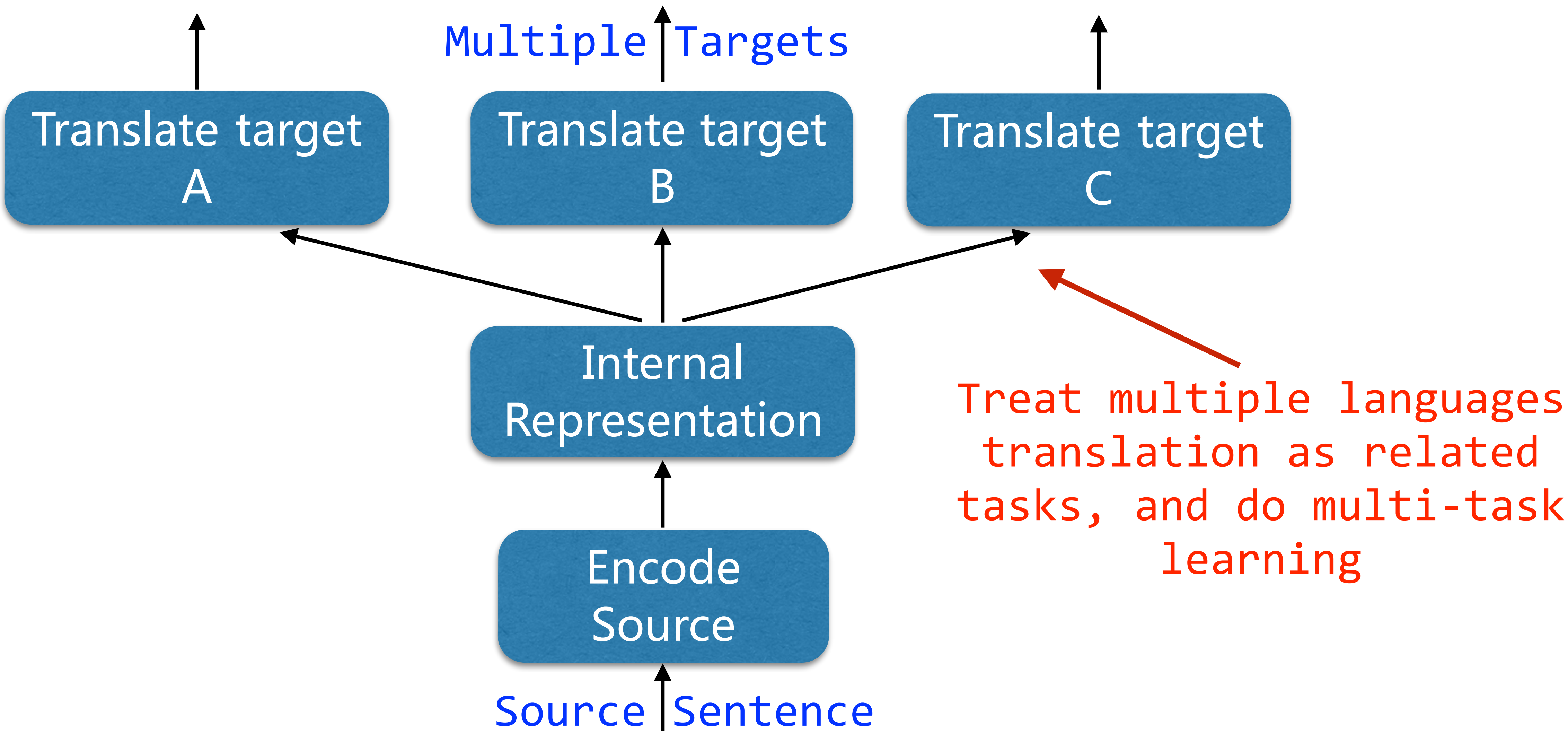
- Phrased-based MT generates multiple phrase tables
- Data sparsity problem is severe in resource-poor parallel corpora
- It is hard for phrase tables to share corpora information

Motivation

How can we share data information of multiple parallel corpora and translate a source sentence into multiple targets within a unified model?



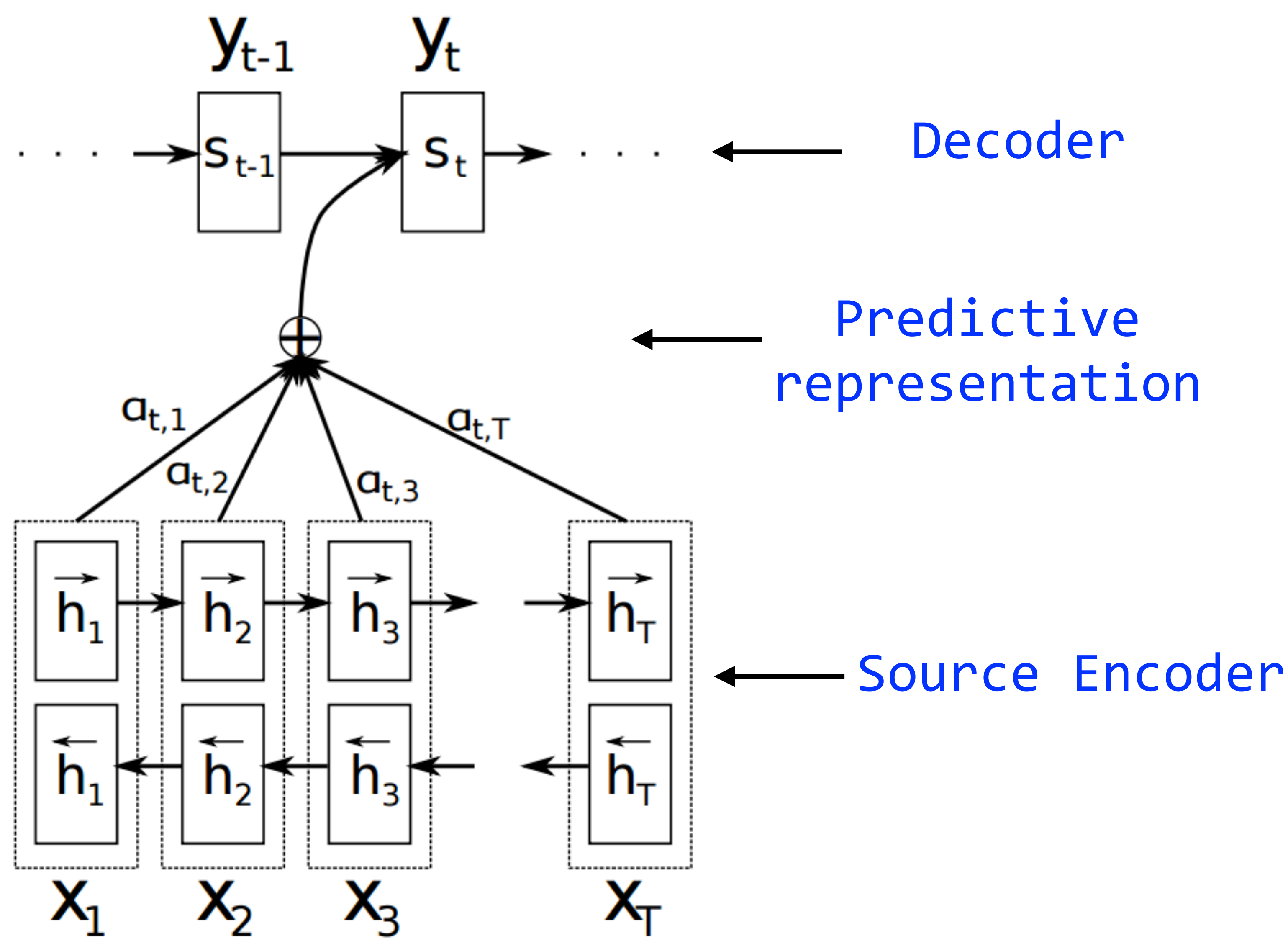
Our Solution



- Share source language information within a shared encoder.
- Do multi-task learning with multiple parallel corpora in a unified model

Neural Machine Translation

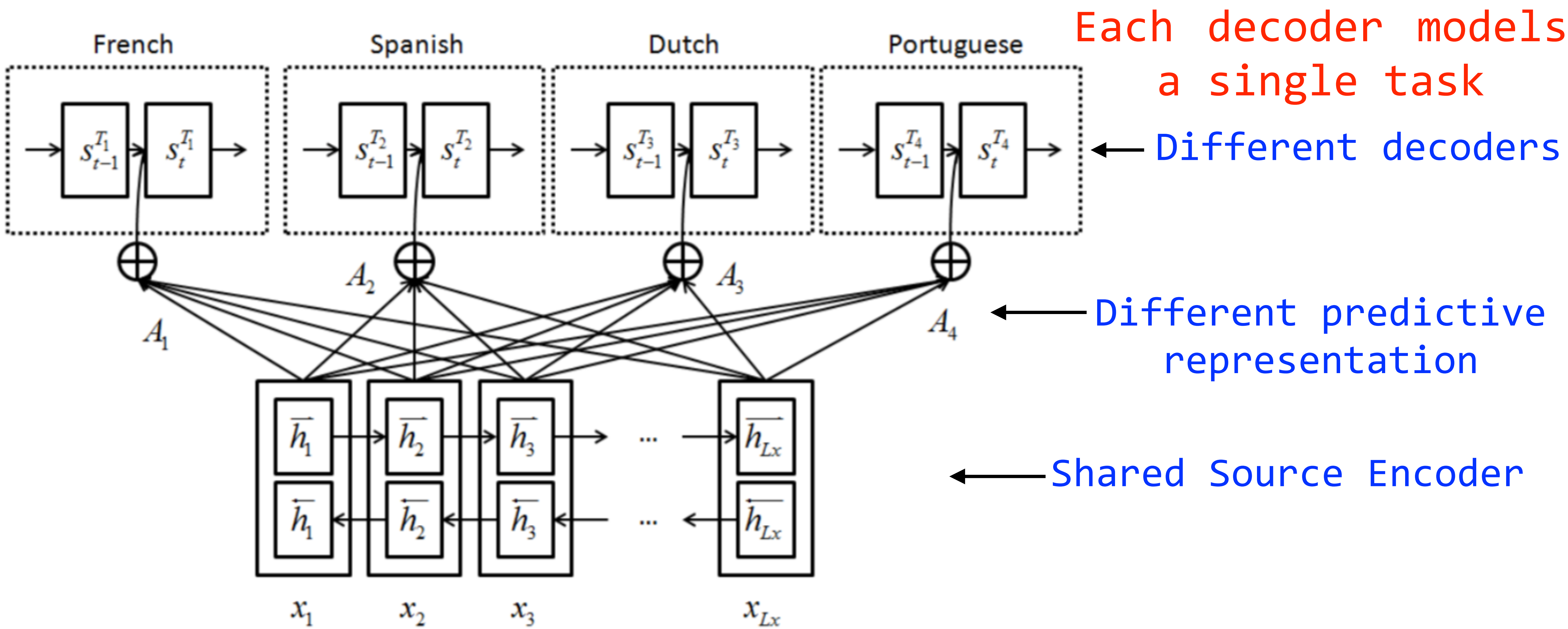
Base Model: NMT



- Source sentences and target sentences are modeled with encoder and decoder, each of which is a gated recurrent neural network.
- Soft alignment model is applied between encoder and decoder.

* figure is cited from: NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Multi-task Learning Framework



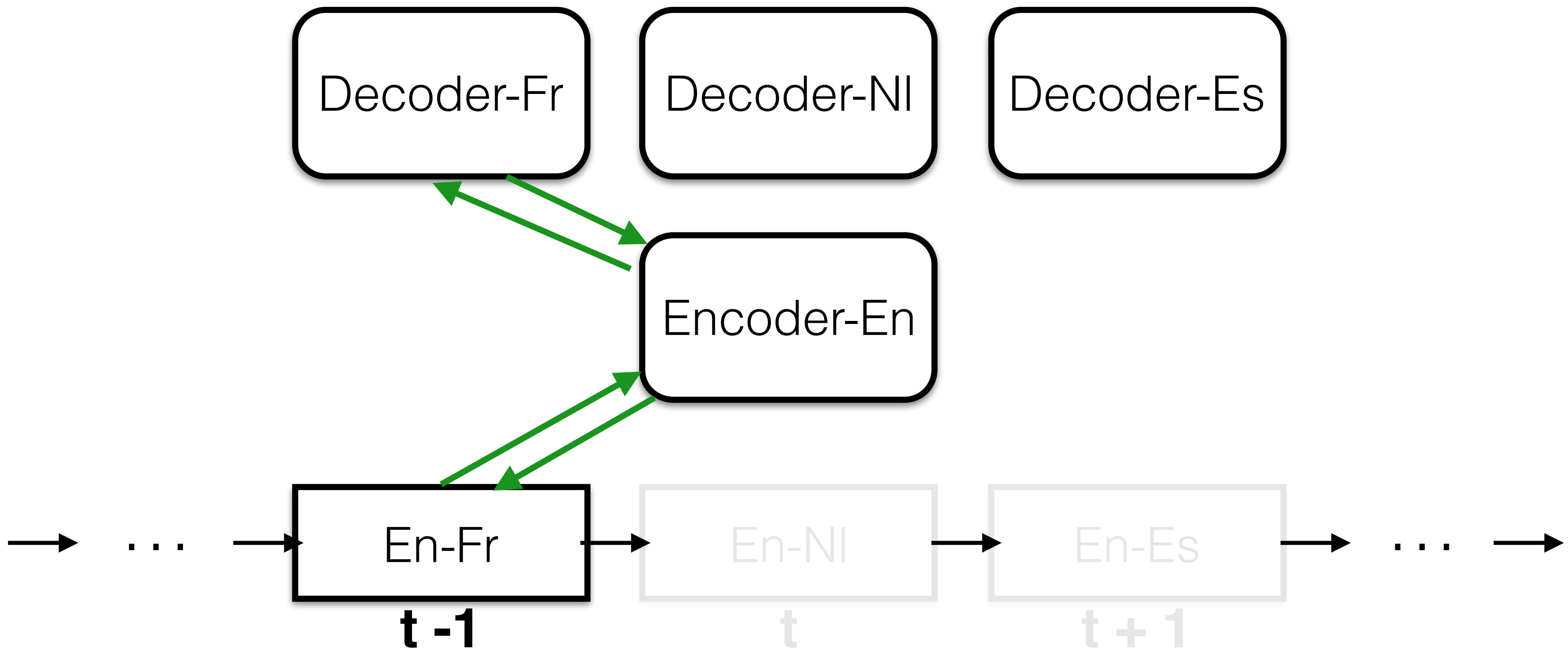
- Share encoder across different language pairs
- Decoders and soft-alignment models are separated on different target languages

Training Objective

$$L(\Theta) = \operatorname*{argmax}_{\Theta}\left(\sum_{T_p}\left(\frac{1}{N_p}\sum_{i}^{N_p}\log p(\mathbf{y_i}^{T_p}|\mathbf{x_i}^{T_p};\Theta)\right)\right)$$

- Maximize the summation of log-likelihood of all language pairs
- Log-likelihood of each parallel sentence is the log of conditional probability of sequence y_i given sequence x_i
- T_p is the language pair index, and N_p is the size of parallel corpora. Θ denotes all model parameters we want to learn

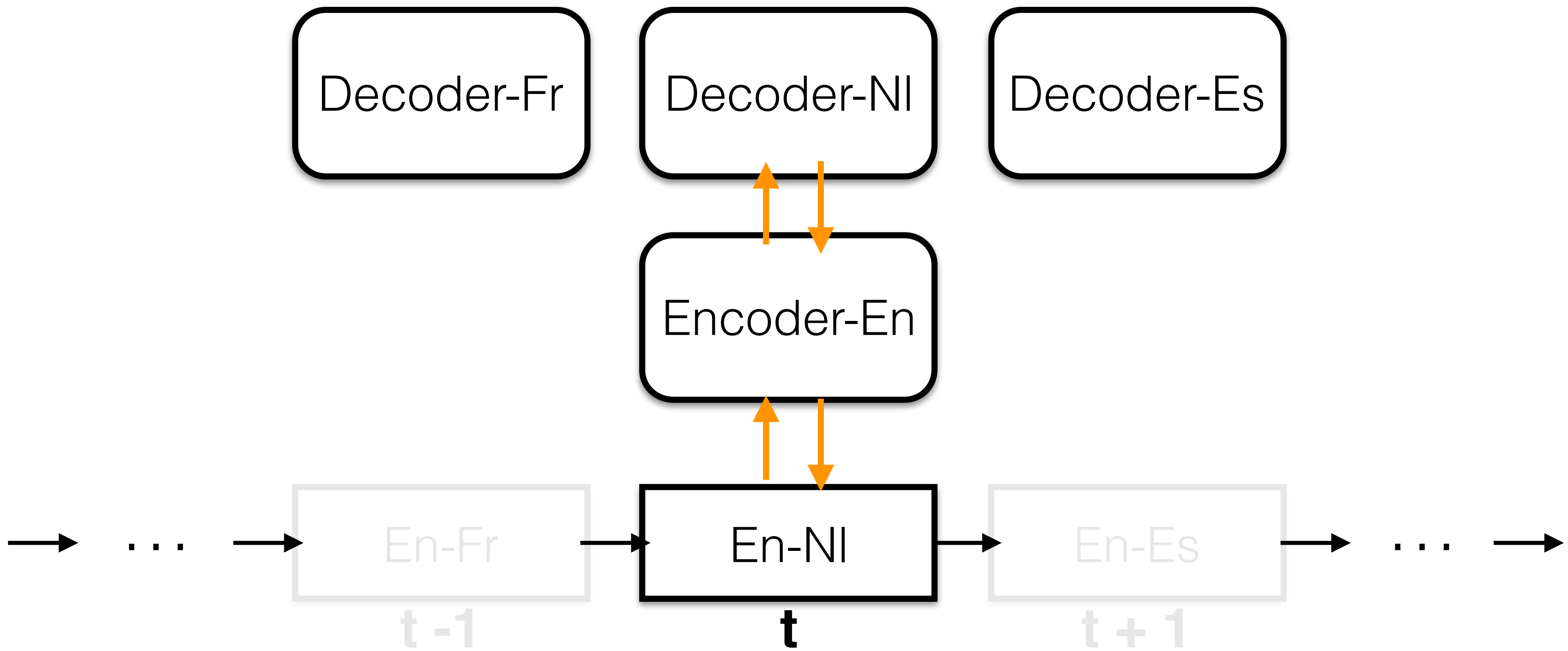
Optimization



Several mini-batches between language pairs

- Learning with mini-batch stochastic gradient descent
- Synchronize encoder parameters every several mini batches
- Train several mini batches between language pairs for speedup

Optimization



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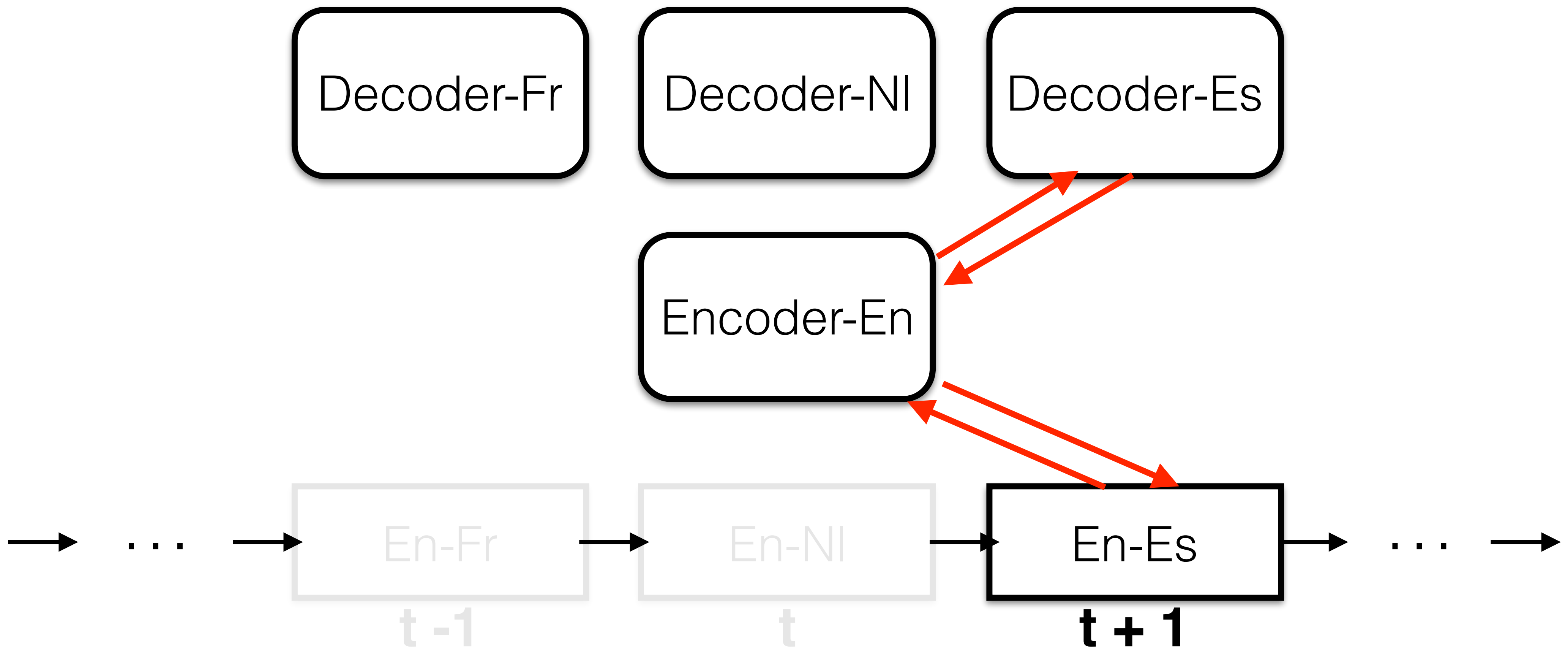

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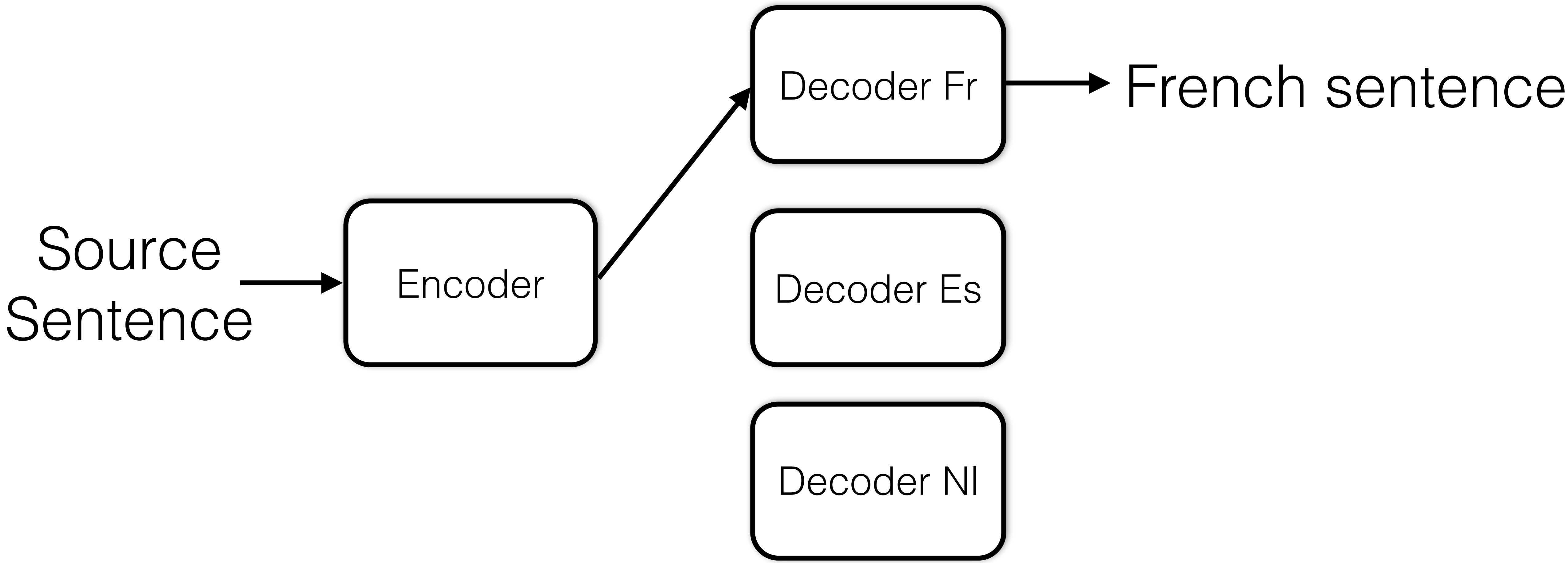
Translation



`Beam Search with beam size = 10`

Experiments

Validate our framework with two experiments

- Resource-Poor setting: Multi-task learning NMT helps to alleviate data sparsity problem of resource-poor language pairs.
- Resource-Rich setting: Multi-task learning NMT also improves translation performance of resource-rich language pairs.

Model analysis

- Comparison with Moses
- Qualitative analysis of results on why multitask learning works for machine translation

Datasets

Training Data: Europarl dataset

Lang	En-Es	En-Fr	En-Nl	En-Pt	En-Nl-sub	En-Pt-sub
Sent Size	1,965,734	2,007,723	1,997,775	1,960,407	300,000	300,000
Src Tokens	49,158,635	50,263,003	49,533,217	49,283,373	8,362,323	8,260,690
Trg Tokens	51,622,215	52,525,000	50,611,711	54,996,139	8,590,245	8,334,454

- Notes: En-Nl-sub and En-Pt-sub are sub-sampled to about 15% of full parallel corpus

Testing data: Europarl Common Test Set, WMT 2013

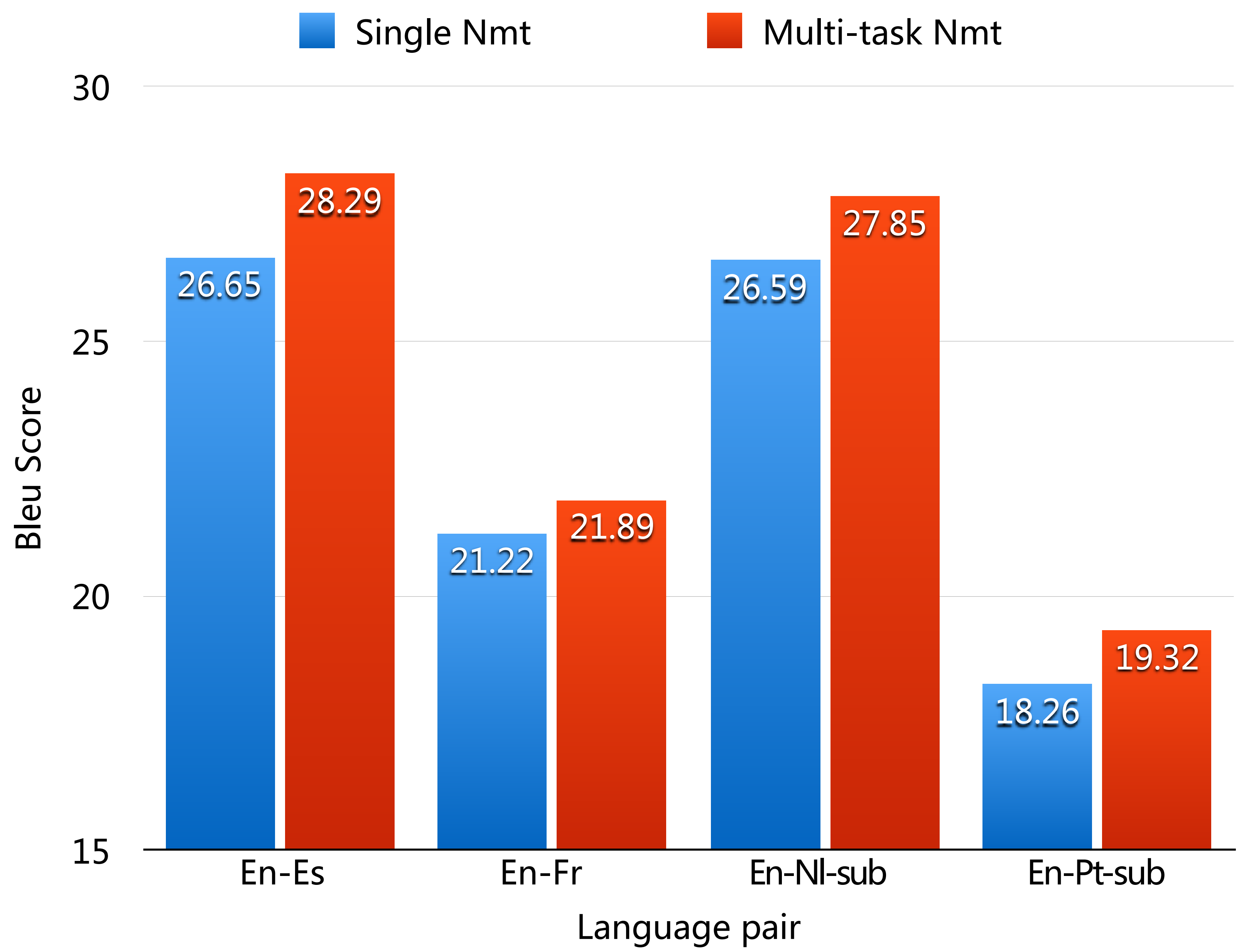
Language Pair	En-Es	En-Fr	En-Nl	En-Pt
Common Test	1755	1755	1755	1755
WMT 2013	3000	3000	-	-

- Notes: En-Nl and En-Pt test sets are not available in WMT dataset

Preprocessing

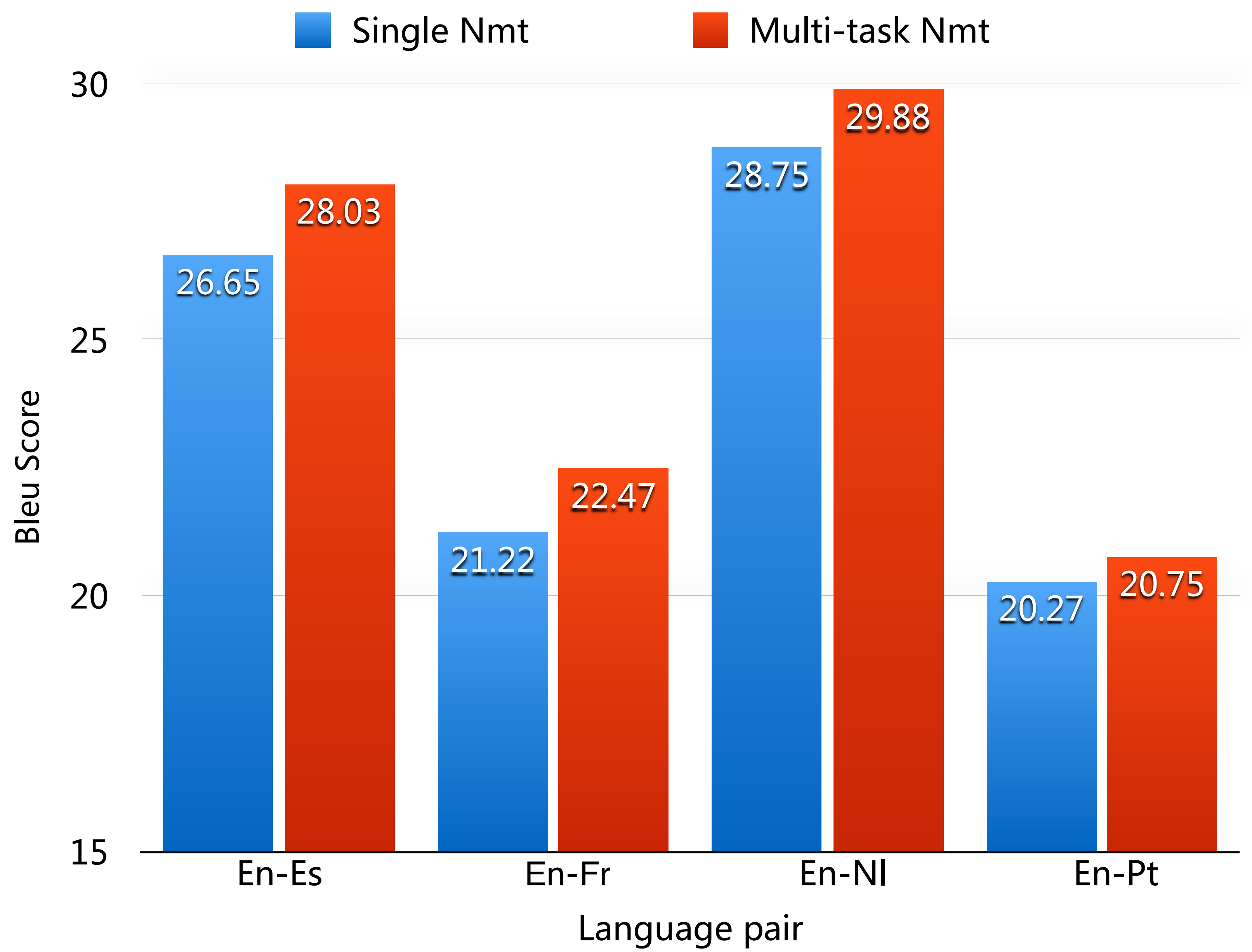
- 30k words vocabulary for source language
- 30k words vocabulary for every target language
- OOV words are marked with UNK

Resource-Poor Setting



- Translation performance of resource-poor language pairs benefit from multi-task learning.

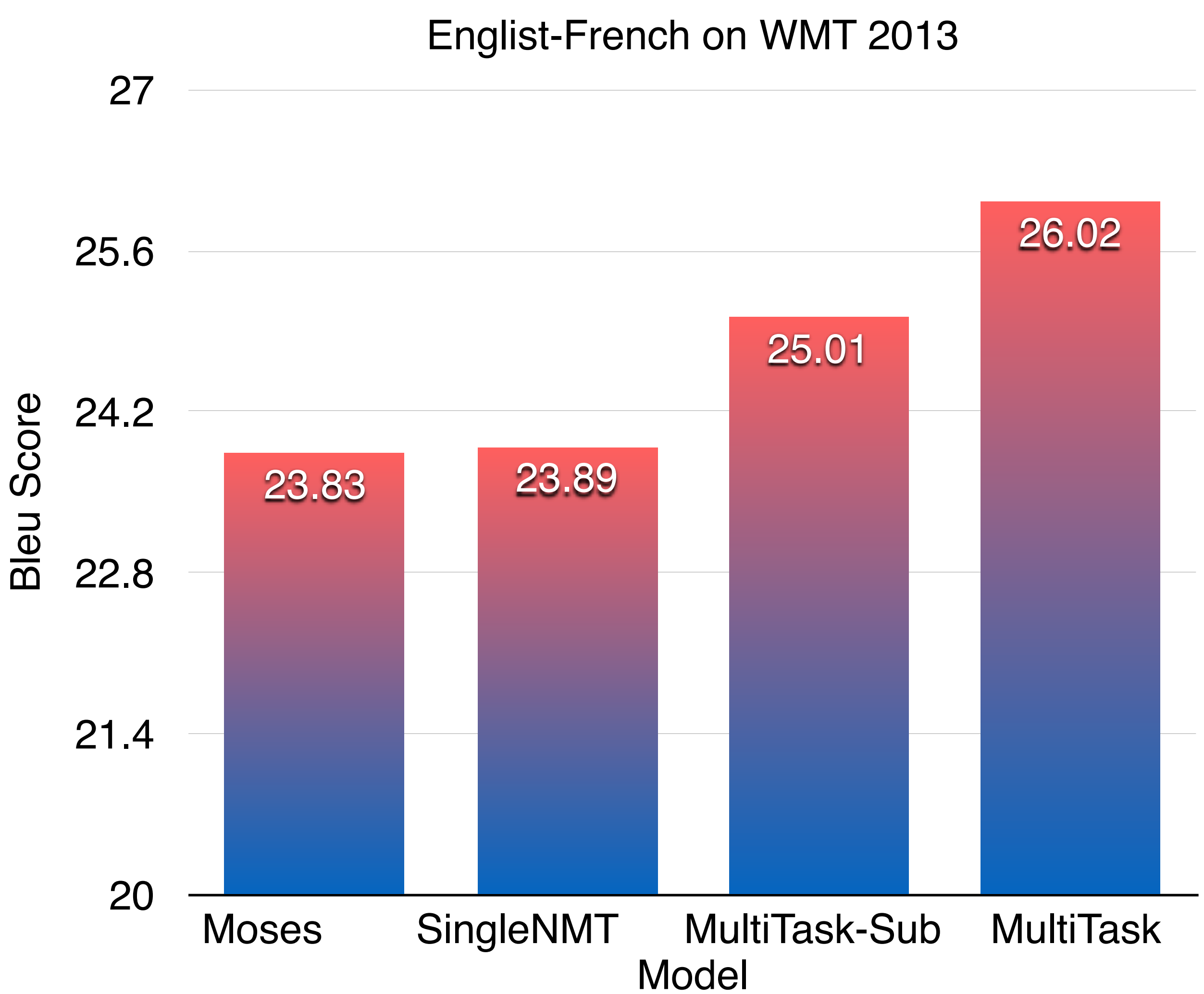
Resource-Rich Setting

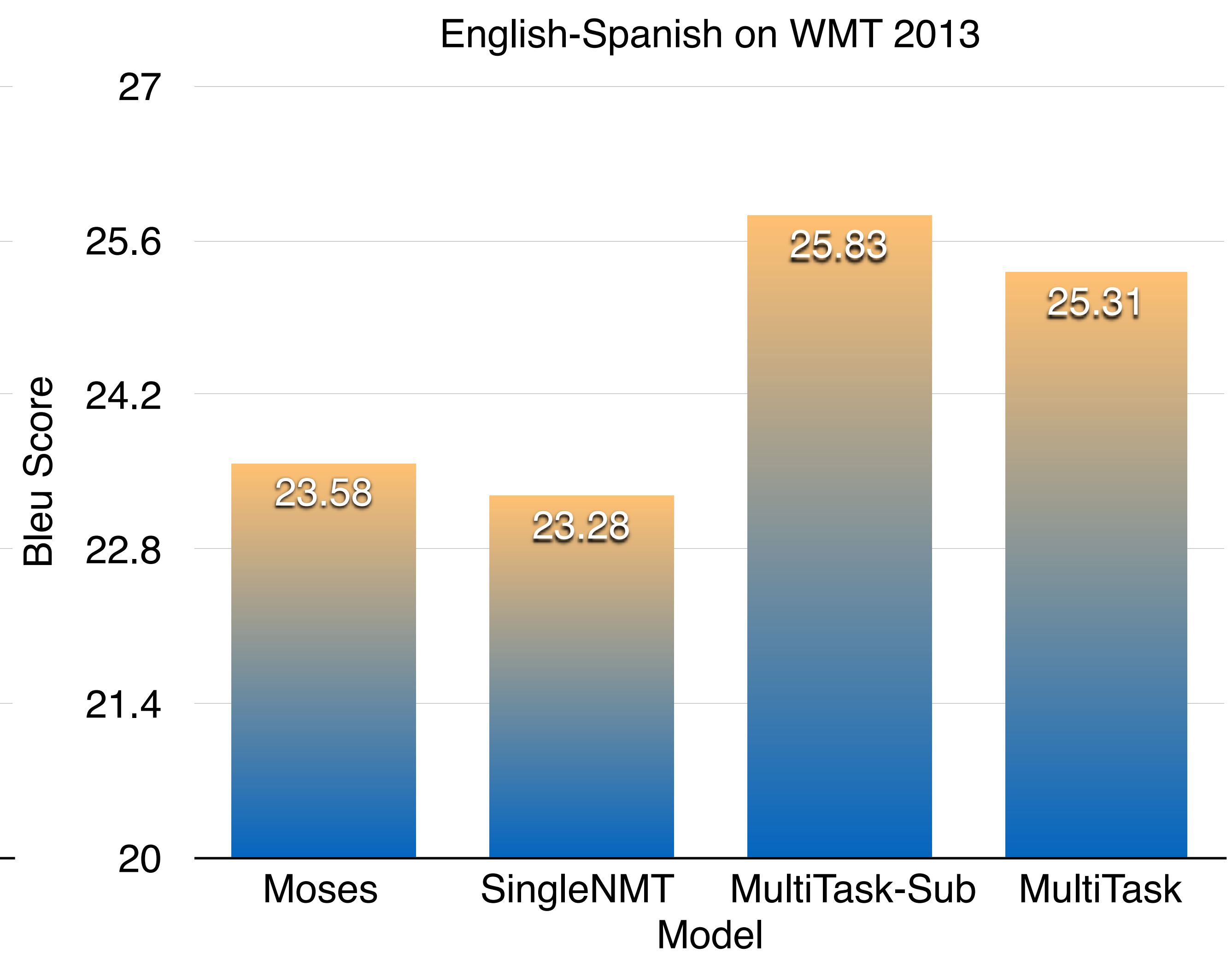


- Translation performance can also be improved given full training corpora

Comparison with Moses

Compare single NMT, Multi NMT, Multi-sub NMT with Moses model





- Single NMT is comparable with Moses.
- Multi-task learning outperforms single NMT and Moses

Why does multi-task learning work in machine translation?

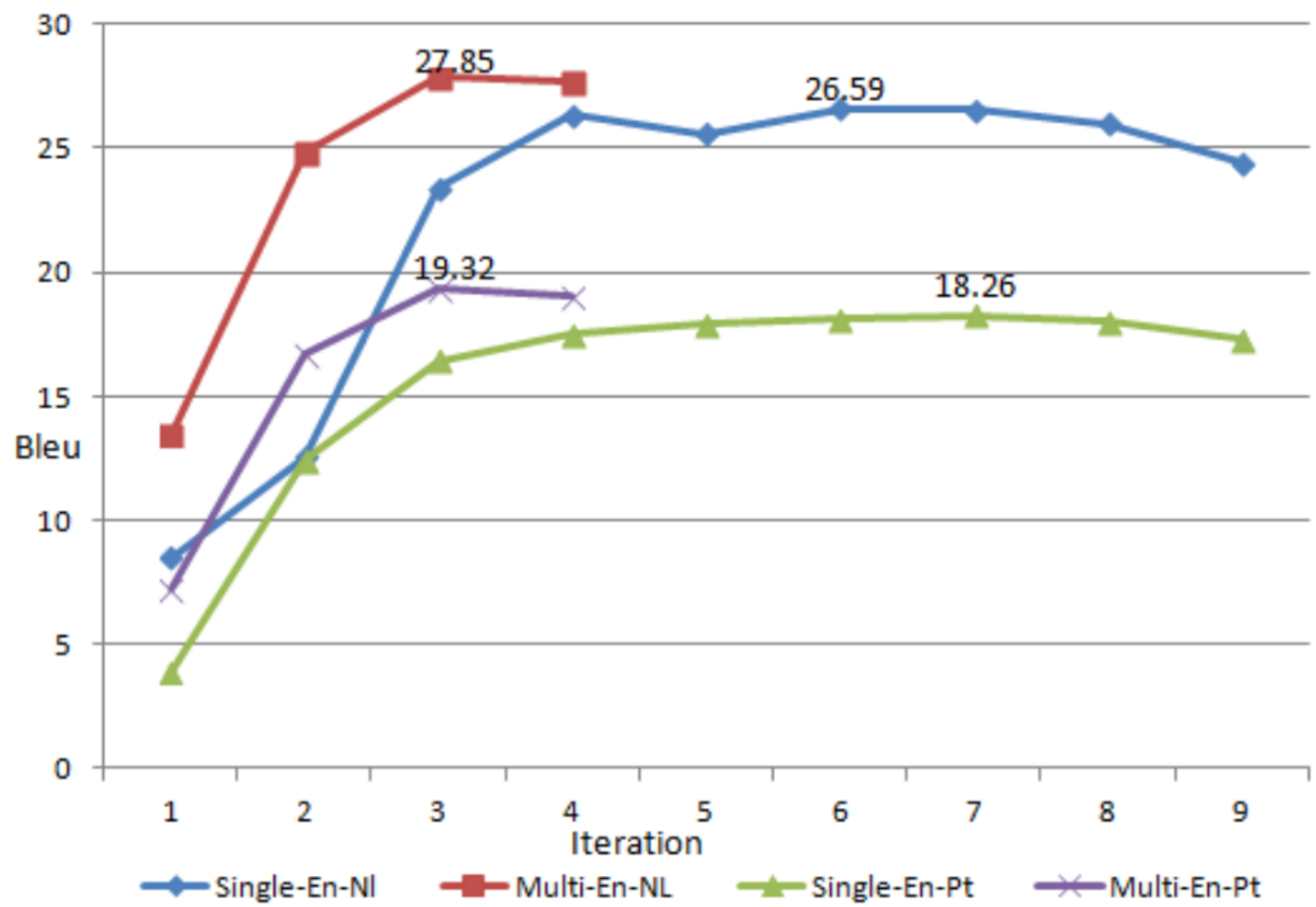
Multitask Model	Source word nearest neighbor
provide	deliever(0.78), providing(0.74), give(0.72)
crime	terrorism(0.66), criminal(0.65), homeless(0.65)
regress	condense(0.74), mutate(0.71), evolve(0.70)
six	eight(0.98), seven(0.96), 12(0.94)

NMT resource-poor Model	Source word nearest neighbor
provide	though(0.67), extending(0.56), parliamentarians
crime	care(0.75), remember(0.56), three(0.53)
regress	committing(0.33), accuracy(0.3), longed-for
six	eight(0.87), three(0.69), thirteen(0.65)

- The sharing of source information between different tasks helps to learn better source word representation

Why does multi-task learning work in machine translation?

Convergence comparison between Multi-NMT and Single NMT under resource-poor setting



- Better source word representation will help translation performance converge faster and better

Summary

- We propose a novel multi-task learning framework for machine translation
- Our framework is able to translate one source language into many different target languages within a unified model
- Experiments show that our approach can boost translation performance in every target language in both resource-poor setting and resource-rich setting.

Future work

- Extend the modeling of multiple languages into multiple domains translation.
- Consider modeling the correlation between different target decoders as well.

Thanks!