

Challenges in Adaptive Neural Machine Translation

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Our Adventures with ModernMT (2015-2017)

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Symbiotic Human and Machine Translation



MT seamlessly

- adapts to user data
- learns from post-editing

user enjoys

- enhanced productivity
- better user experience

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Usable technology for the translation industry



- easy to install and deploy
- fast to set-up for a new project
- effective, also on small projects
- scalable with data and users
- works with commodity hardware

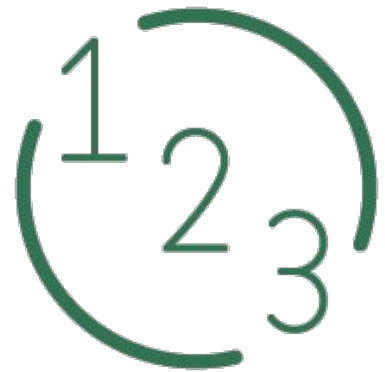
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The Modern MT way

- (1) connect your CAT with a **plug-in**
- (2) drag & drop your **private TMs**
- (3) start translating!



Modern MT in a nutshell

zero training time
adapts to context
learns from user corrections
scales with data and users



Fast training

Training data is a **dynamic** collection of Translation Memories



At any time:

- new TMs are **added**
- existing TMs are **extended**

Training time comparable to uploading time!

Context aware translation

SENTENCE

party

CONTEXT

We are going out.

CONTEXT

We approved the law

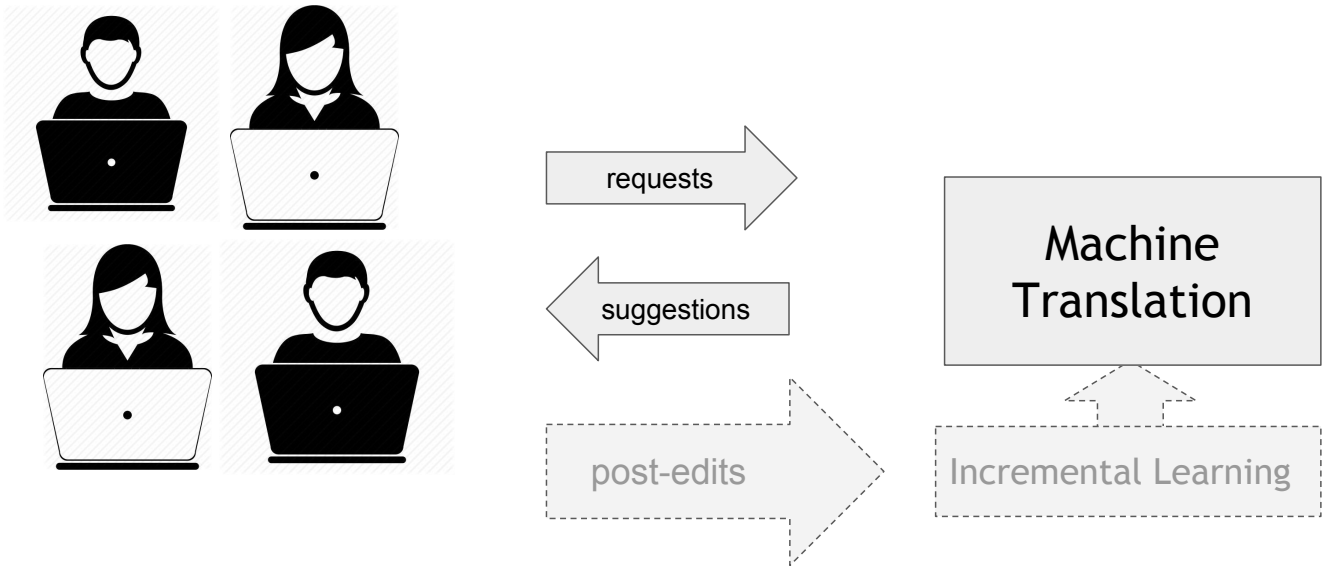
TRANSLATION

fête

TRANSLATION

parti

Incremental learning



Core technology [original plan]

context analyser
phrase-based decoder
adaptive models
incremental structures
parallel processing



Language support

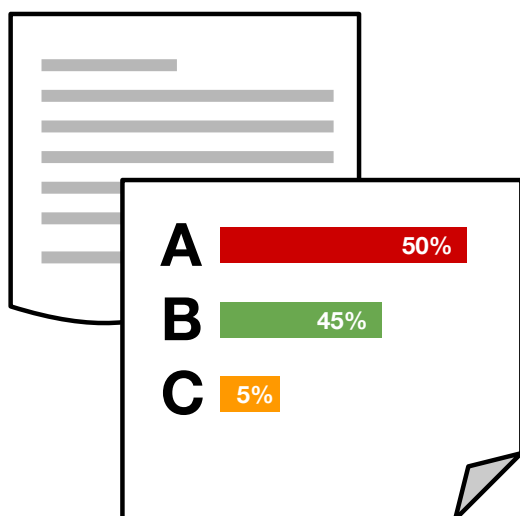
- **45** languages
- **fast pre-/post-processing**
- **simple interfaces**
- **tags** and **XML** management
- localization of **expressions**
- **TM cleaning**



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Simple. Adaptive. Neural.

Context Analyzer

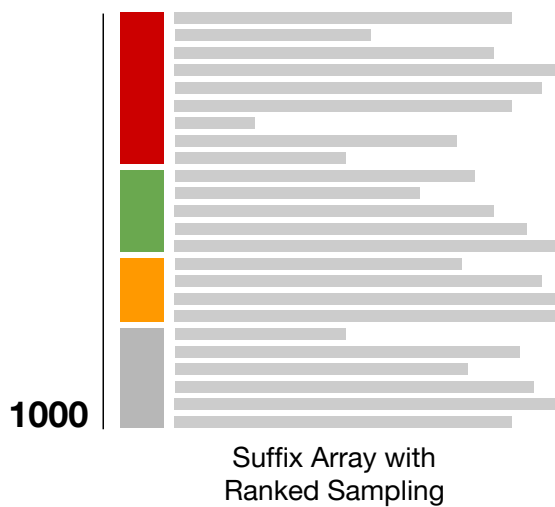


- analyze input text
- retrieve best matching TMs
- compute matching scores
- **dynamic structure**

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Adaptive Phrase Table

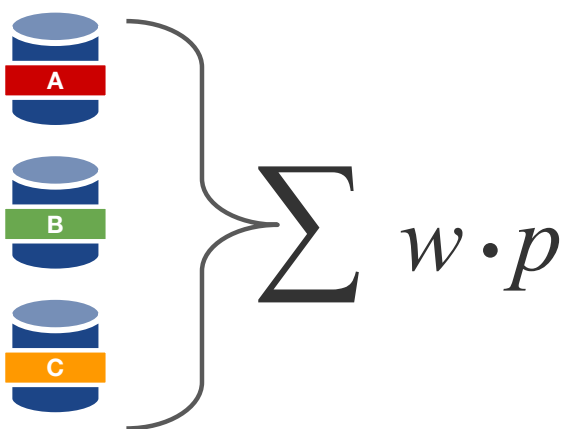


- suffix array indexed with TMs
- phrases sampled on demand
- priority sampling over TMs
- **dynamic structure**

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Adaptive Language Model

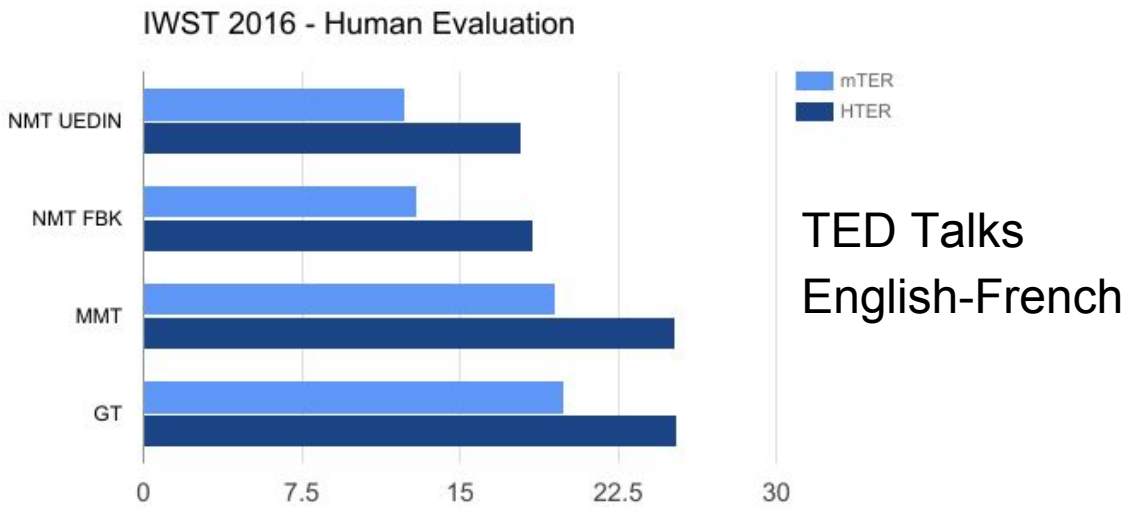


- large static background model
- n-grams stats indexed with TMs
- combination of *active* TM LMs
- TM LMs computed on the fly
- **dynamic structure**

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Statistical vs. Neural MT



M. Cettolo, et al. (2016), *The IWSLT 2016 Evaluation Campaign*, IWSLT.

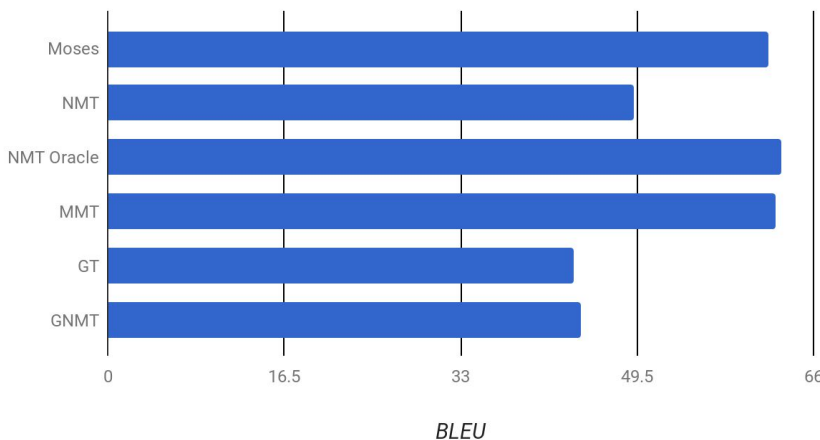
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Second Prototype (0.14 January 2017)

Test on EN-FR with Publicly Available Data



Open benchmark:

- Training speed:
12x Moses - 100x NMT
- MT quality (BLEU):
+1 vs Moses
-0.5 vs NMT Ada

Domains: ECB, Gnome, JRC, KDE, OpenOffice, PHP, Ubuntu, UN-TM

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Simple. Adaptive. Neural.

What happened

Research on adaptive neural MT

Believed PBMT was competitive on technical translation

Finally realised superiority of NMT quality

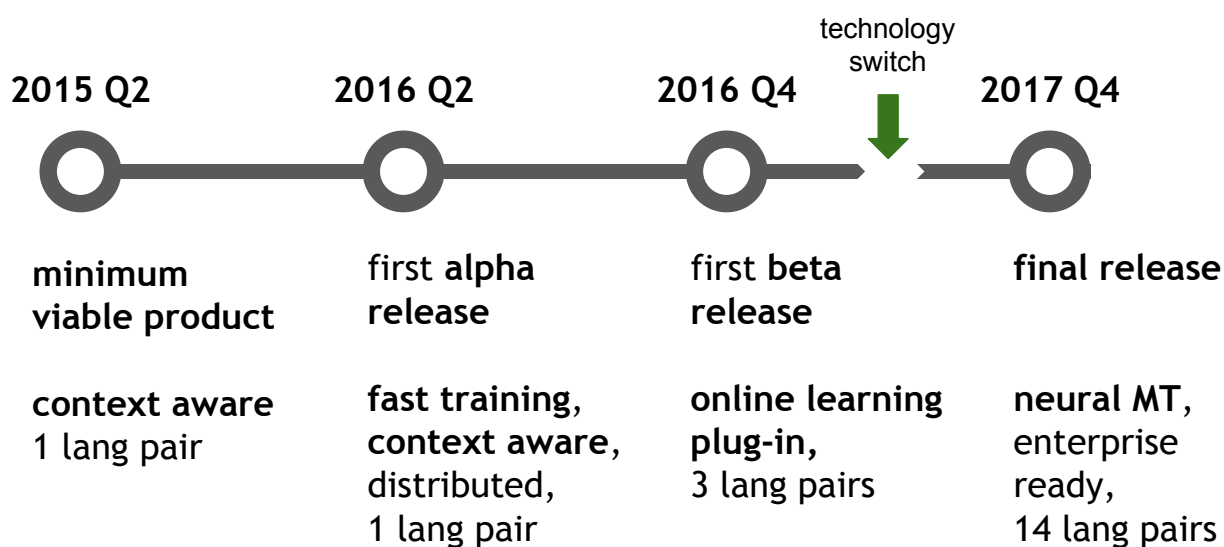
Completed PBMT release and **switched to NMT**

Data collection for 14 translation directions

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Simple. Adaptive. Neural.

Roadmap from last review meeting

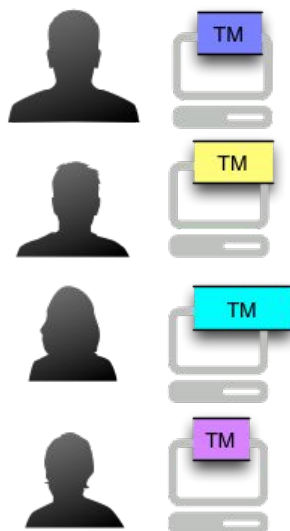


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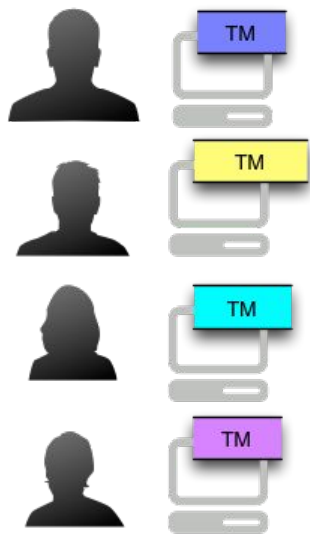
Simple. Adaptive. Neural.

Multi-Domain Neural MT

Multi-user scenario



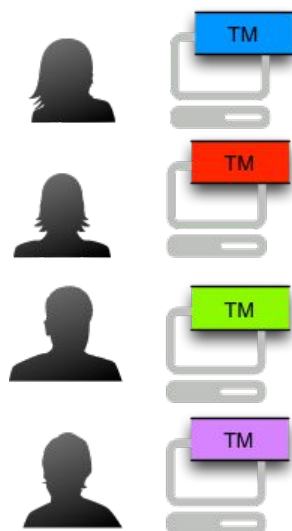
Multi-user scenario



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Multi-user scenario

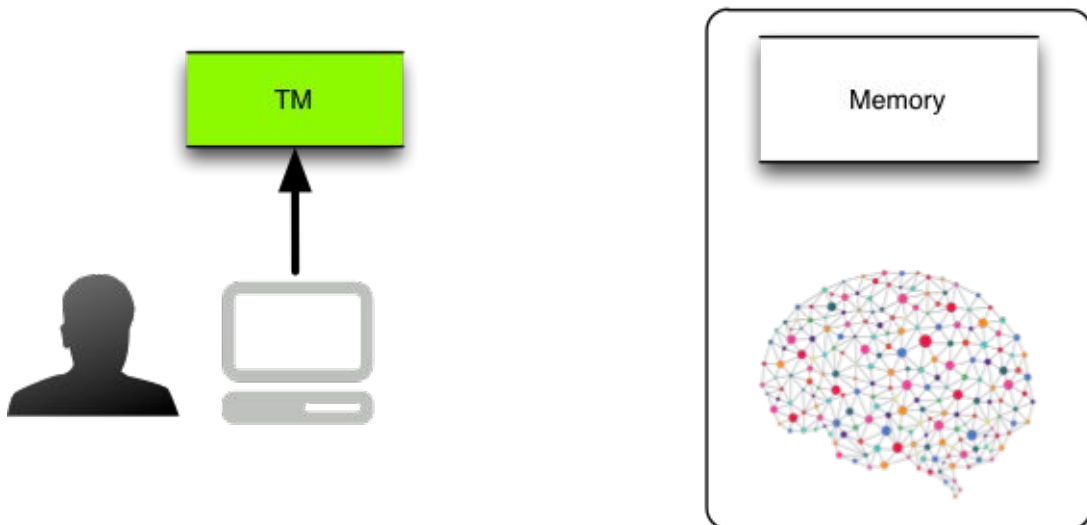


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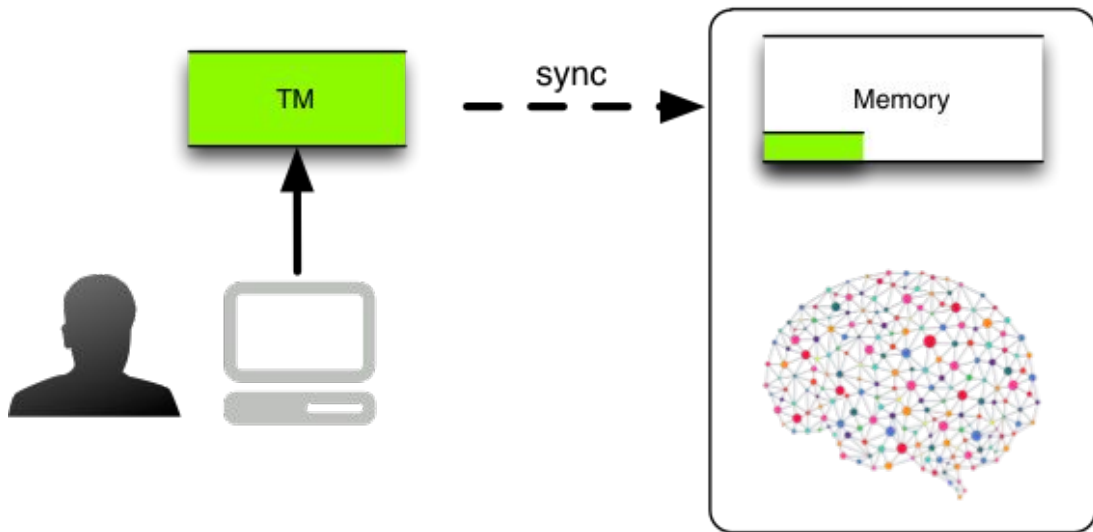
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Adaptive Neural MT (Adaptation *a priori*)

All we need is a memory



All we need is a memory

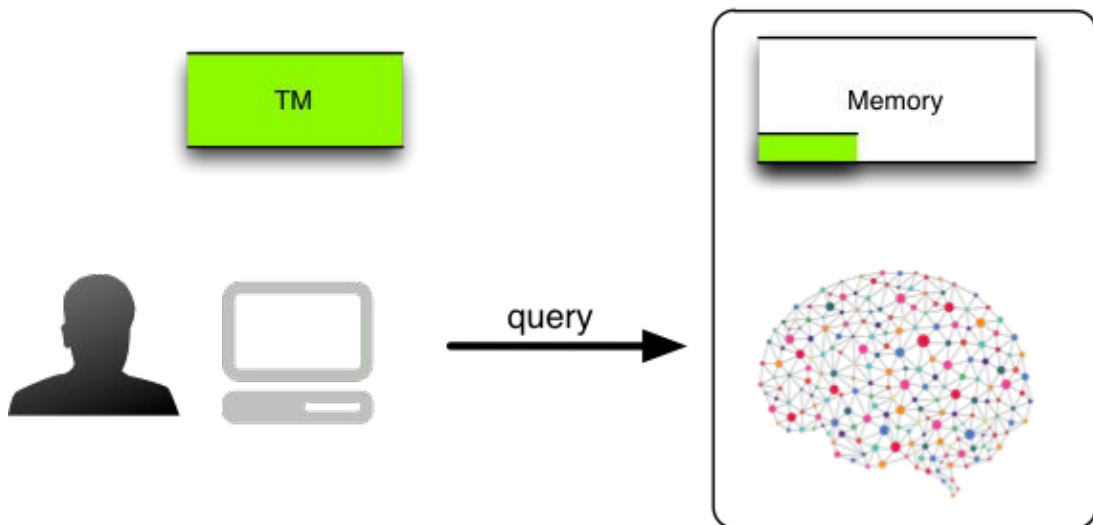


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All we need is a memory

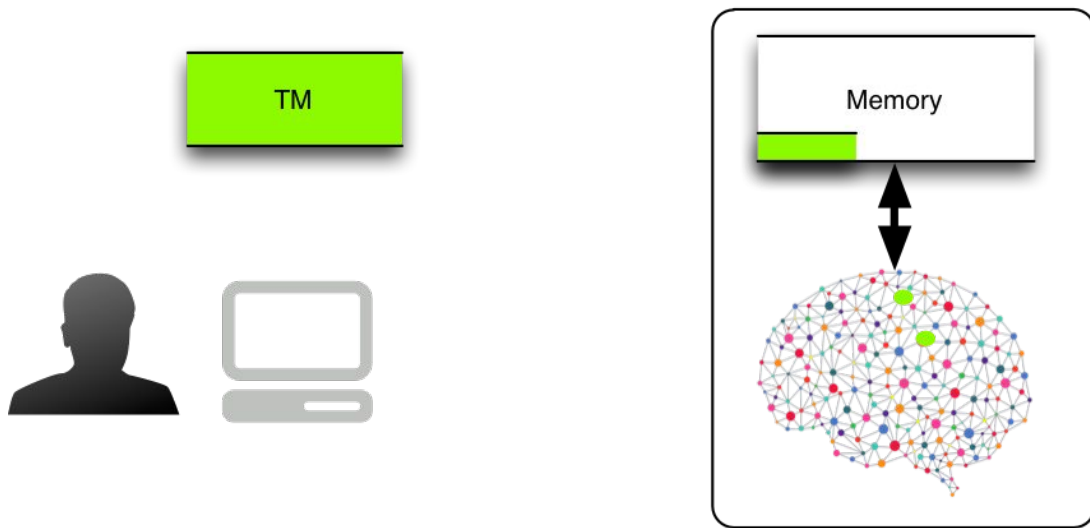


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All we need is a memory

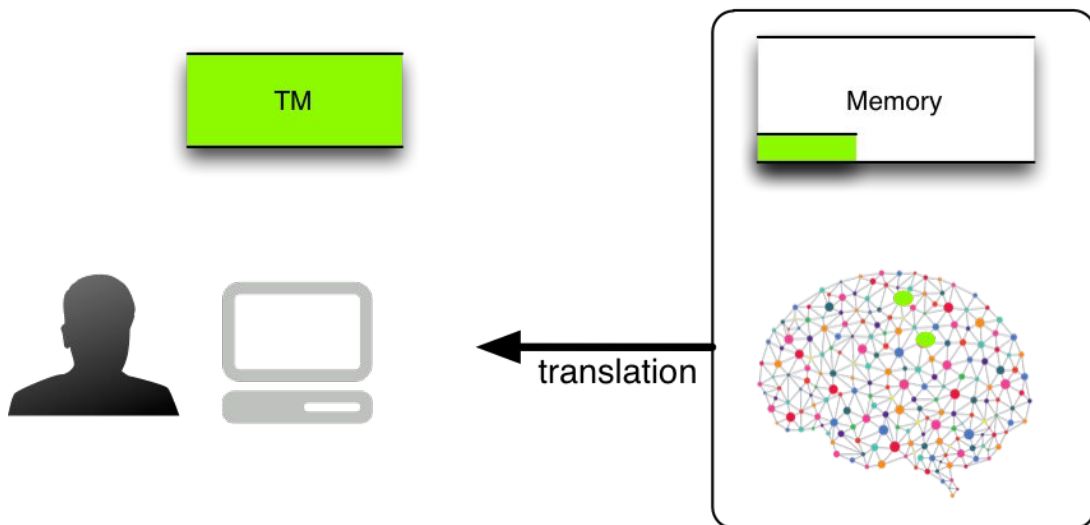


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All we need is a memory

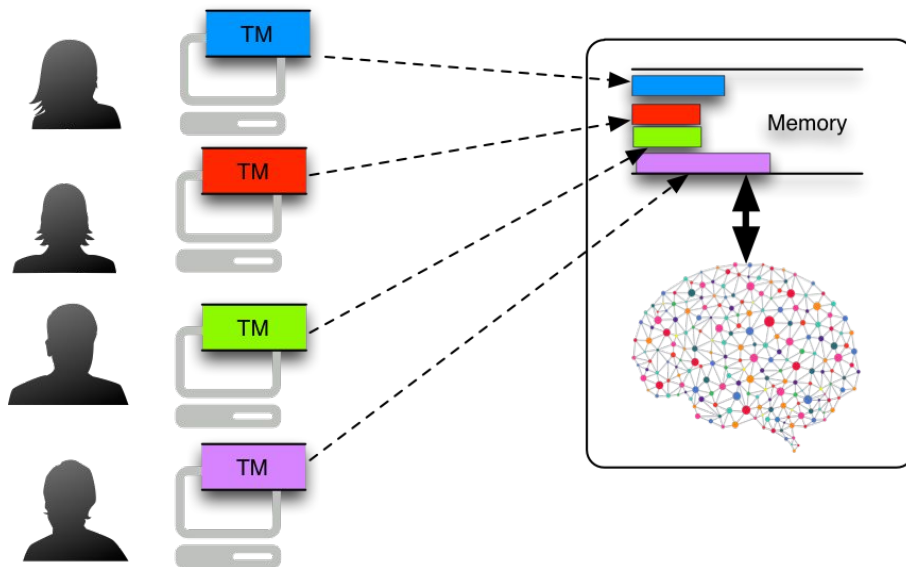


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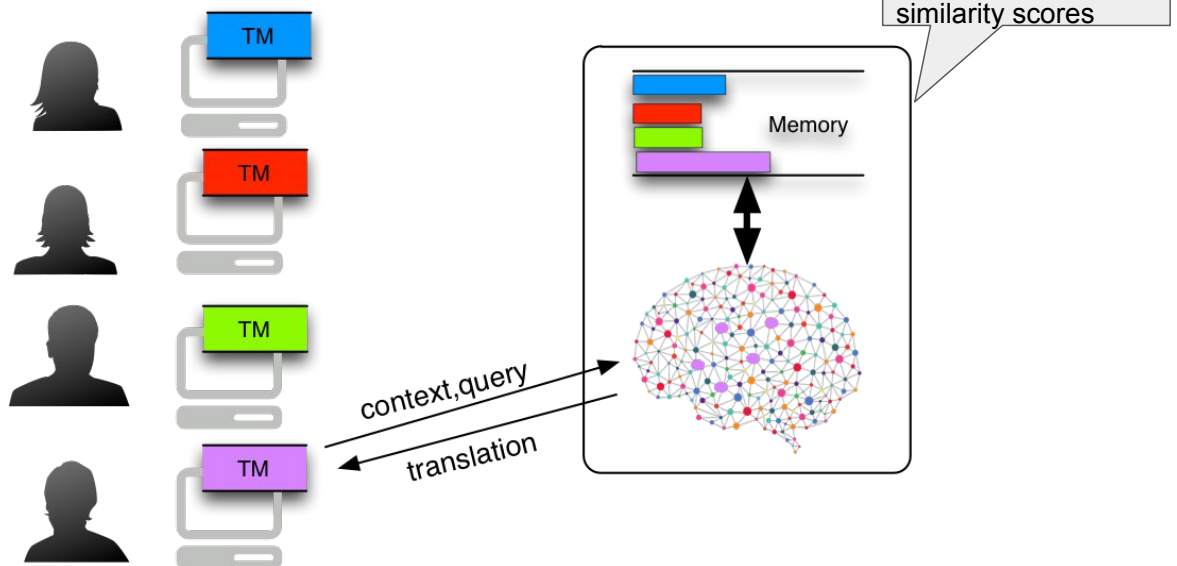
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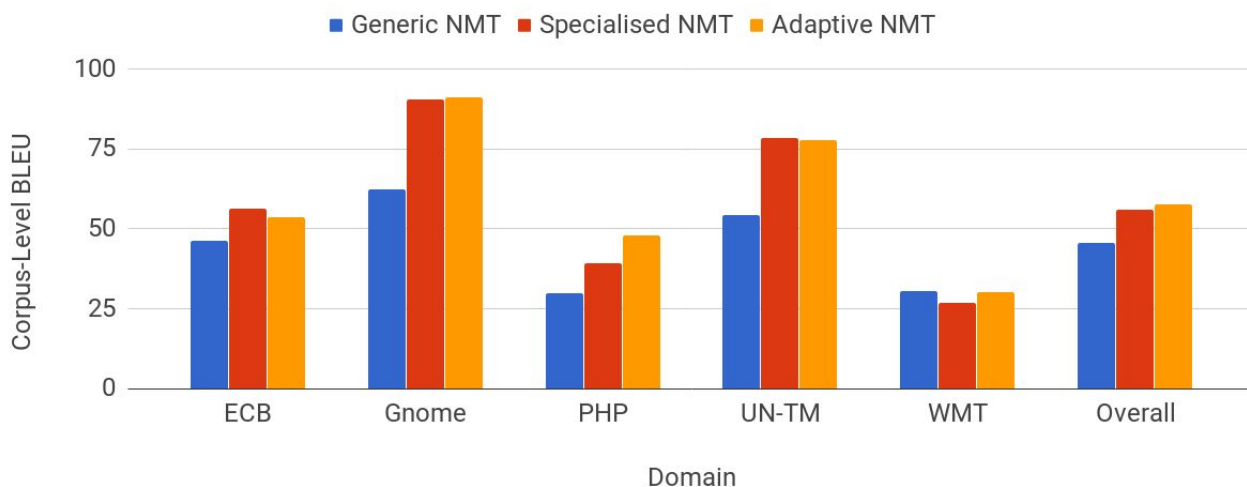
Multi-user adaptive NMT



Multi-user adaptive NMT



Adaptation, too!



Farajian et al. (2017) "Multi-domain NMT through unsupervised adaptation", *WMT*.

Production Systems

Timeline 2017

- Sep: integration of MateCat
- Oct: NMT code released
- Nov: co-development
release of 14 engines
- Dec: performance boost

 **Marcello Federico**
@marcfede

MMT team just released adaptive NMT in 14 directions for the @MateCat plugin!



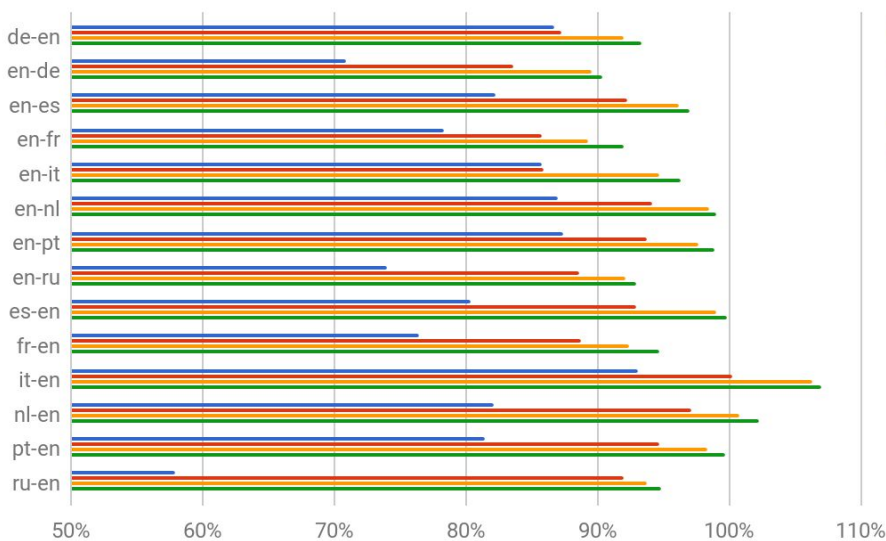
5:10 PM - 30 Nov 2017

10 Retweets 22 Likes



Automatic Evaluations

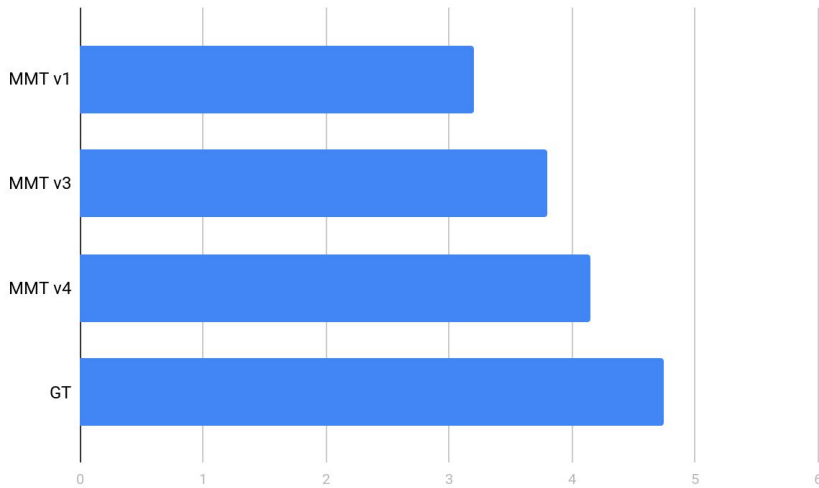
IWSLT



Relative BLEU
scores wrt
Google Translate

Micro HE Assessment

Progression in one month on English-Italian



Performance of generic MMT
1-6 scale
(w/o adaptation)

Quality Estimation

Quality Evaluation

MMT Eval 27/11/17 EN-IT index

Nonostante fosse ancora largamente sconosciuto, Robert Redford fece il suo debutto sullo schermo in War Hunt (1962), affiancando John Saxon in un film ambientato durante gli ultimi giorni della Guerra di Corea.

OUTPUT 1: == Storia ==
====
====
====
====
====



Add comment

OUTPUT 2: Nonostante ancora una sconosciuta, Robert Redford fece il suo debutto dello schermo in War Hunt (1962), co-protagonista con John Saxon in un film organizzato durante gli ultimi giorni della guerra coreana.



Add comment

OUTPUT 3: Mentre era ancora in gran parte sconosciuto, Robert Redford fece il suo debutto sul grande schermo in War Hunt (1962), recitando insieme a John Saxon in un set cinematografico durante gli ultimi giorni della Guerra di Corea.



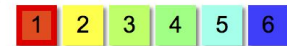
Add comment

Quality Evaluation

MMT Eval 27/11/17 EN-IT index

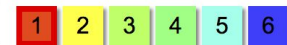
L'Agenzia per il Rilevamento Geologico degli Stati Uniti (USGS) ha individuato l'epicentro del terremoto a 12.8 miglia (20.6 chilometri) di profondità, a circa 150 miglia (240 chilometri) da Bengkulu, Sumatra.

OUTPUT 1: == Note == == Bibliografia == == Altri progetti == == Collegamenti esterni == * Sito ufficiale



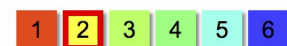
Add comment

OUTPUT 2: == Note == == Altri progetti == == Collegamenti esterni == * Sito ufficiale



Add comment

OUTPUT 3: Lo United States Geological Survey (USGS) ha riportato l'epicentro del terremoto a 20,8 chilometri di profondità ea circa 150 miglia (240 chilometri) da Bengkulu, Sumatra.



Add comment

Noisy training data

EN: What history teaches us

IT: === Storia =====

Data Cleaning

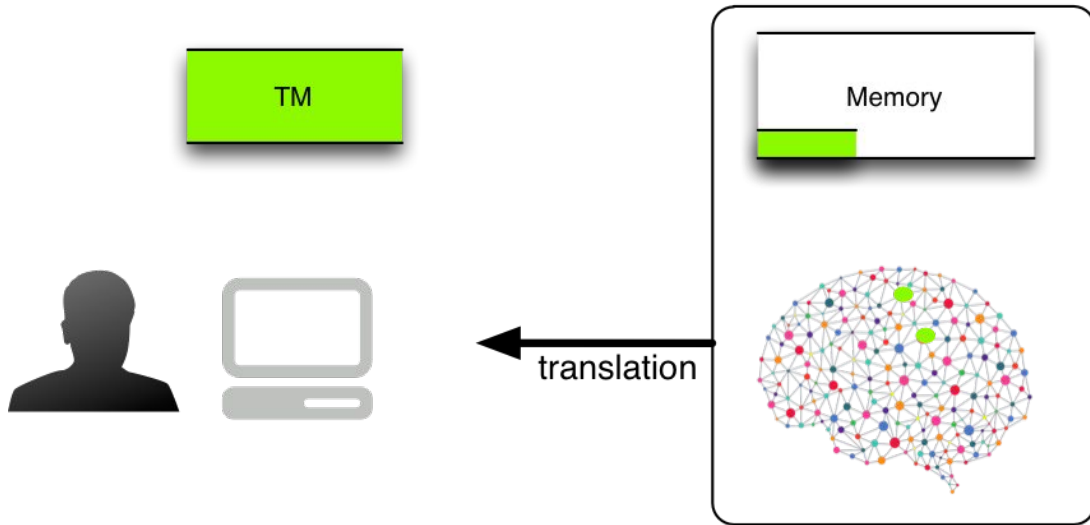
We added a simple QE module to filter out bad examples:

- Apply Fast-Align in two directions
- Compute Model 1 scores in two directions
- Combine and normalize scores
- Filter out on the distribution of scores

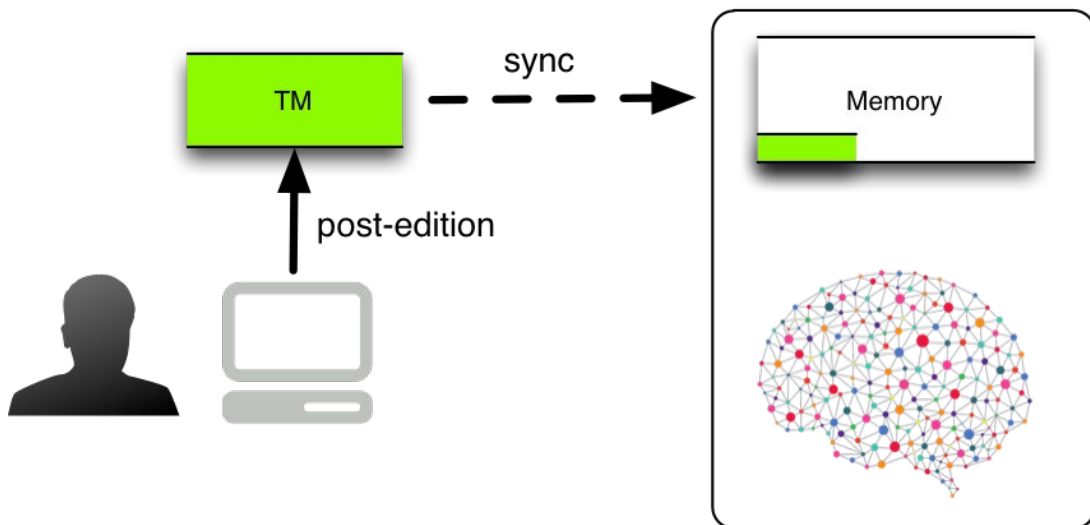
More Recent Adventures

Incremental Learning

Incremental Learning



Incremental Learning

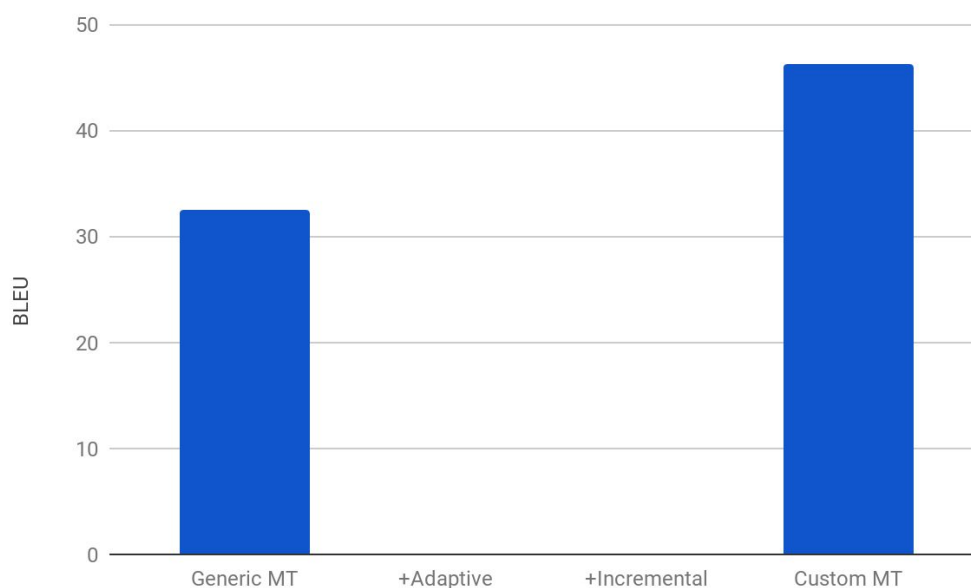


What happens when a new TM is uploaded?

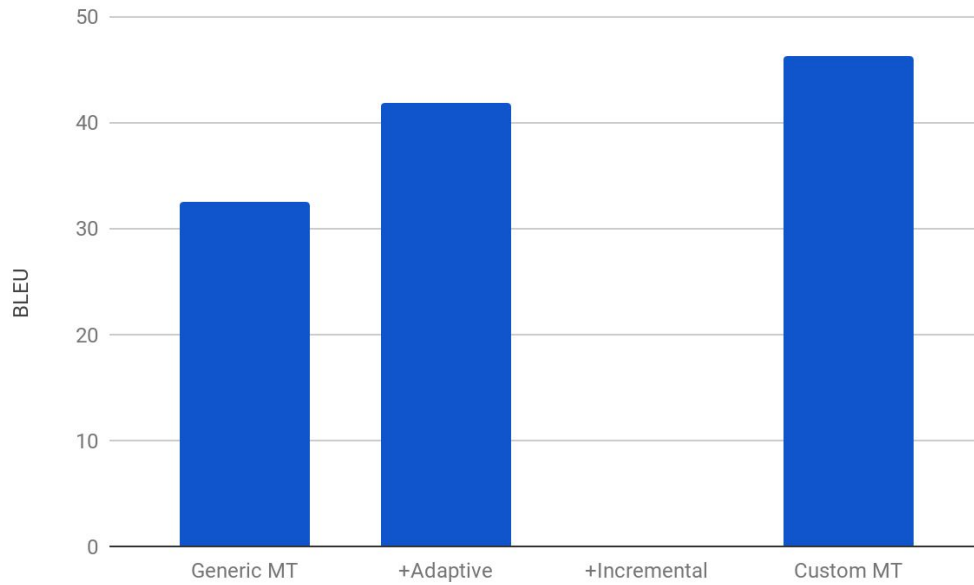
We compare:

- Generic MT: production engine [En-It]
- Custom MT: Generic MT tuned on TM [takes hours]
- +Adaptive MT: Generic MT adapted on TM [real-time]
- +Incremental MT: TM updated with simulated PE

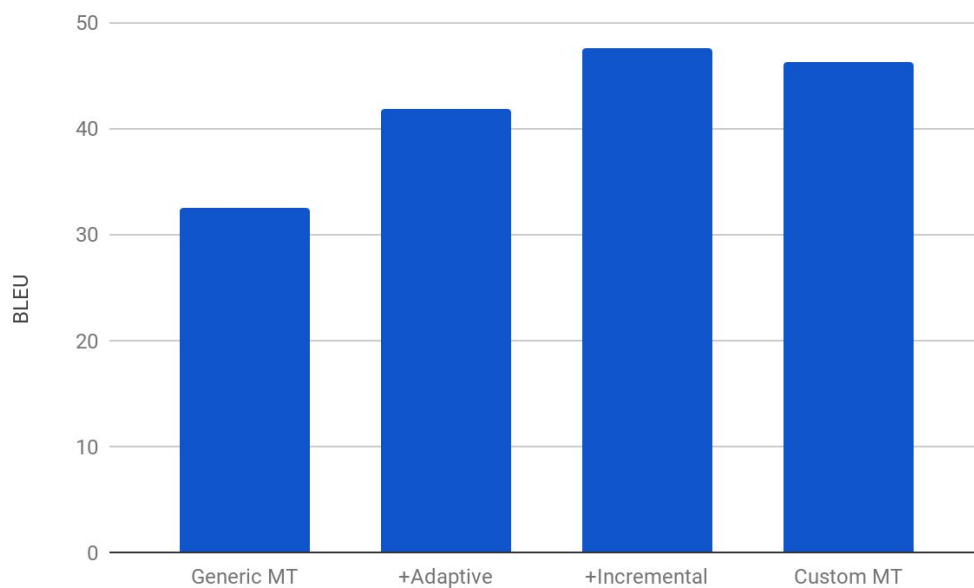
Incremental Learning



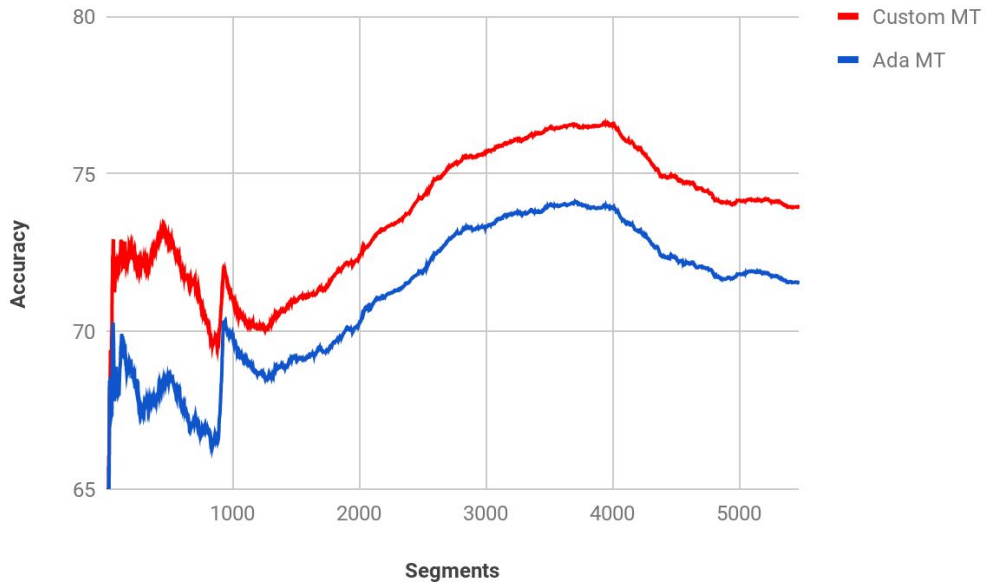
Incremental Learning



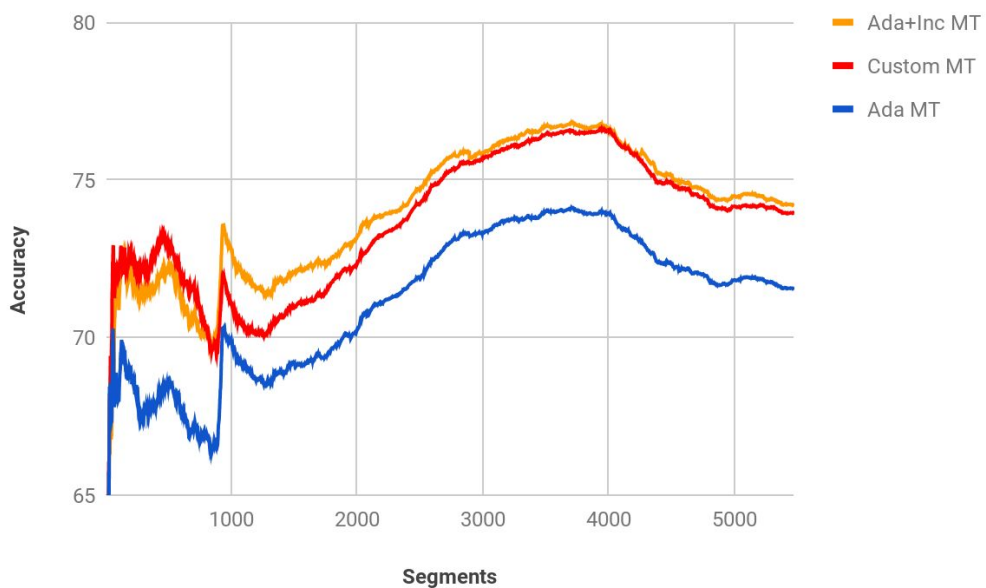
Incremental Learning



Incremental Learning



Incremental Learning



Online learning (Adaptation *a posteriori*)

Online Learning

Use post-editing as new training instances

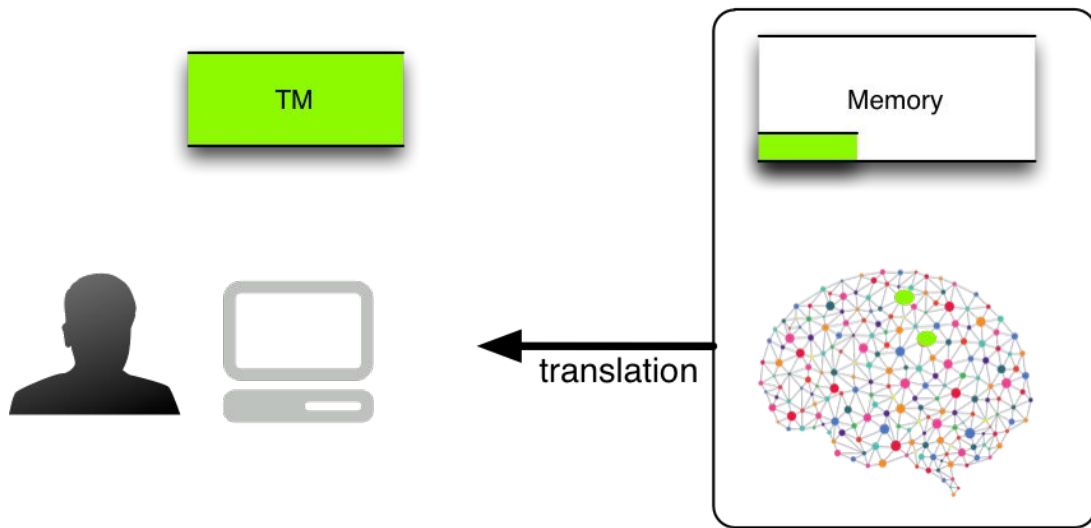
Perform one/more iterations

Can be combined with *a priori* adaptation

Updates generic or adapted model

Turchi et al. (2017), *Continuous learning from human post-edits for NMT, EAMT*.

Online Learning

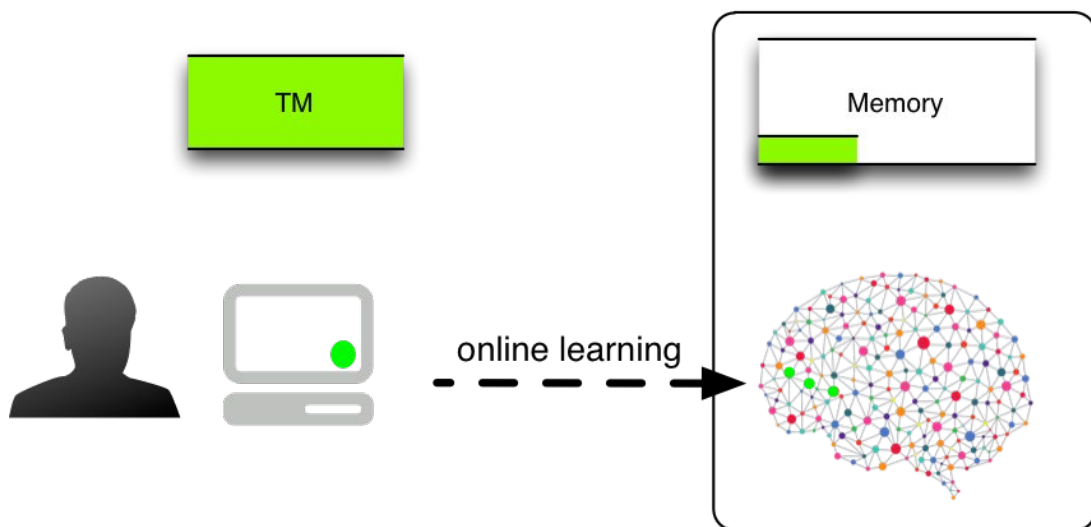


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Online Learning

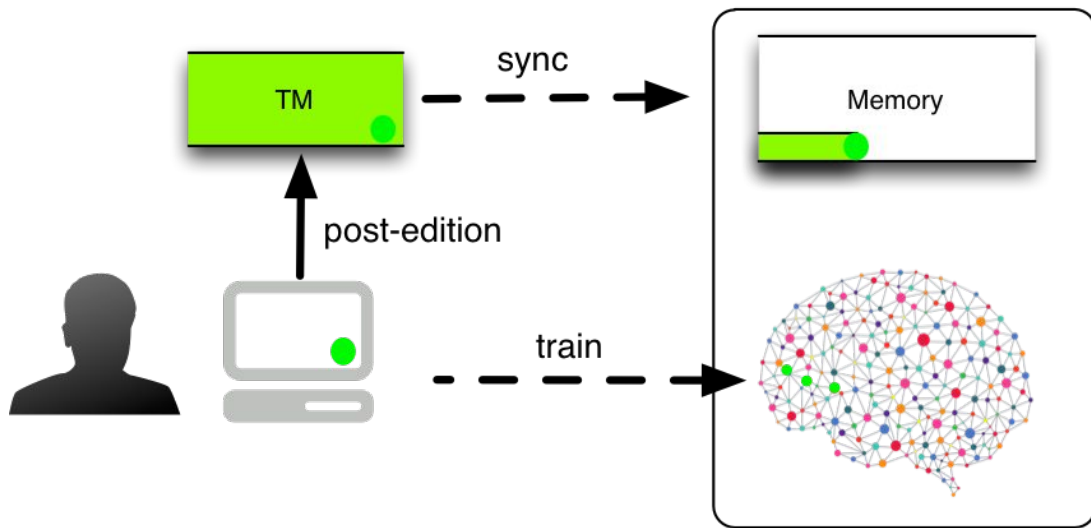


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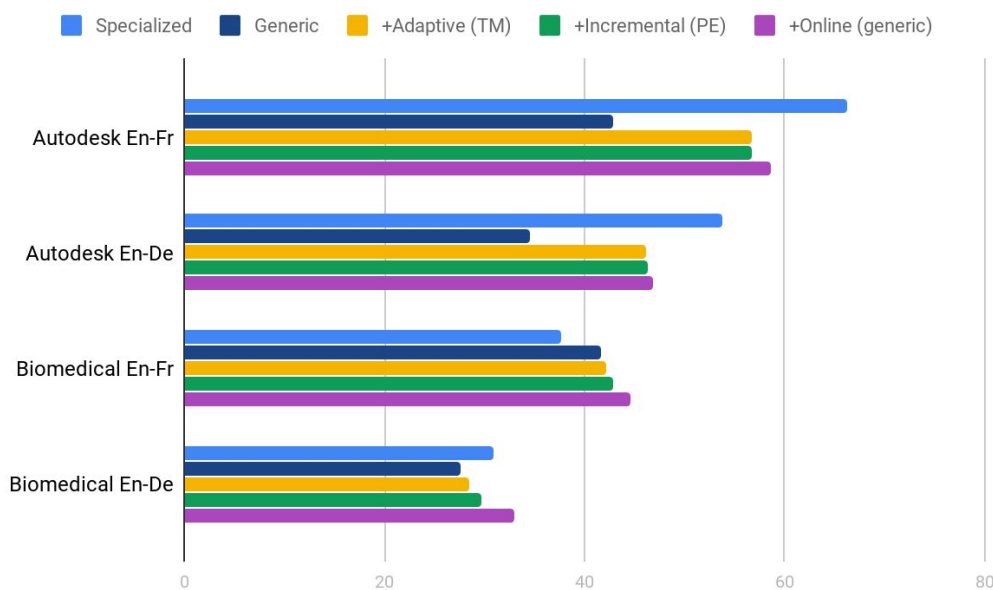
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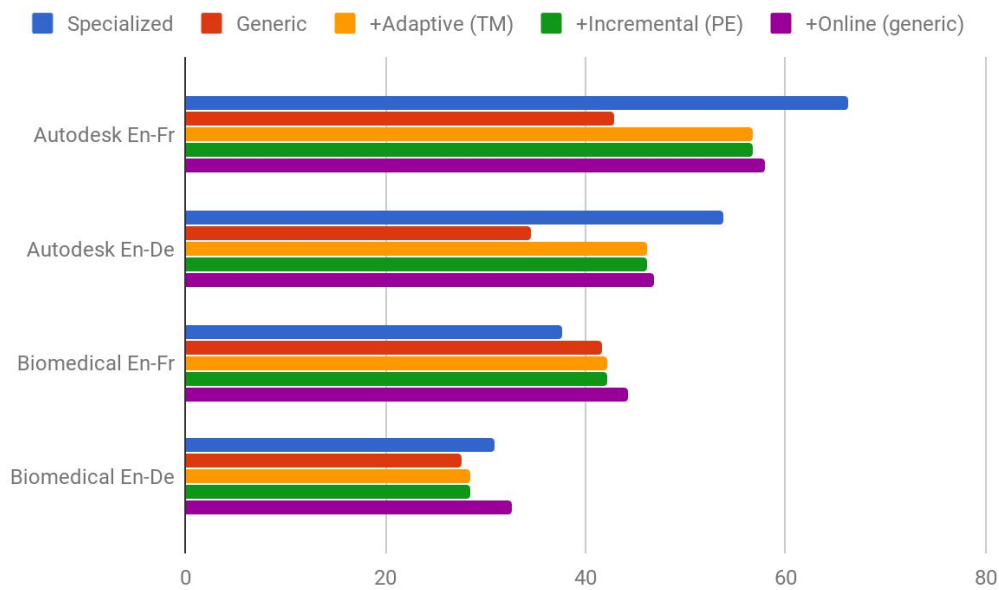
Incremental+Online Learning



Incremental+Online Learning (single domains)



Incremental+Online Learning (two domains)



Challenges

Online-learning contribution is consistent

Does it scale with number of domains?

Incremental learning contributes marginally

Probably depends on test set size

We are not always able to beat specialized models

How to improve further adaptation ?

Automatic Post-Editing

Automatic Post-Editing

Can improve MT without touching it inside

We can adapt an “external” MT service!

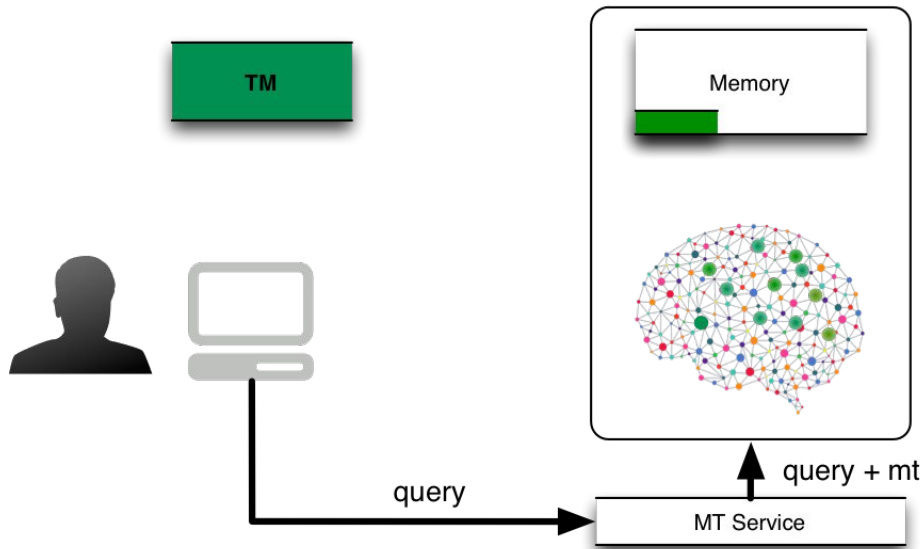
Similar to NMT: two inputs (*src, mt*), one output (*ape*)

Can be trained with less data than NMT

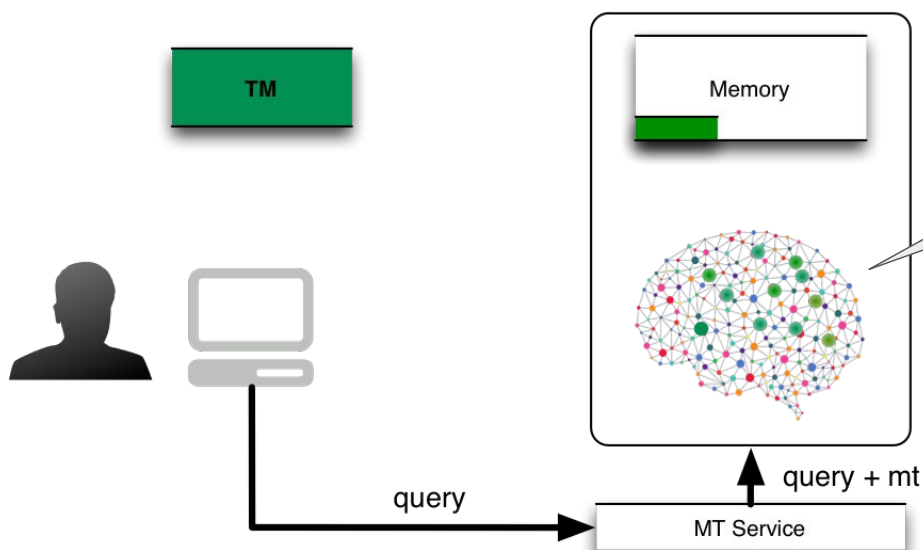
We can deploy instance based adaptation

Chatterjee et al. (2017), *Multi-source Neural APE: FBK's participation*, WMT.

Automatic Post-Editing

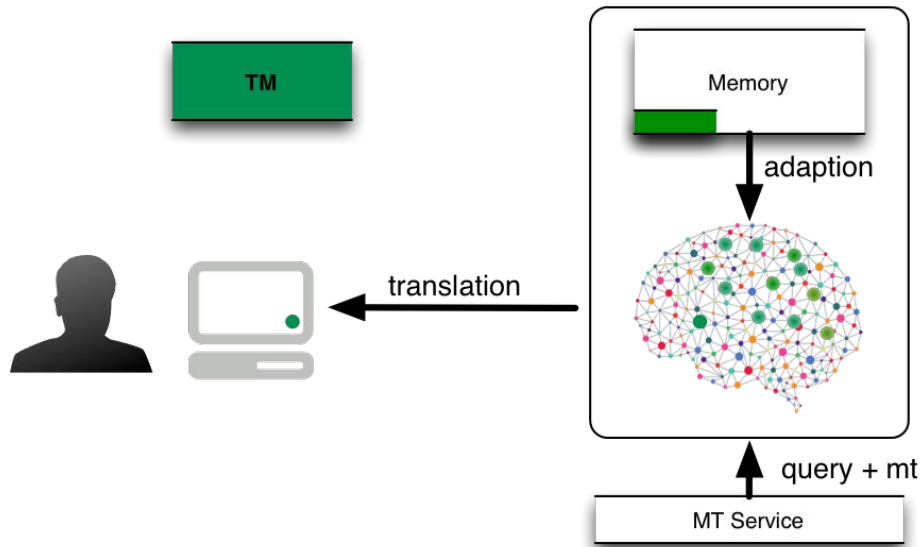


Automatic Post-Editing

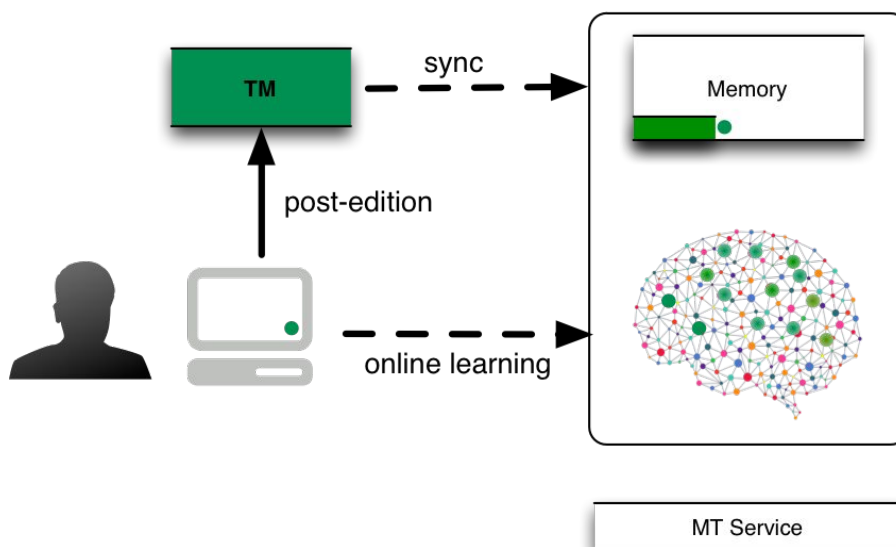


Neural APE uses two encoders and two attention models, which are merged and used by one decoder.

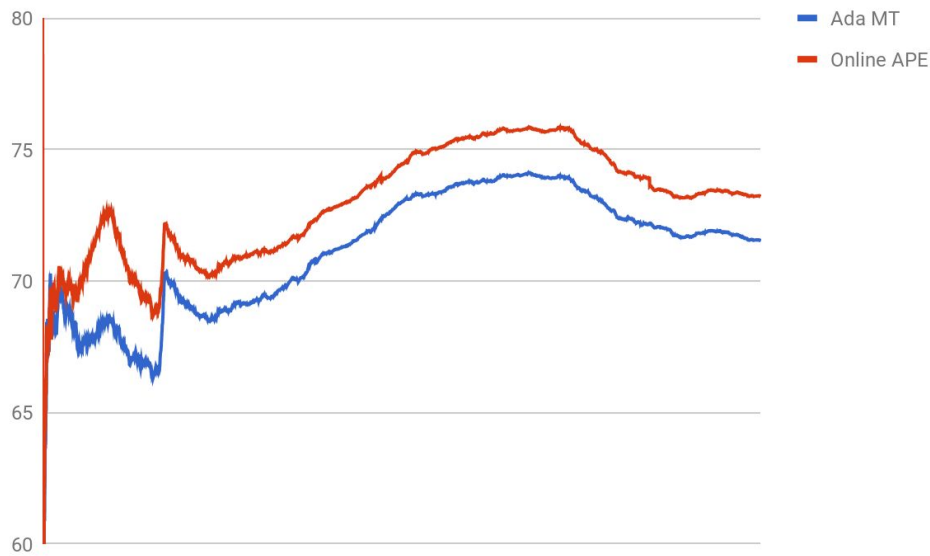
Automatic Post-Editing



Automatic Post-Editing

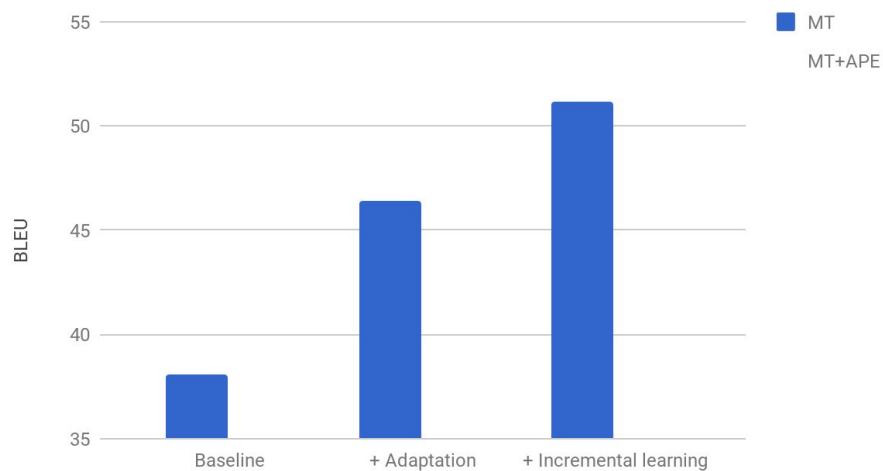


Automatic Post-Editing

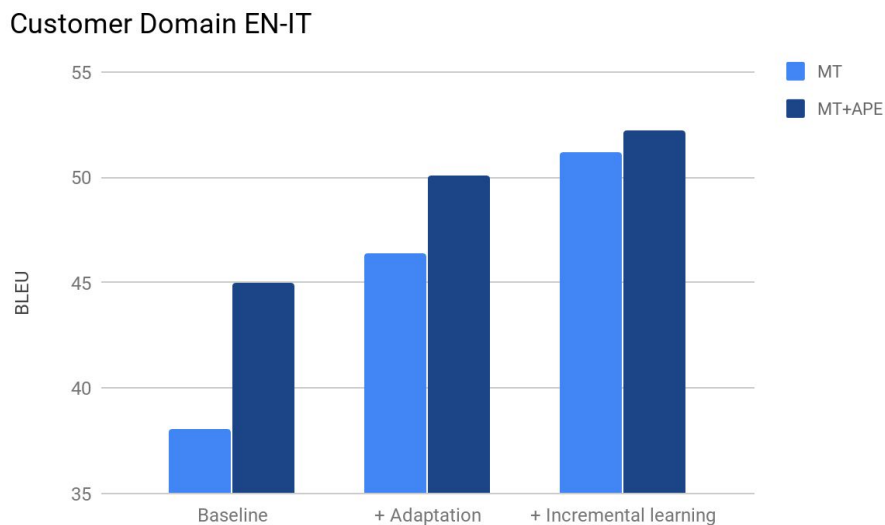


Automatic Post-Editing

Customer Domain EN-IT



Automatic Post-Editing



Automatic Post-Editing

Can improve on top of static and adaptive engine!

Uses incremental learning, adaptation and online learning

Portable (in principle) on the multi-domain setting

Limited gain on top of full-fledged adaptive NMT

Can be an extra component to manage

Conclusions

Conclusions

Multi-user scenario goes beyond simple domain adaptation

We need to handle multiple evolving *domains*

Domain customization is not an option

Real-time adaptation/learning works!

But, there is still room for improvement!

Thank You

Website

www.ModernMT.eu

Github

github.com/ModernMT/MMT

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