UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Streaming neural machine translation systems from European languages into English

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MLLP Machine Learning and Language Processing

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Contents

1 Introduction

Motivation

- Increase accessibility of multimedia content to non-speakers of the original language
- Remove language barriers in virtual meetings and video-conferences in real time

Framework

- Research internship at the VRAIN MLLP research group
- Technology-transfer contract between MLLP and CERN
  - Fr$\rightarrow$En machine translation (MT) systems for offline and real-time scenarios

Introduction

Goals

- To study the current state-of-the art approaches for offline and real-time MT, including domain adaptation techniques and automatic evaluation.
- To apply the most important tools employed in MT research for data processing, model training, inference and evaluation.
- To explore and refine data filtering and processing techniques to improve the quality of MT systems.
- To develop general domain and in-domain MT systems that provide accurate enough translations for the purposes of CERN.
- To develop simultaneous MT systems for the streaming MT scenario with low latency and good enough quality.

2 Preliminaries

Machine Translation

- In MT, we search for the best translation $\hat{\mathbf{y}}$ of $\mathbf{x}$ given by

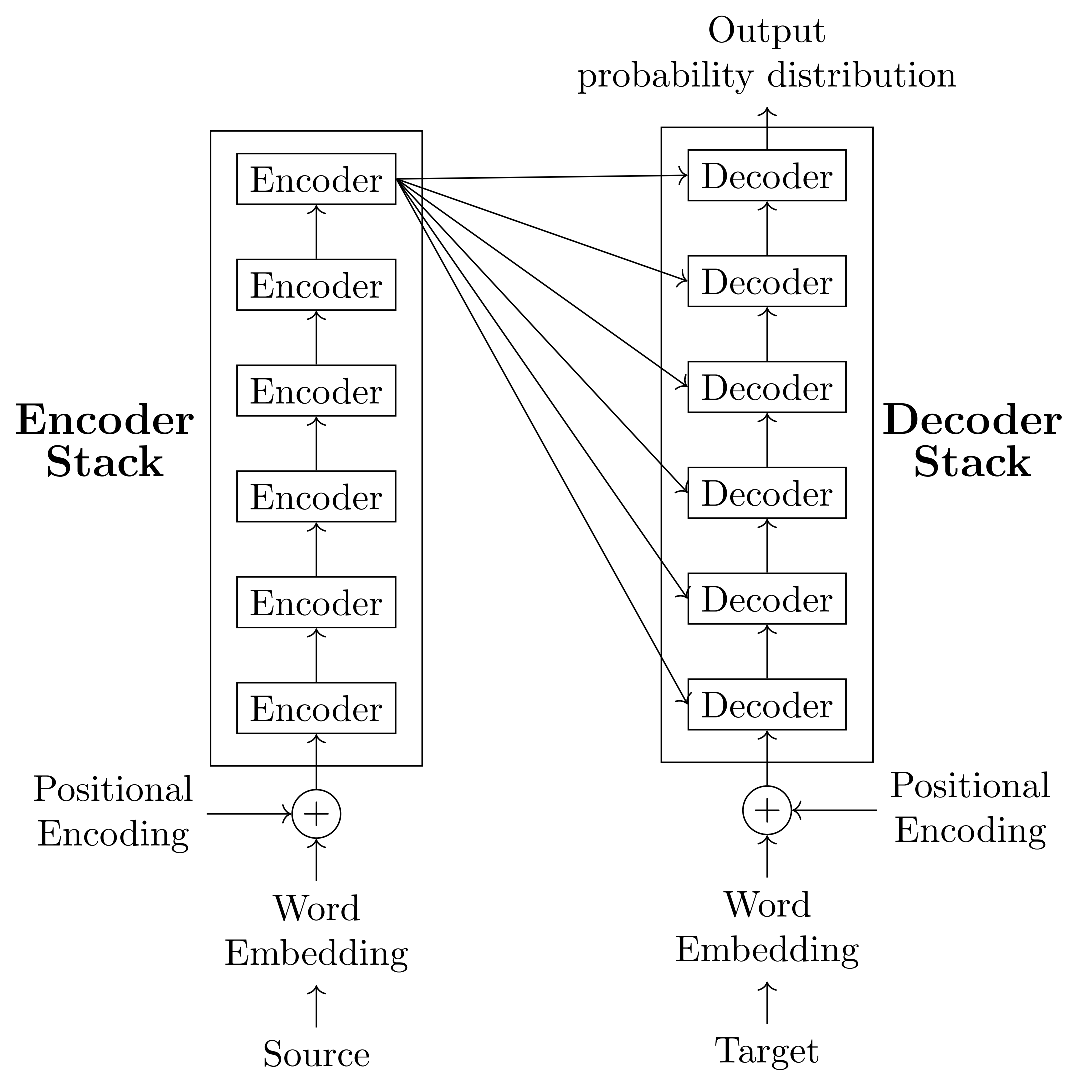
$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y} \in \mathcal{Y}^*} p(\mathbf{y}|\mathbf{x})$$

- $\mathbf{x}$ is the *source* sentence and $\mathbf{y}$ is the *target* sentence
- The neural models we will use approximate $p(\mathbf{y}|\mathbf{x})$ directly
- The *beam search* algorithm is used to instantiate the argmax

Preliminaries

Transformer

- Deep learning architecture based on the *attention* mechanism
- State-of-the-art in many tasks and modalities
- Considers the full source phrase when translating



Preliminaries

Evaluation

- Manual evaluation is very costly
- Automatic evaluation
  - ***BLEU: Bilingual Evaluation Understudy*** $\rightarrow$ higher is better
  - Others: chrF and TER

Tools

- Model training and inference: fairseq
- Data processing: Moses, subword-nmt, SentencePiece, etc.

3 Training Data

General Domain

Source	Corpus	Bilingual pairs	Words	
			English	French
Internet	WikiMatrix	2.7 M	57.8 M	63.1 M
	WikiMedia	1.0 M	24.1 M	25.8 M
	Giga Fr-En	22.5 M	575.8 M	672.2 M
	ParaCrawl	216.6 M	3.7 G	4.1 G
	CCAligned	15.6 M	156.7 M	171.1 M
	CommonCrawl	0.1 M	4.1 M	4.7 M
	EUBookshop	10.8 M	224.6 M	244.5 M
	UNPC	30.3 M	658.4 M	816.4 M
	News Commentary	3.2 M	70.7 M	76.6 M
Parliamentary Meetings	DGT-TM	4.9 M	86.3 M	95.4 M
	Europarl	1.2 M	28.6 M	29.9 M
	Europarl-ST	96.5 K	2.3 M	2.6 M
	Total	**309.0 M**	5.6 G	6.3 G

Training Data

Domain of CERN

Monolingual CDS Corpus

	Objects	Sentences	Words
Titles	519 K	519.0 K	4.6 M
Abstracts	130 K	652.0 K	15.6 M
Documents	296 K	48.9 M	1.1 G
Total	945 K	**50.0 M**	1.1 G

Bilingual CERN News Corpus

Dataset	Documents	Bilingual Pairs	Words	
			English	French
Training	3409	51.9 K	841.9 K	909.4 K
Validation	144	2.2 K	331.7 K	405.3 K
Test	128	1.8 K	274.0 K	333.3 K
Total	3681	**55.9 K**	1.5 M	1.7 M

Training Data

Data Processing

Raw text	`Thank you, Mr Segni, I shall do so gladly.`
Tokenization	`Thank you , Mr Segni , I shall do so gladly .`
Truecasing	`thank you , Mr Segni , I shall do so gladly .`
Byte-Pair Encoding	`thank you , Mr Se@@ gn@@ i , I shall do so gl@@ ad@@ ly .`
Raw text	`Thank you, Mr Segni, I shall do so gladly.`
Truecasing	`thank you, Mr Segni, I shall do so gladly.`
SentencePiece	`thank_ you ,_ Mr_ Seg ni ,_ I_ shall_ do_ so_ glad ly ._`

- Filtering → removes noise from data
  - Language identification
  - Sentence length
  - Source-to-Target length ratio
- Tokenization → divides text into *tokens*
- Truecasing → maintains the most frequent version of each token
- Subword Segmentation → represent the vocabulary with fewer tokens
  - Byte-Pair Encoding
  - SentencePiece

4 Domain Adaptation

Fine-Tuning

- Include *domain bias* in the modeling of $p(\mathbf{y} \mid \mathbf{x})$
- A model trained for a general task is used in a fine-grained task or domain
- We modify the model parameters to *adapt* it to the domain using in-domain data
- CERN's domain: particle physics

Backtranslations

- Translate monolingual text in the target language to the source language
  - Construct a synthetic bilingual corpus
- Leverage monolingual data in the target language and domain of interest
- Enhance the translation model's implicit language model (of the target language)

5 Streaming MT

- To simultaneously transalte $\mathbf{x}$ into the target $\hat{\mathbf{y}}$, we find the best translation by

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}\in\mathcal{Y}^*} p_g(\mathbf{y} \mid \mathbf{x}) = \arg\max_{\mathbf{y}\in\mathcal{Y}^*} \prod_i p(y_i \mid \mathbf{x}_{\leq g(i)}, \mathbf{y}_{<i}).$$

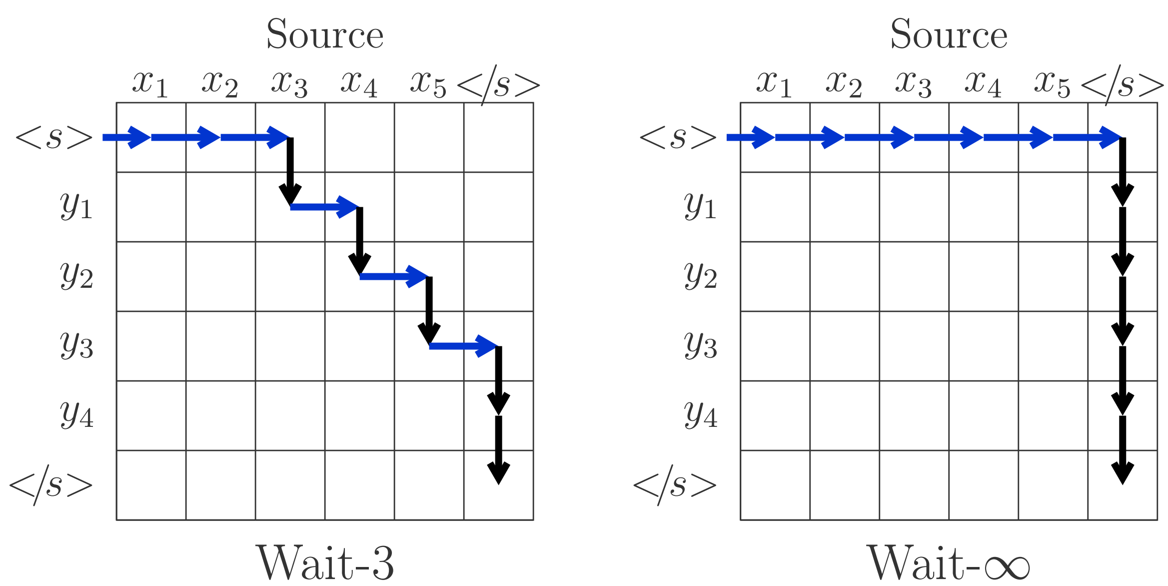
- The model only has access to a prefix of the full source to translate
- It needs a *policy* to decide when to perform a reading or writing action

Offline	Hay libros que valen la pena volver a leer.								
	wait whole sentence								There are books that are worth reading again.
Simultaneous	Hay libros	que	valen	la	pena	volver	a	leer.	
	wait 2 words There	are	books	that	are	worth	reading	again.	

Streaming MT

Wait-k Models

- Inspired by how human interpreters wait for enough context before translating
- The model reads k tokens before emitting translations
  - Afterwards, it alternates between writing and reading operations

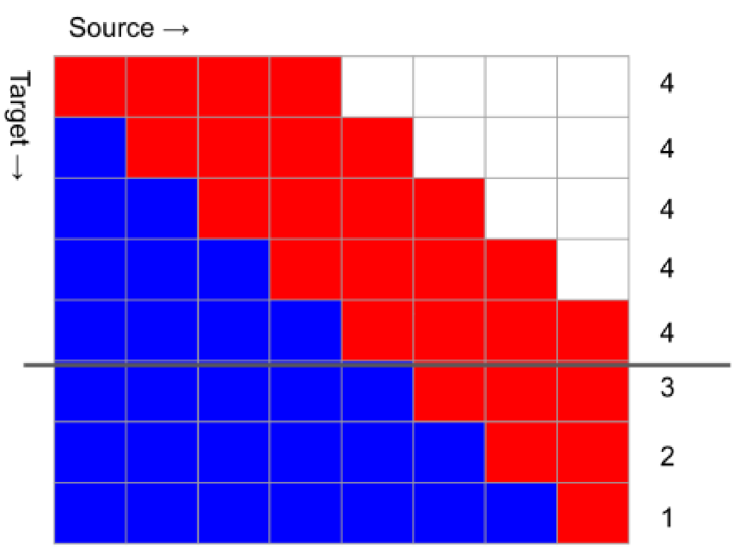


- ***Test-Time Wait-k*** introduces the wait-k policy to offline MT models
- ***Multi-Path Wait-k***: simultaneous MT training scheme that considers different values for k

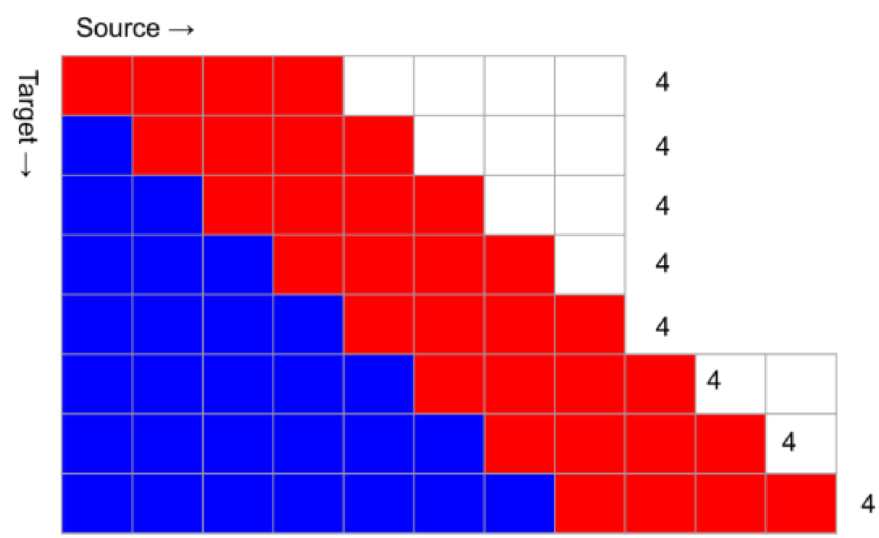
Streaming MT

Latency Evaluation

- Automatic evaluation of latency, independent of the hardware and environment
  - ***AL***: Average Lagging
  - ***DAL***: Differentiable Average Lagging



AL



DAL

6 Results

- *Baseline*: X5Gon system trained in 2019

Offline MT Systems

General Domain

Name	Filtering			Processing				
	Langid	Length	Ratio	Apostrophes	Tokenize	Truecase	BPE	SPM
V1	-	-	-	-	X	X	X	-
V2	X	<150	1.5	-	X	X	X	-
V3	X	<150	1.5	X	-	X	-	X

In-Domain

- V3-FT-CN: V3 fine-tuned on the CERN News corpus
- V3-FT-BT: V3 fine-tuned on 50K backtranslations of the CDS corpus
- V4: V3 + backtranslations

Results

General Domain Evaluation

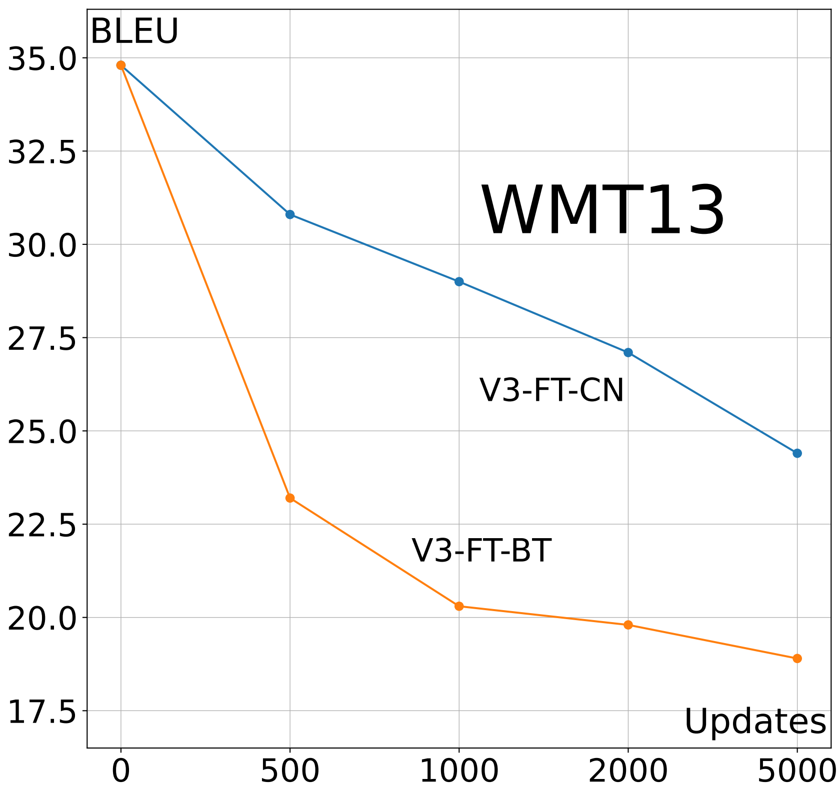
System	BLEU	
	WMT13	WMT14
X5Gon	34.7	39.4
V1	**35.1**	39.2
V2	**35.1**	**39.5**
V3	34.8	39.3
V4	34.6	39.1

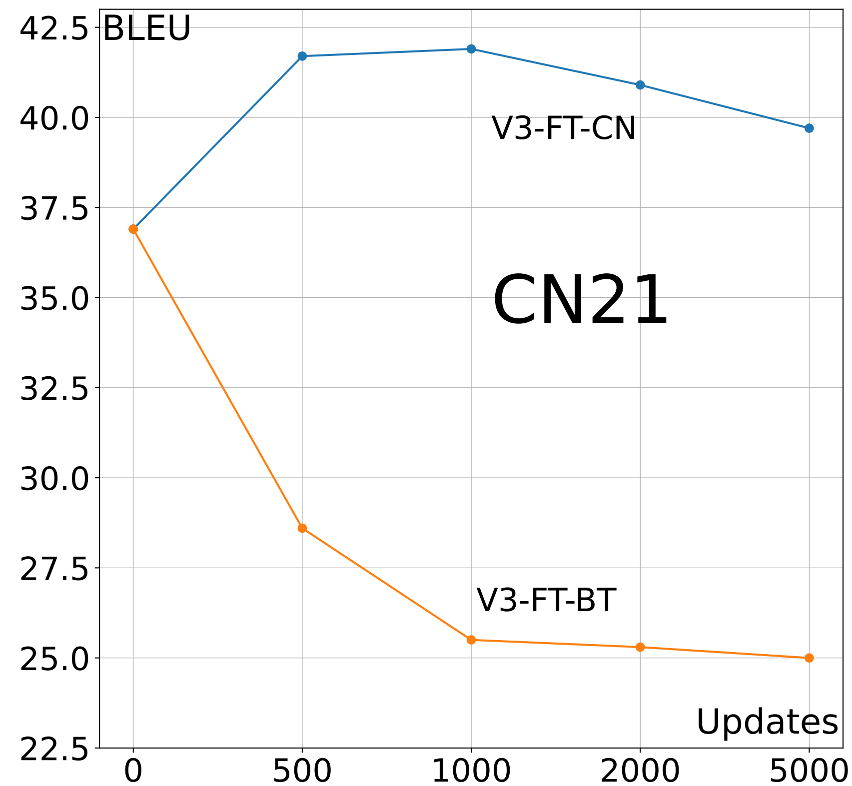
In-Domain Evaluation

System	BLEU	
	CN21	CN22
X5Gon	35.3	36.8
V3	**36.9**	**38.6**
V4	36.6	38.2

Results

Fine-Tuning



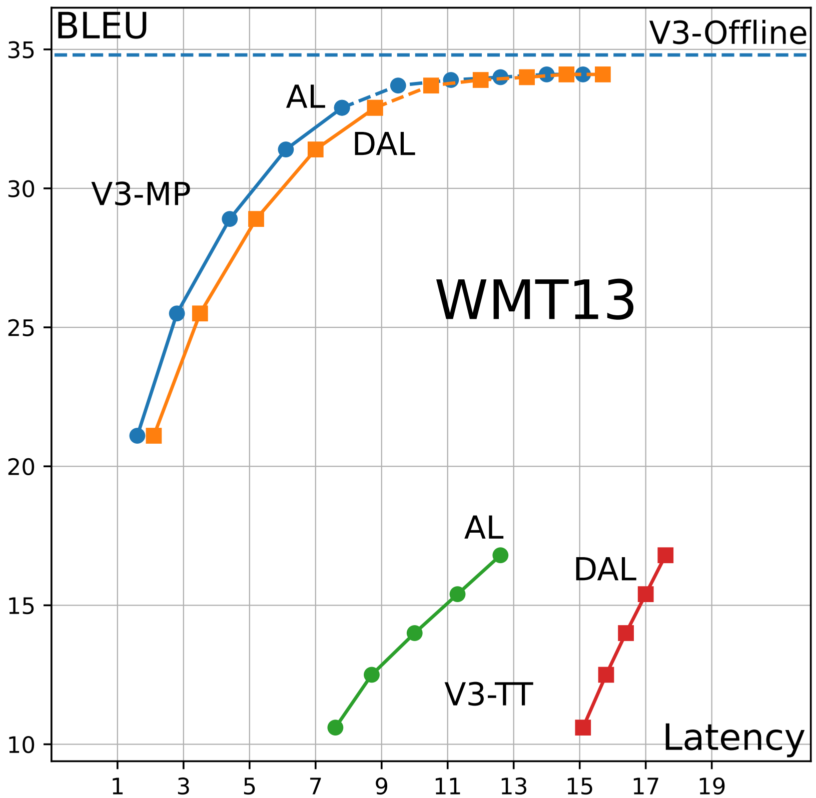


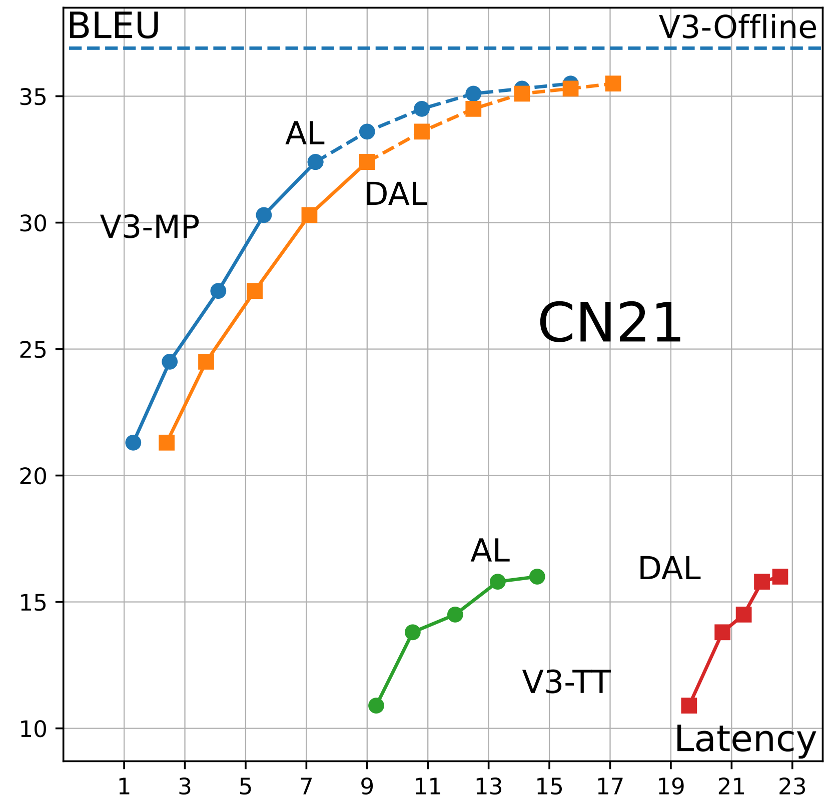
- Best model: V3 fine-tuned using CERN News with 1000 updates

Corpus	BLEU (WMT14)	BLEU (CN22)
X5Gon	39.4	36.8
V3-FT-CN	31.7	42.9

Results

Streaming MT





- Selected models: V3 Multi-Path Wait-k with $k \geq 7$

Corpus	BLEU	AL	DAL
WMT14	33.8	5.9	7.1
CN22	30.9	5.5	7.1

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7 Conclusions

Achieved Goals

- Studied SOTA for offline and simultaneous MT, domain adaptation and automatic evaluation
- Leveraged current tools used for MT research to develop various MT systems
- Refined the data processing pipeline and improved MT system performance
- Developed in-domain MT systems, improving the baseline by a relative 11%
- Developed high-accuracy and low-latency simultaneous MT systems for streaming applications

Future work

- Deploy the MT systems in CERN's network
- Carry out domain adaptation for simultaneous MT systems
- Explore:
  - Domain adaptation beyond fine-tuning with *adapter layers*
  - Adaptive policies for simultaneous translation by identifying *meaningful units*

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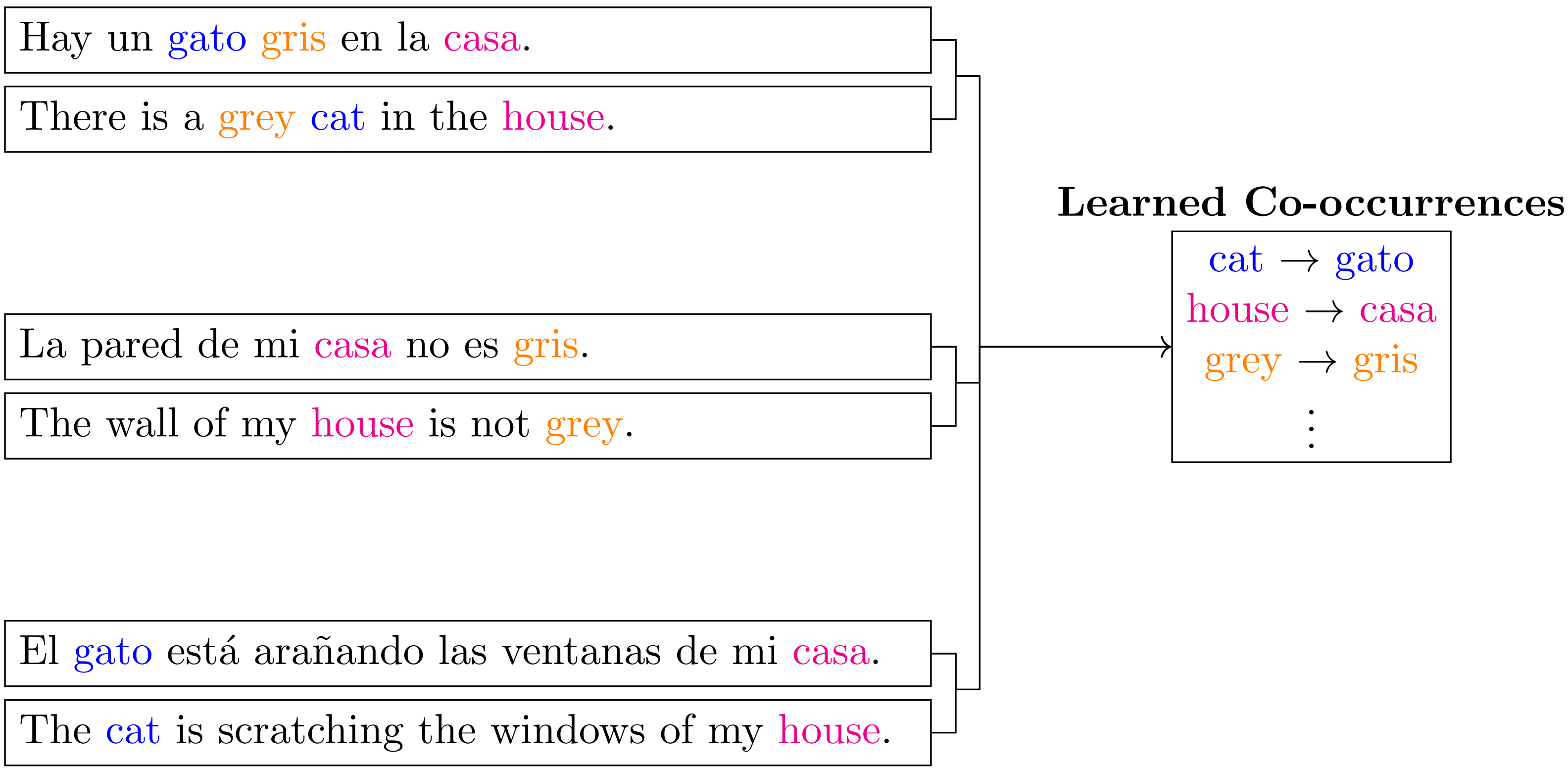
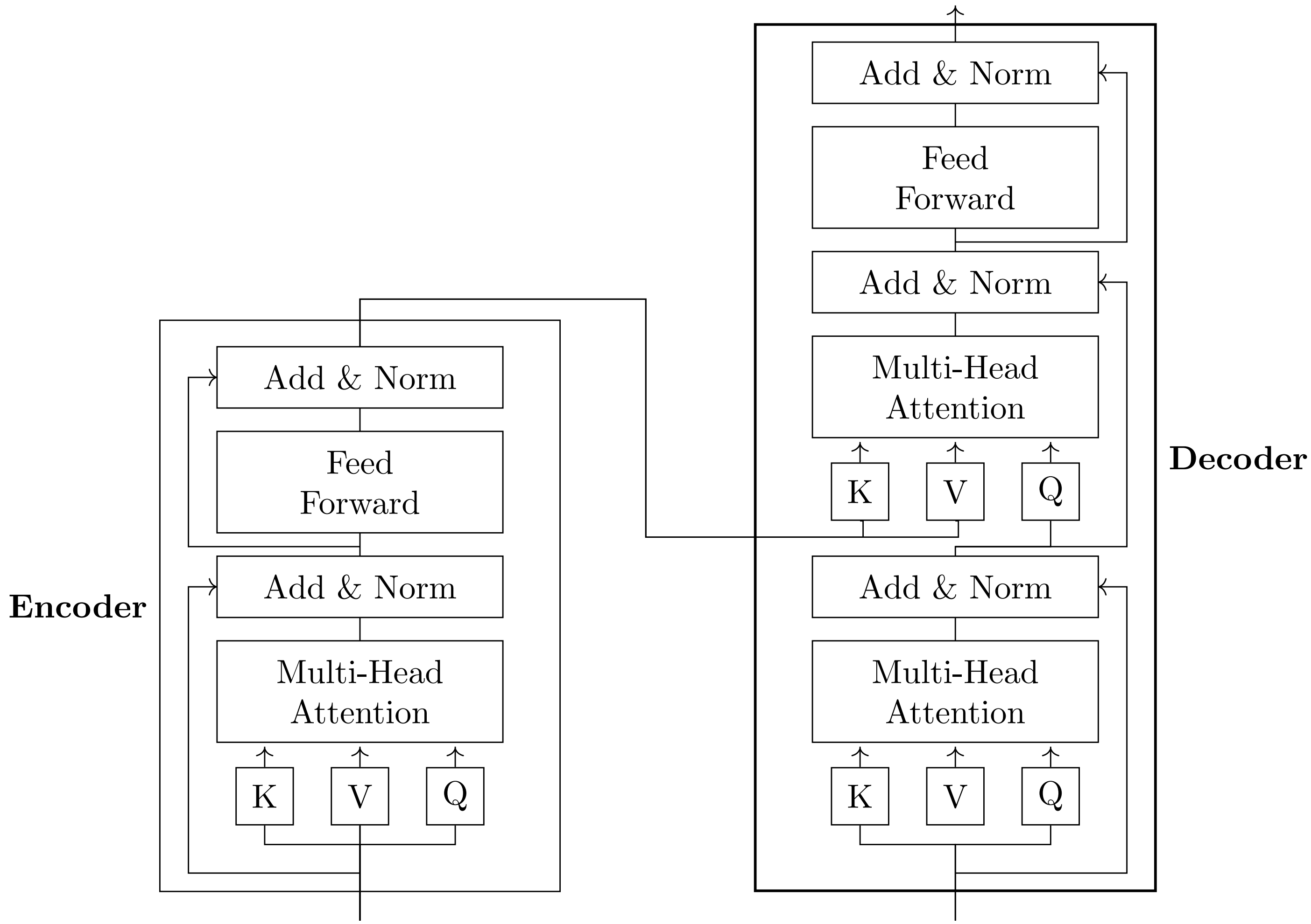
Appendix

IBM Model 1



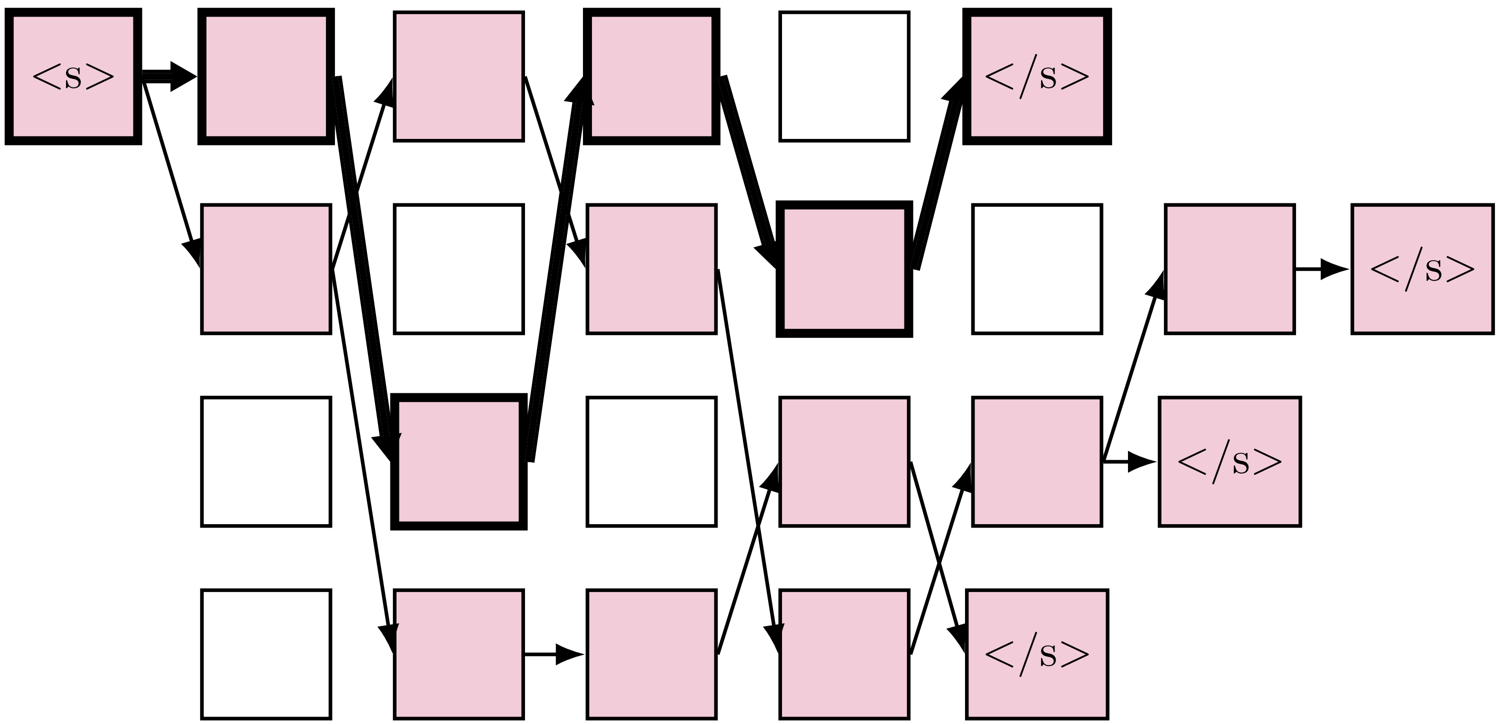
Appendix

Transformer Encoder-Decoder



Appendix

Beam Search



Appendix

Quality Evaluation

BLEU

$$BLEU(4) = BrevityPenalty \times AveragePrecision(4)$$

$$BrevityPenalty = \begin{cases} 1 & |output| > |reference| \\ \exp\left(1 - \frac{|output|}{|reference|}\right) & |output| \leq |reference| \end{cases}$$

$$AveragePrecision(N) = \frac{1}{N}\sum_{n=1}^{N} log p_n, \qquad p_n = \frac{\text{matching n-grams}}{\text{total n-grams in output}}$$

chrF

$$chrF\beta = (1+\beta)^2 \frac{chrP \times chrR}{\beta^2 \times chrP + chrR}$$

TER

$$TER = \frac{\text{word-level edit distance}}{|\text{reference}|}$$

Appendix

Simultaneous Translation

- $g(i)$ is the number of source tokens read when writing a translation at position i.

Wait-k

$$g_{\text{wait}-k}(i) = \left\lfloor k + \frac{i-1}{\gamma} \right\rfloor, \qquad \gamma = \mathbb{E}\left[\gamma_n\right], \qquad \gamma_n = \frac{|\mathbf{y}_n|}{|\mathbf{x}_n|}.$$

Multi-Path Wait-k

For one wait-k path $\mathbf{z}^k_{<i}$:

$$p(\mathbf{y} \mid \mathbf{x}, \mathbf{z}^k) = \prod_i p(y_i \mid \mathbf{x}_{\leq \mathbf{z}^k_i}, \mathbf{y}_{<i}, \mathbf{z}^k_{<i}).$$

We optimize over multiple wait-k paths:

$$\mathbb{E}_K[p(\mathbf{y} \mid \mathbf{x}, \mathbf{z}^k)] \approx \prod_{k \sim \mathcal{U}(K)} p(\mathbf{y} \mid \mathbf{x}, \mathbf{z}^k).$$

Appendix

Average Proportion

$$AP = \frac{1}{|\mathbf{x}||\mathbf{y}|} \sum_{i=1}^{\mathbf{y}} g(i)$$

Average Lagging

$$AL_g = \frac{1}{\tau} \sum_{i=1}^{\tau} \left(g(i) - \frac{i-1}{\gamma} \right), \qquad \tau = \tau_g(|\mathbf{x}|) = \min_{i:g(i)=|\mathbf{x}|} i$$

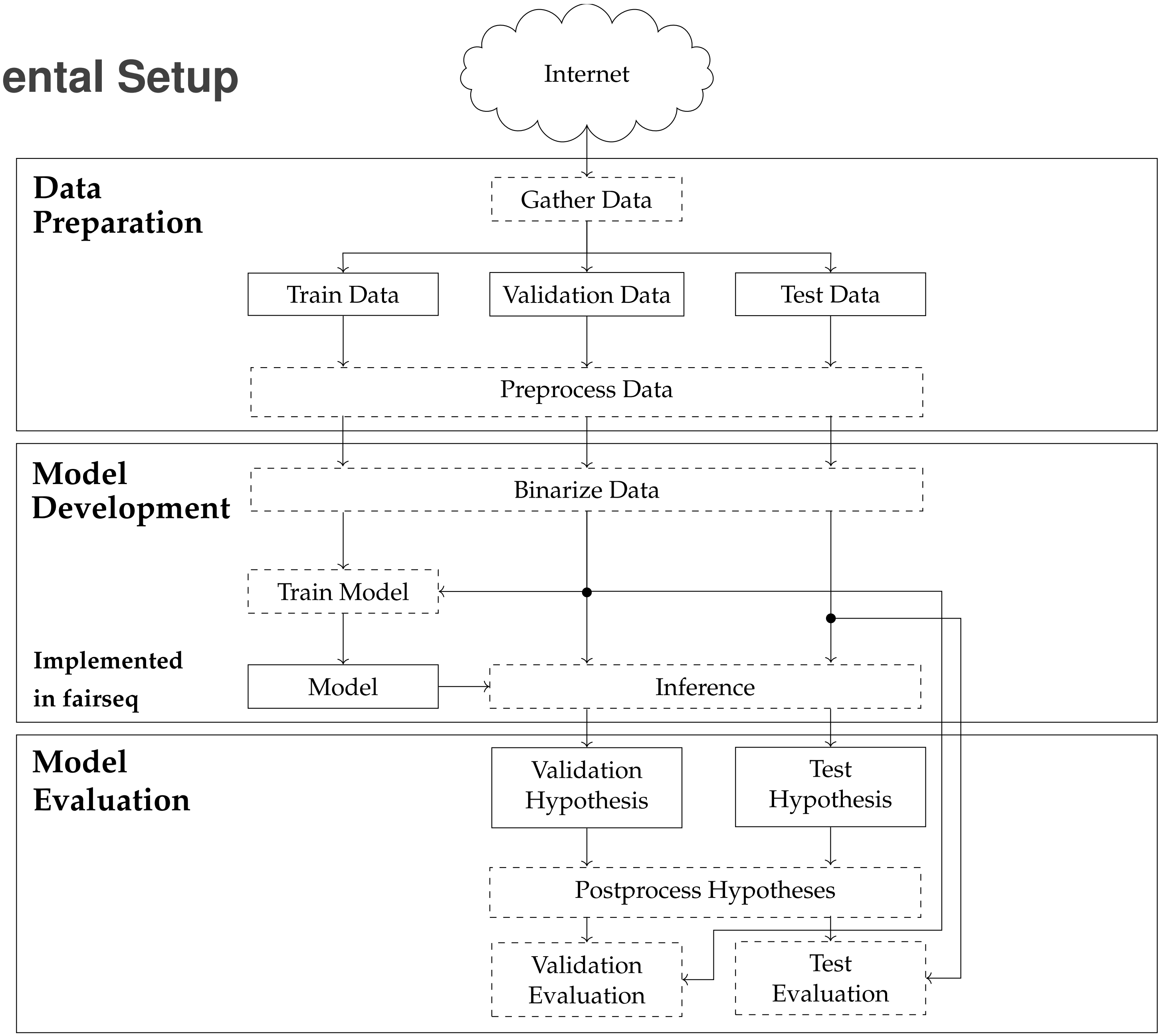
Differentiable Average Lagging

$$DAL_d = \frac{1}{|\mathbf{y}|} \sum_{i=1}^{|\mathbf{y}|} \left(g_{d'}(i) - (i-1)d \right), \qquad d = \frac{1}{\gamma} = \frac{|\mathbf{x}|}{|\mathbf{y}|}$$

$$g_{d'}(i) = \begin{cases} g(i) & i = 1 \\ \max\left(g(i), g_{d'}(i-1) + d \right) & i > 1 \end{cases}$$

Appendix

Experimental Setup



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Streaming MT Systems

- V3-TT: Test-Time Wait-k applied to V3
- V3-MP: Multi-Path Wait-k training with same data processing as V3