

Generative Adversarial Networks in Neural Machine Translation

Master 2 Internship - Computer Science Research - Paris-Saclay
University

Author:
NGO HO Anh Khoa
anh-khoa.ngo-ho@u-psud.fr

Supervisor:
ALEXANDRE Allauzen
allauzen@limsi.fr





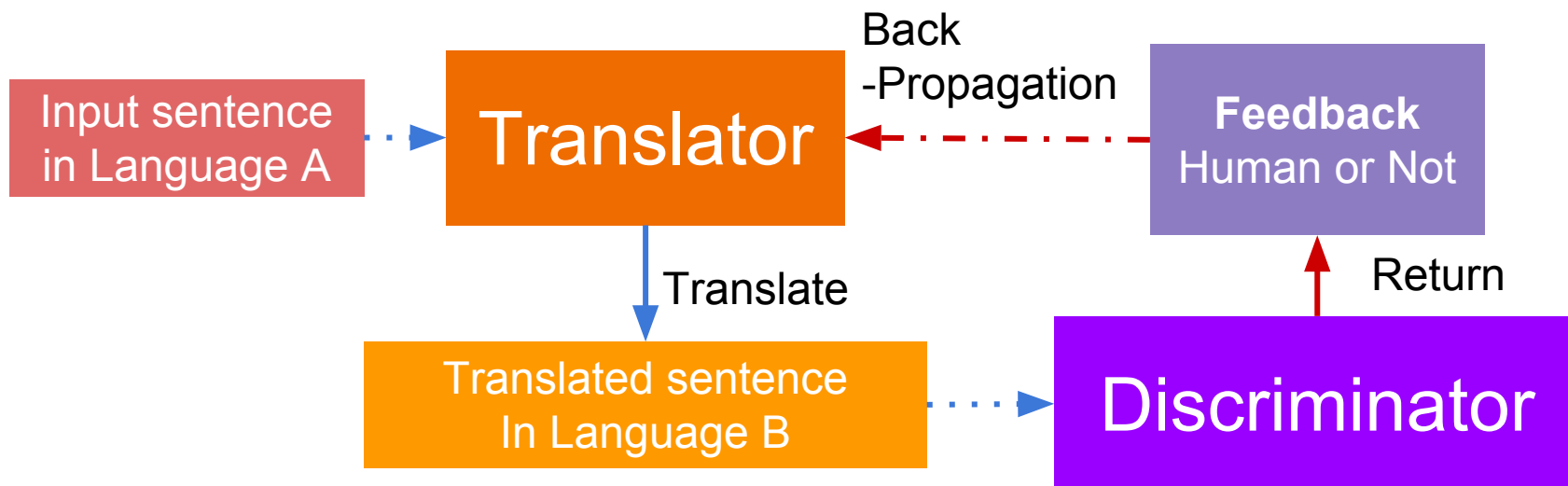
Outline

- Main idea: **Applying GANs in NMT, based on the work of [Yang et al, 2017]**
- Model architecture
- Algorithm
- Results and Experiments
- Conclusion



Main idea

Applying GANs in NMT [Yang et al, 2017]

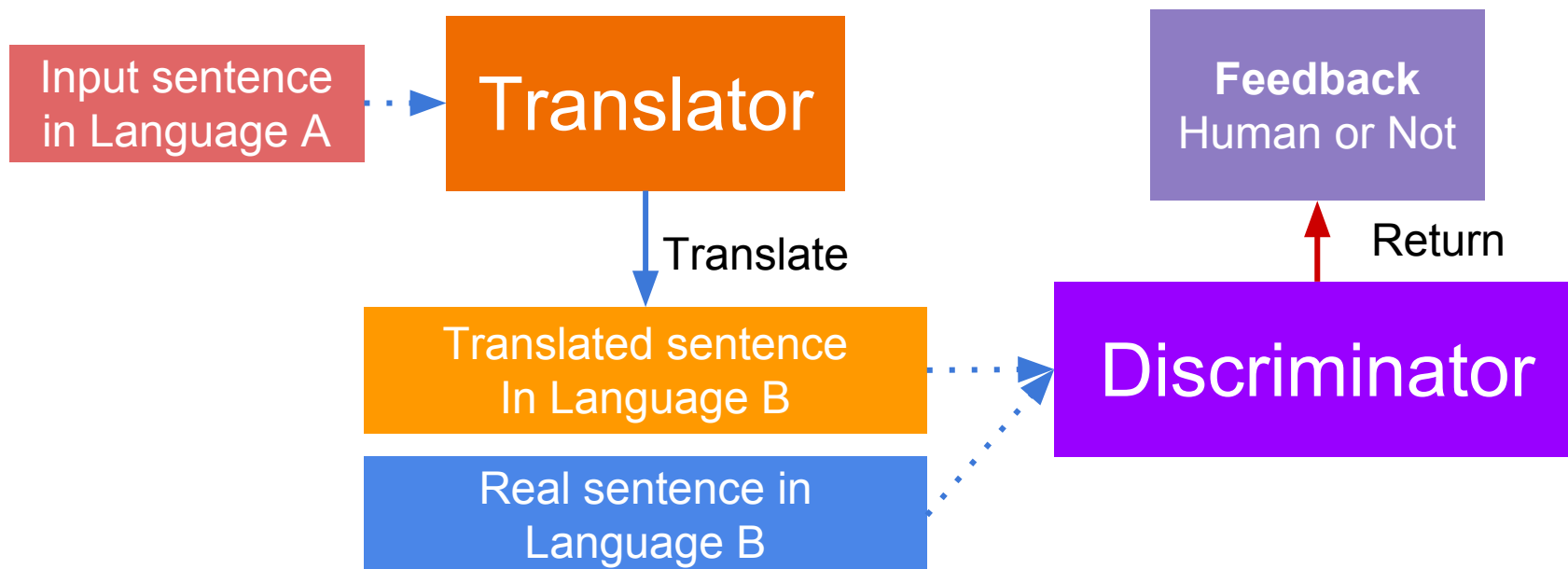


- There are two objectives:
 - **Translator tries to fool Discriminator**
 - **Discriminator tries to distinguish well**



Main idea

Applying GANs in NMT [Yang et al, 2017]



- There are two objectives:
 - Translator tries to fool Discriminator
 - **Discriminator tries to distinguish well**



Model architecture

GANs in NMT

- **Translator:** Attention-based NMT model
 - Maximize the expected end reward of a sequence (Reinforcement learning)

$$\nabla J_G = \sum_{y_t} R_D^G((y_{1:t-1}, x), y_t) \nabla_{\theta} \log p_G(y_t | y_{1:t-1}, x) \quad (3.2)$$

- **Discriminator:** Binary classifier discriminates the machine-translated sentence from the human-translated sentence.
 - Probability of a sentence being human translated. $D(y, x)$



Model architecture

GANs in NMT

- **Translator:** Attention-based NMT model
 - Maximize the expected end reward of a sequence (Reinforcement learning)

$$\nabla J_G = \sum_{y_t} R_D^G((y_{1:t-1}, x), y_t) \nabla_{\theta} \log p_G(y_t | y_{1:t-1}, x) \quad (3.2)$$

- **Reward strategies:** $R_D^G((y_{1:t-1}, x), y_t)$
 - Monte-Carlo search strategy [Yang et al, 2017]
 - **Discriminator strategy** [Li et al, 2017]
 - **Language model strategy**



Model architecture

GANs in NMT

- **Reward strategy:**
 - Monte-Carlo search strategy [Yang et al, 2017]
 - Discriminator is a **full sentence** classifier.
 - MC search samples the rest of sequence for each token.

$$R_D^G((y_{1:t-1}, x), y_t) = \begin{cases} \frac{1}{N} \sum_{n=1}^N D(y_{1:L_n}^n, x), y_{1:L_n}^n \in MC^G((y_{1:t}, x), N) & \text{for } t < L \\ D(y_{1:T}, x) & \text{for } t = L \end{cases} \quad (3.4)$$



Model architecture

GANs in NMT

- **Reward strategy:**
 - Discriminator strategy [Li et al, 2017]
 - Discriminator is a **partially generated sentence** classifier.
 - Example: "Discriminator is a classifier ."
 - "Discriminator", "Discriminator is", "Discriminator is a", "Discriminator is a classifier", "Discriminator is a classifier ."

$$R_D^G((y_{1:t-1}, x), y_t) = D(y_{1:t}, x) \quad (3.5)$$



Model architecture

GANs in NMT

- **Reward strategy:**
 - Language model strategy
 - Discriminator reward: Monte-Carlo search strategy or Discriminator strategy.
 - **Language model is an extra quality evaluator.** (Dual learning of [He et al, 2016])

$$R_D^G((y_{1:t-1}, x), y_t) = \alpha * D(y_{1:t}, x) + (1 - \alpha) * LM(y_t|y_{1:t-1})$$

(3.6)



Model architecture

GANs in NMT

- **Teacher Forcing:** [Yang et al, 2017]
 - Return reward from **true target sentence**.

$$\nabla J_G = \sum_{y_t} 1 * \nabla_{\theta} \log p_G(y_t | y_{1:t-1}, x) \quad (3.7)$$

GAN

Discriminator

Translated sentence
In Language B

Translator

Back-Propagation

Likelihood

Teacher
-Forcing

Real sentence
in Language B

Algorithm

while *not convergence* **do**

Sample randomly a batch: Input sentences and its human-translated sentences $(X, hY)_{1:S}$

for *g-steps* **do**

for $s \in 1:S$ **do**

G translates X_s into machine-translated sentence $mY_{1:T} = (my_1, \dots, my_T)$ by beam-search

for $t \in 1:T$ **do**

| Compute reward $R_D^G(my_{1:t-1}, my_t)$ by Equation 3.4, 3.5 or 3.6

end

end

Update G with Discriminator: Update with $mY_{1:S}$ by Equation 3.2

Update G with Teacher Forcing: Update with hY by Equation 3.7

end

for *d-steps* **do**

G translate $X_{1:S}$ into machine-translated sentences $mY'_{1:S}$ as Negative examples
 $hY_{1:S}$ Human-generated sentences as Positive examples

Update D: Update by Equation 3.3

end

end



Results and Experiments

English-French translation task

- **Dataset:** BTEC

- Training set: 19972 sentences
- Development set: 506 sentences
- Testing set: 469 sentences

- **Initial models:**

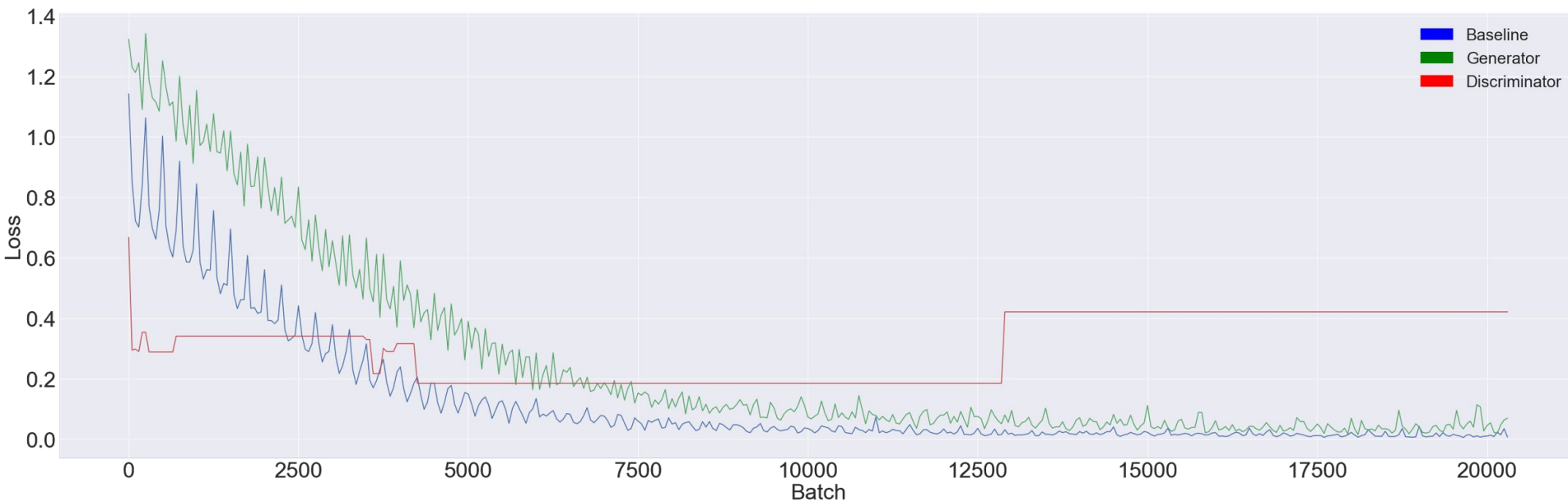
- Baseline: NMT model with BLEU 38.8 on development set
- Accuracy of discriminator:
 - MC search strategy: 0.78
 - Discriminator strategy: 0.83
 - In the range [0.75, 0.85]



Results and Experiments

English-French translation task

- Discriminator strategy:
 - Train loss





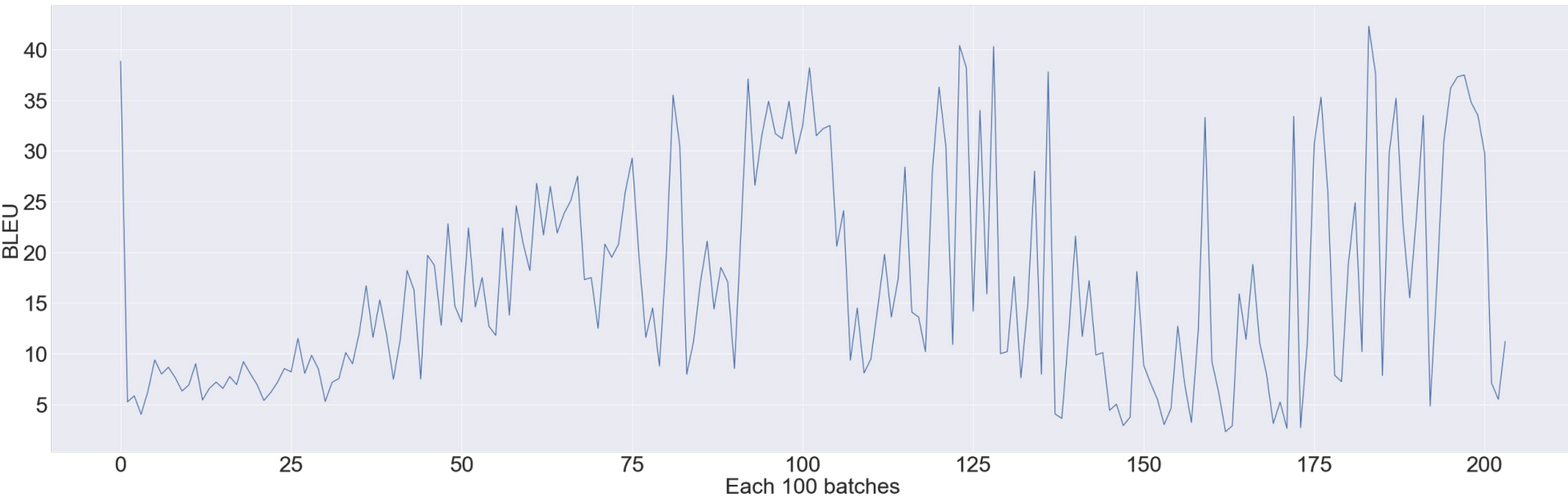
Results and Experiments

English-French translation task

- **Discriminator strategy:**

- Validation BLEU score

Model	Initial model	GANs	Improve
<i>Train</i>	46.71	92.38	+45.67
<i>Dev</i>	38.85	42.340	+3.49
<i>Test</i>	38.39	36.15	-2.24

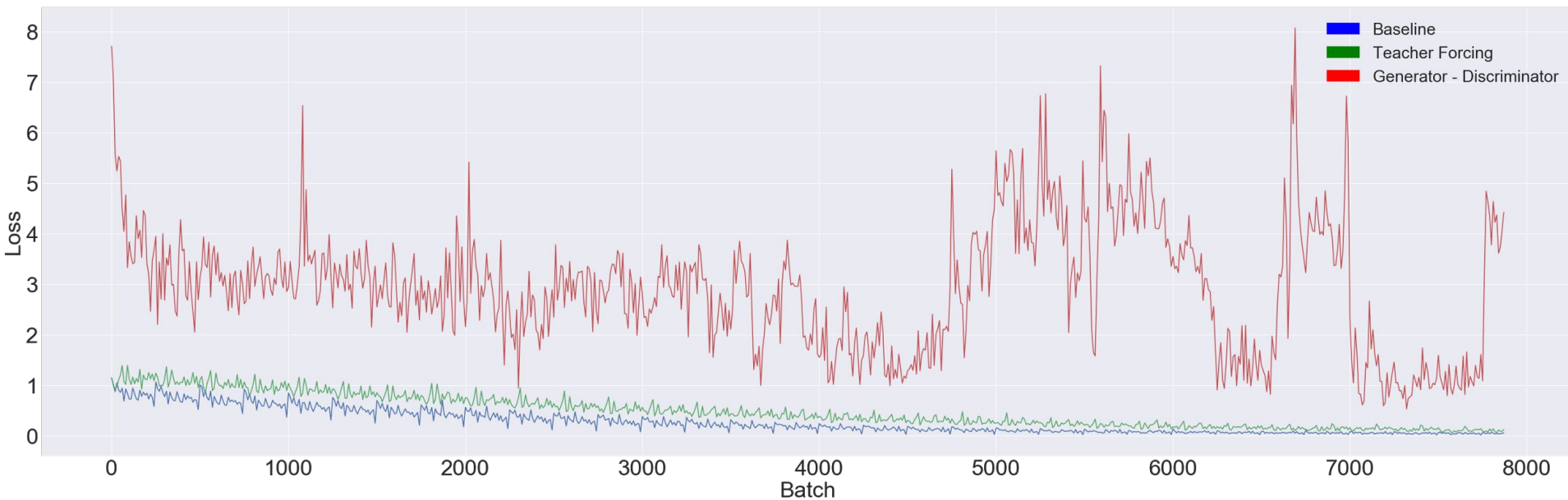




Appendix: Results and Experiments

English-French translation task

- **Discriminator strategy:**
 - Train loss: Teacher forcing and Discriminator reward

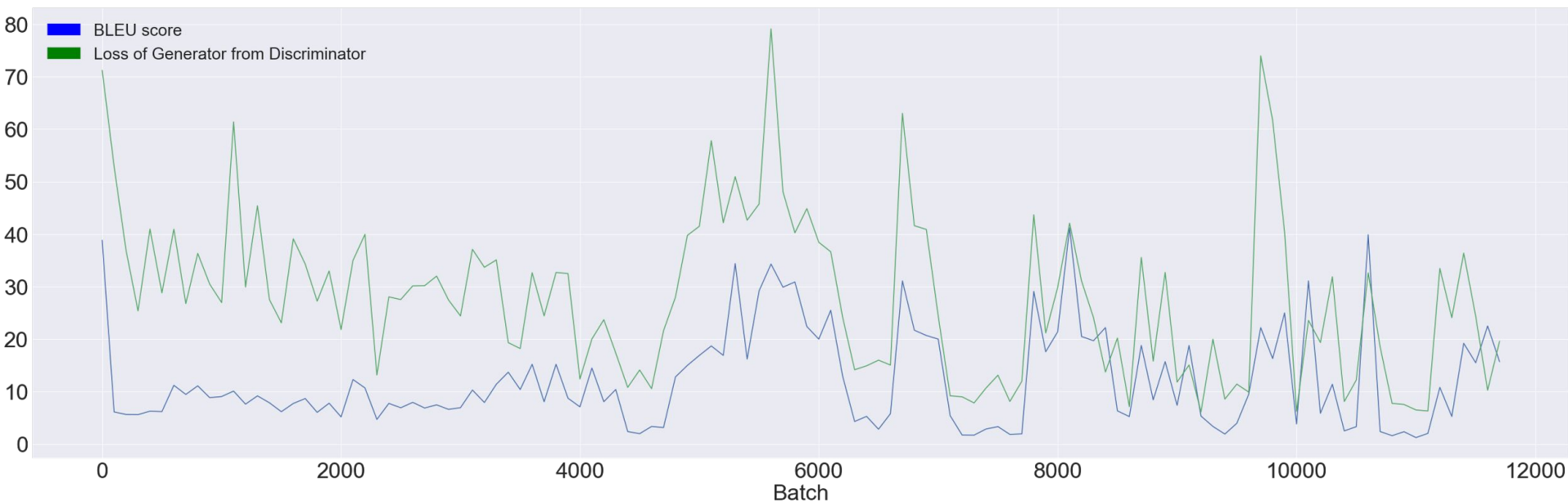




Results and Experiments

English-French translation task

- **Discriminator strategy:**
 - Relationship between BLEU score (Validation) and generator loss with discriminator reward (Train)



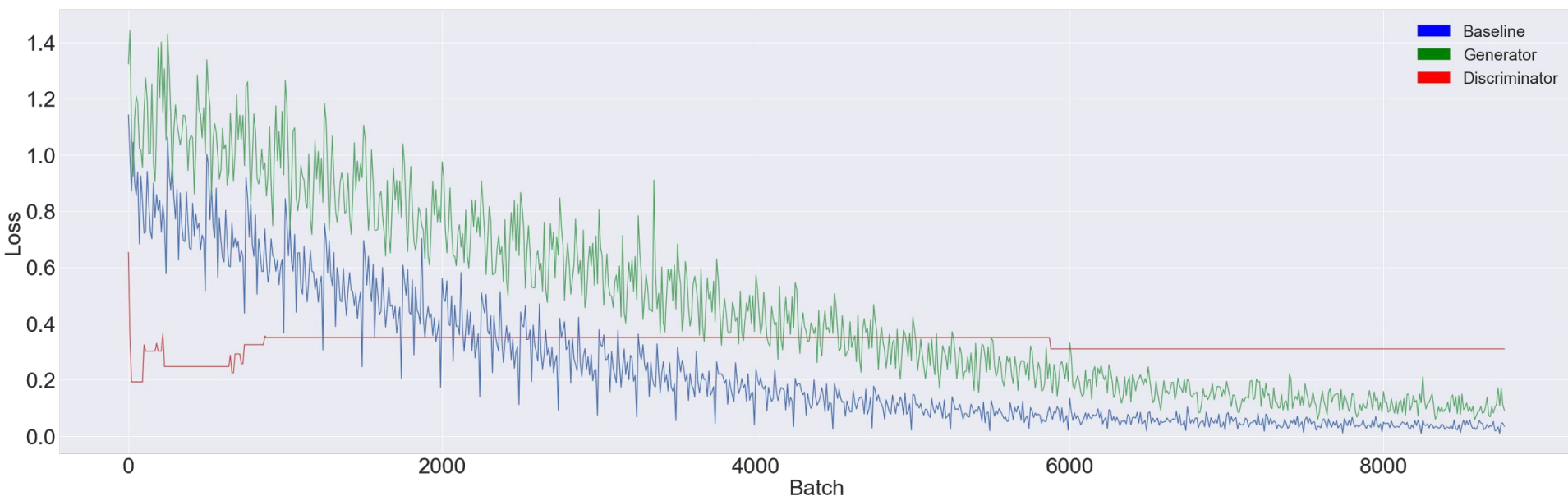
*Values are scaled



Results and Experiments

English-French translation task

- **Language model strategy:** without MC search
 - Train loss



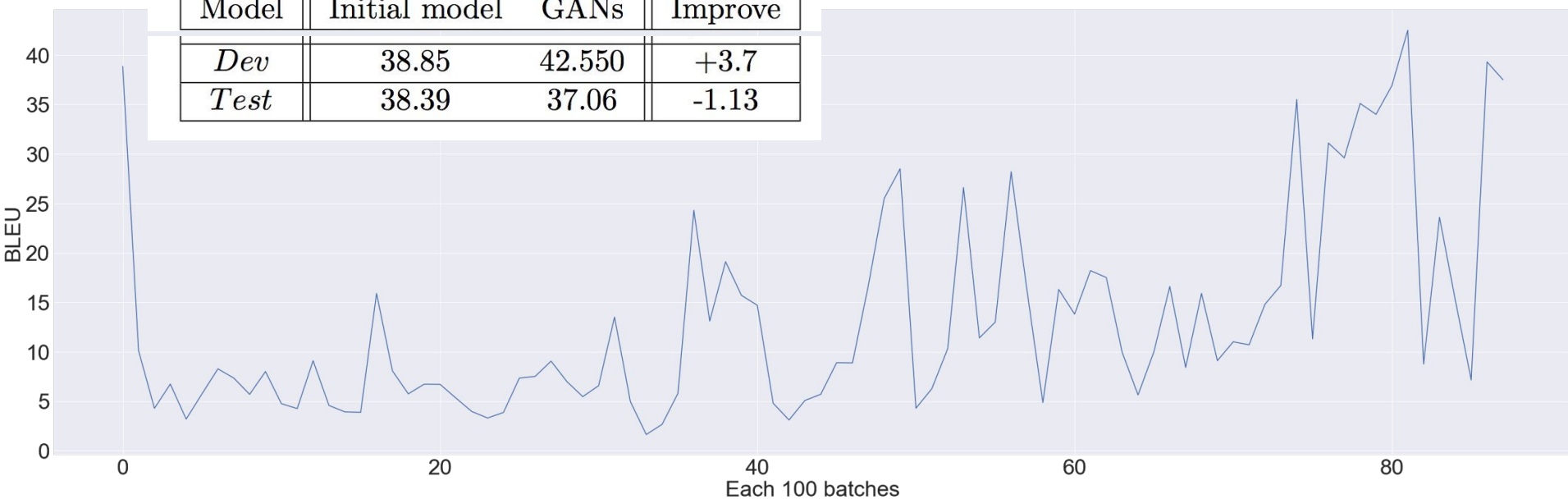


Results and Experiments

English-French translation task

- **Language model strategy:** without MC search
 - Validation BLEU score

Model	Initial model	GANs	Improve
<i>Dev</i>	38.85	42.550	+3.7
<i>Test</i>	38.39	37.06	-1.13





Conclusion

Until now

- GANs have a **similar** but **weaker** effect of the log likelihood on training NMT
- Ongoing work:
 - Analysis about the unstable training
 - Solving joint optimization issues (Discriminator Reward and Professor Forcing)
 - Experiments of the proposed strategies
 - MC search strategy and Language model strategy with MC search
 - Research about Variational Networks



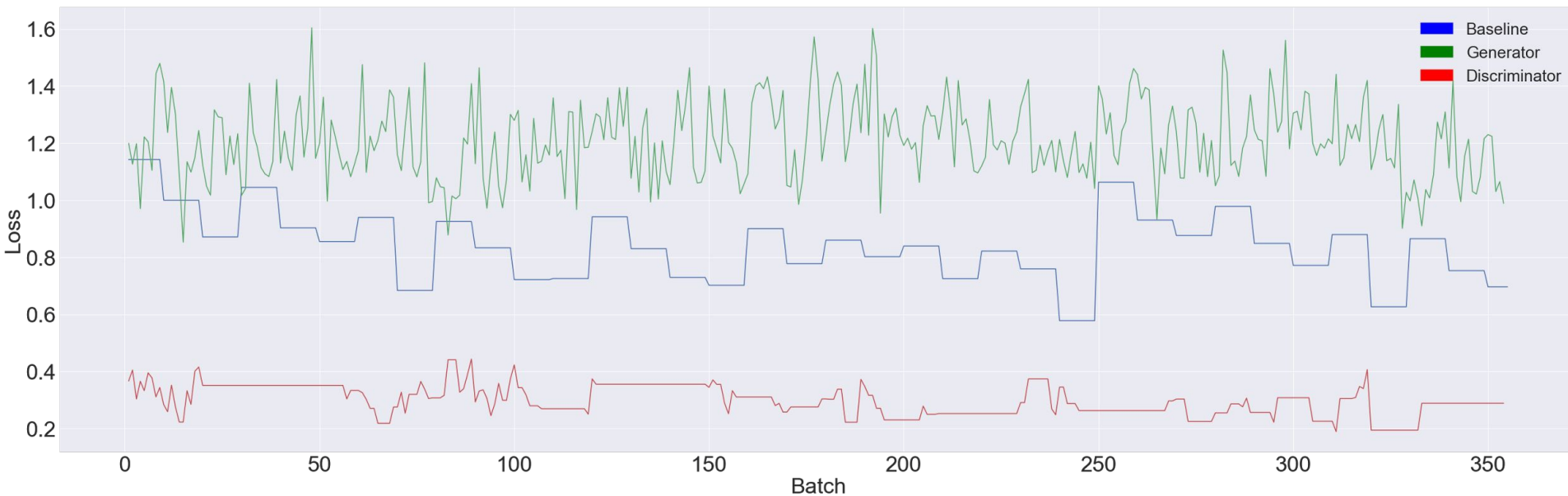
Thank you!



Results and Experiments

English-French translation task

- **Monte-Carlo search strategy:**
 - Train loss



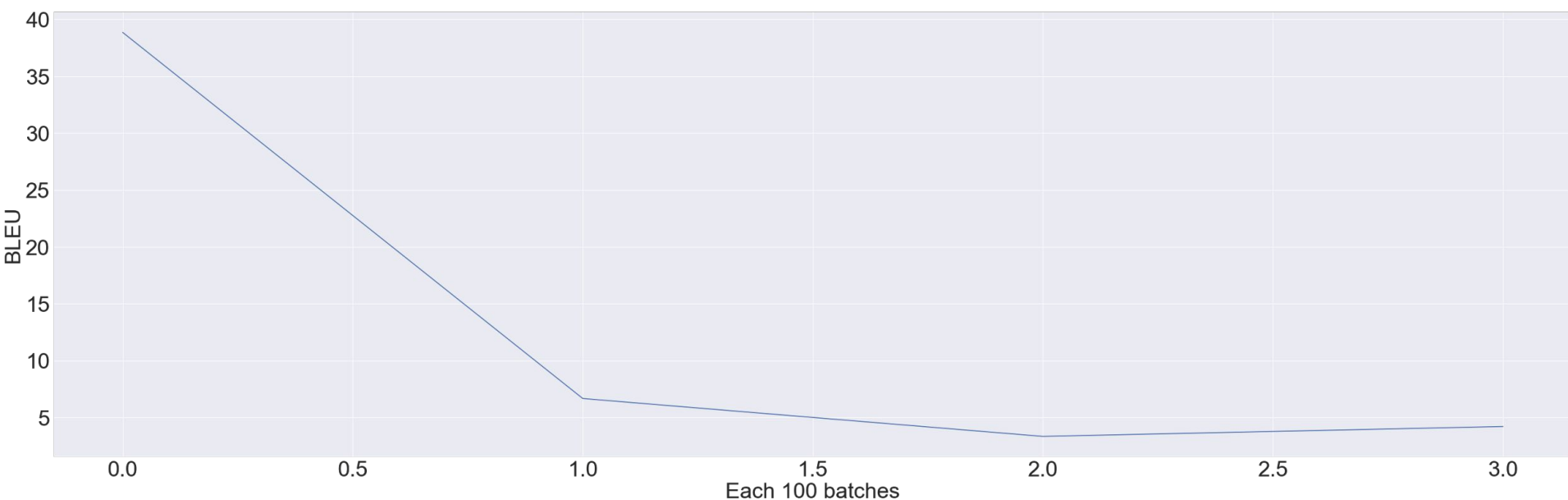


Appendix: Results and Experiments

English-French translation task

- **Monte-Carlo search strategy:**

- Validation BLEU score

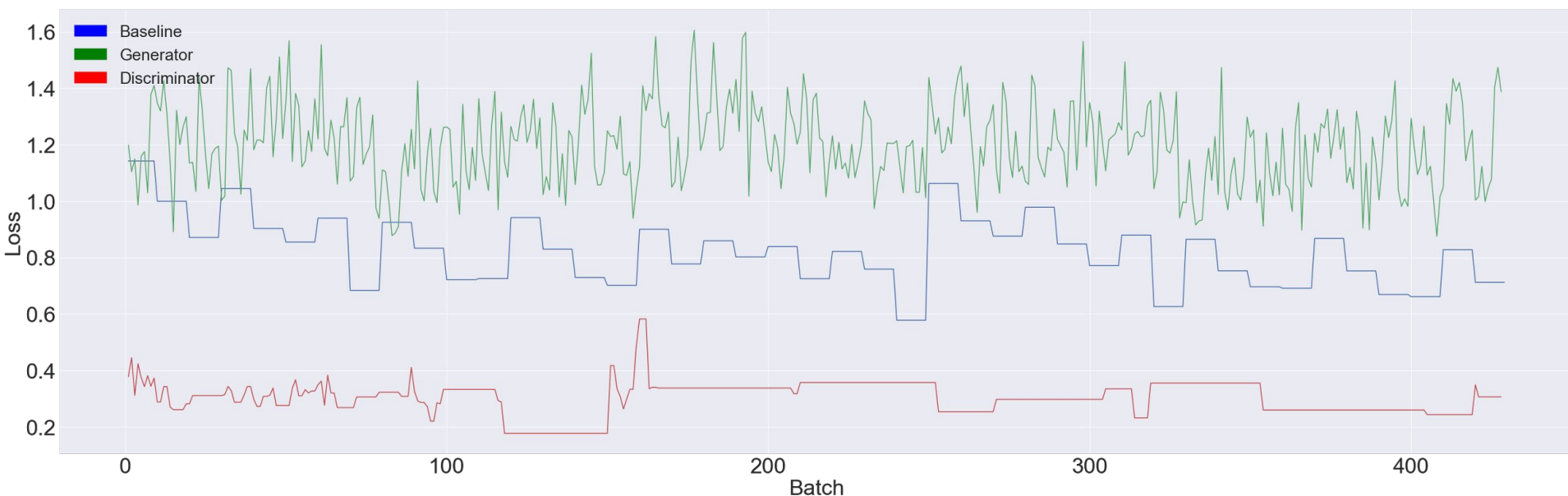




Results and Experiments

English-French translation task

- **Language model strategy:** with MC search
 - Train loss

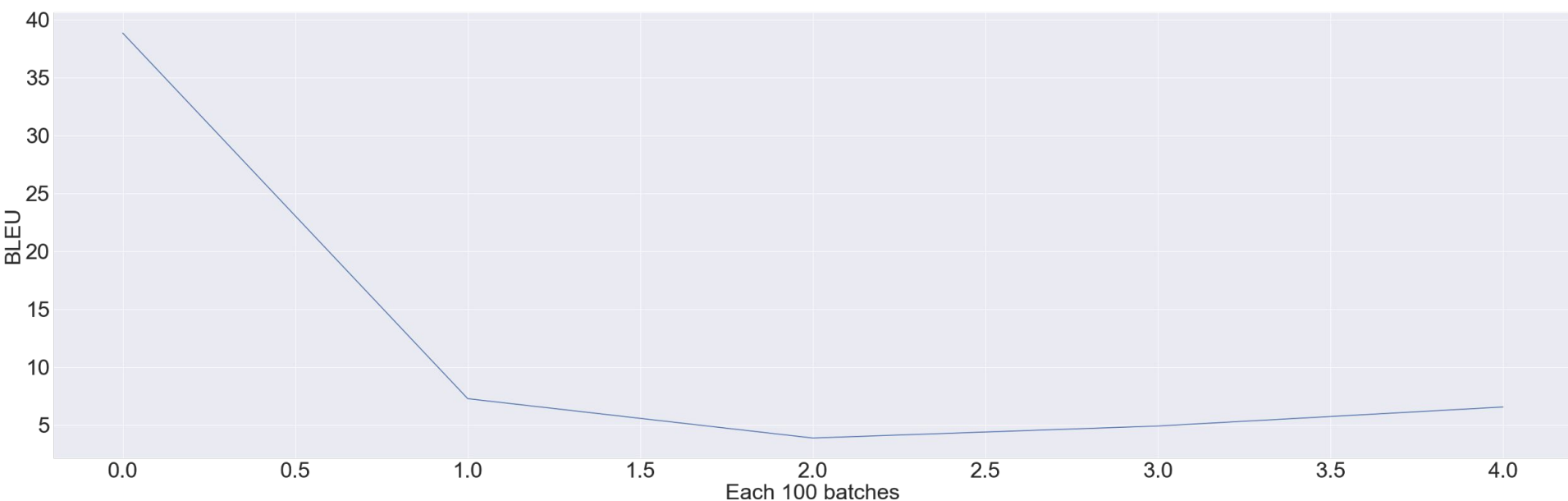




Appendix: Results and Experiments

English-French translation task

- **Language model strategy:** with MC search
 - Validation BLEU score





Results and Experiments

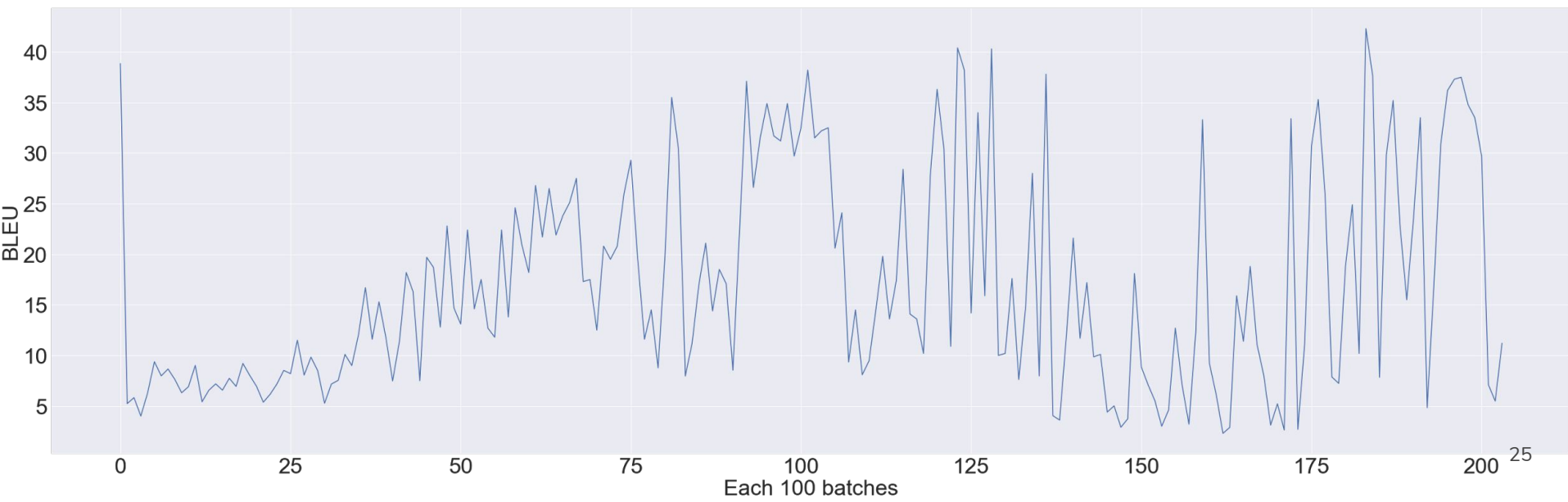
English-French translation task

- **Discriminator strategy:**

- Validation BLEU score

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<i>Train</i>	46.71	92.38	+45.67
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<i>Test</i>	38.39	36.15	-2.24

<i>Dev</i>	38.85	40.400	+1.55
<i>Test</i>	38.39	37.54	-0.85





Appendix: Results and Experiments

English-French translation task

- Monte-Carlo search strategy:

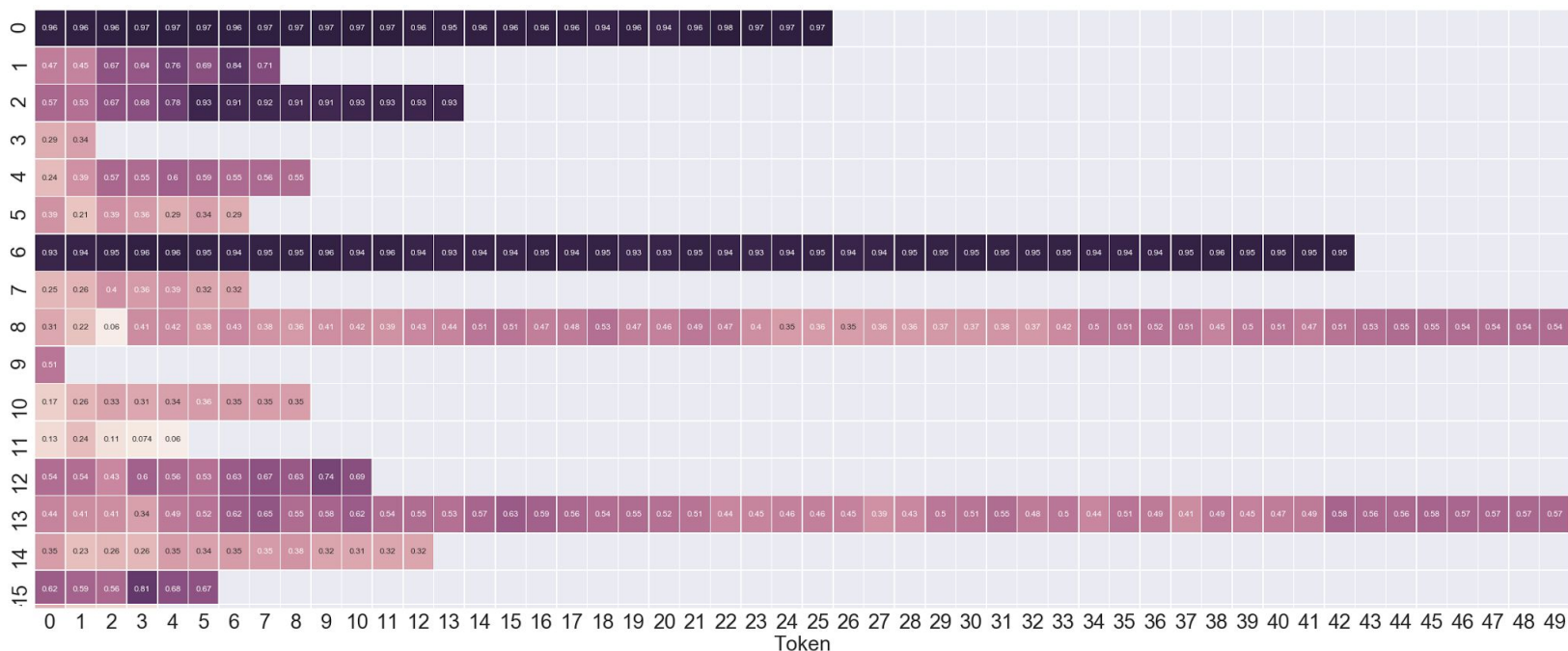


Figure A2: Epoch 1 - Batch 1



Appendix: Results and Experiments

English-French translation task

- Monte-Carlo search strategy:

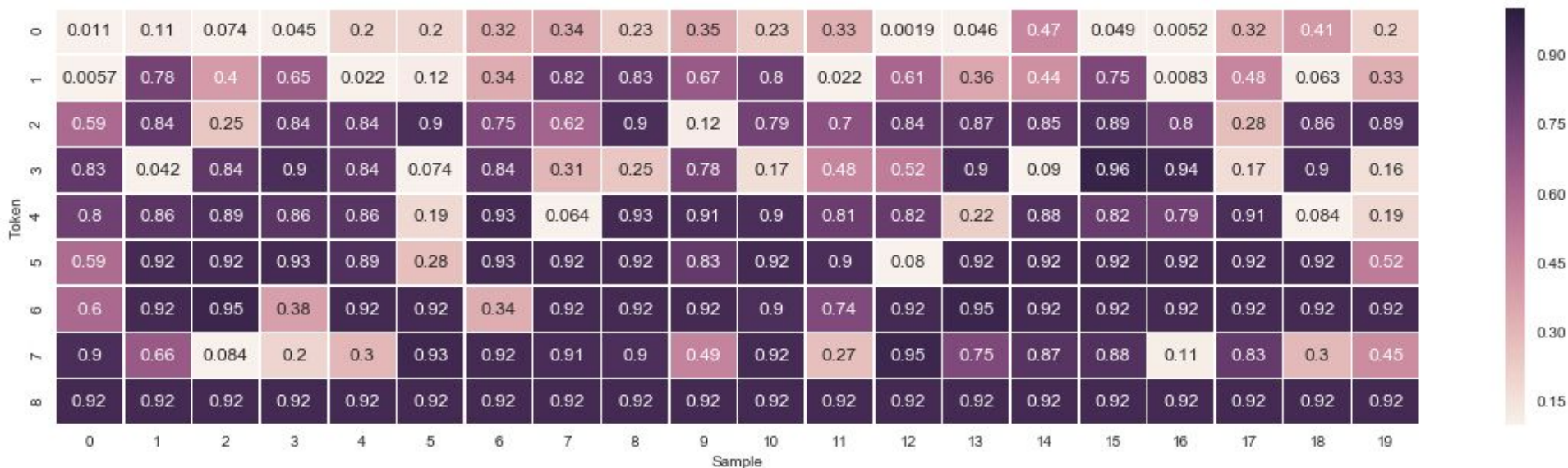


Figure A1: En sentence: I'd like to buy what I need . will you pay me back ?
Fr sentence: pourriez -vous me régler à mon retour ?



Appendix: Results and Experiments

English-French translation task

- Monte-Carlo search strategy:

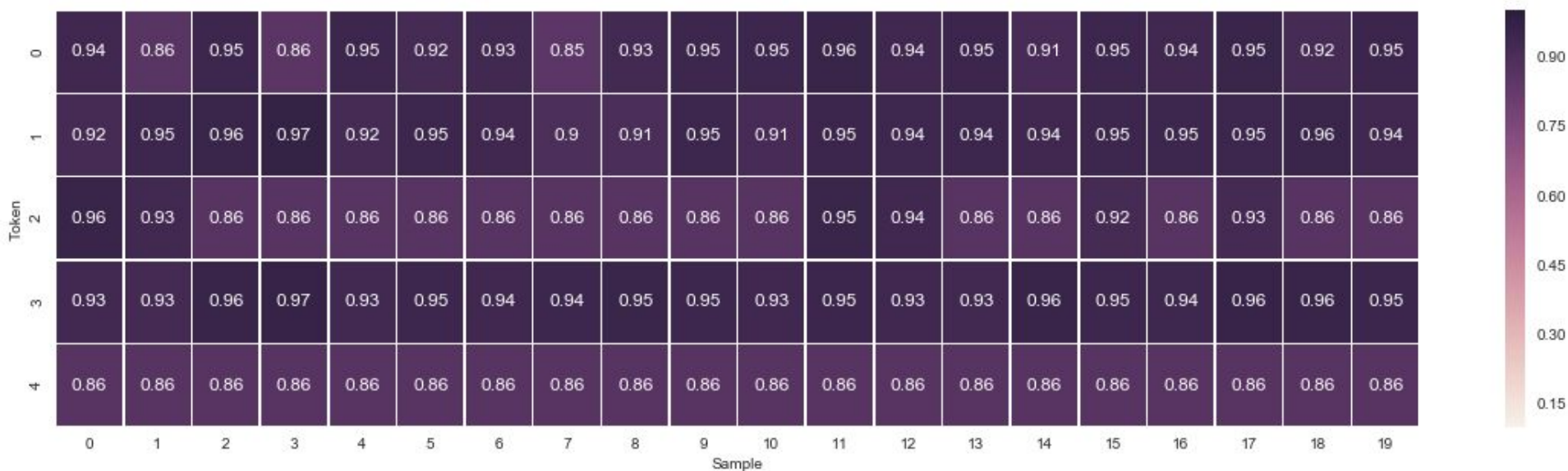


Figure A1: En sentence: yes , it's next door .
Fr sentence: c' est ouvert .



Appendix: Results and Experiments

English-French translation task

- Monte-Carlo search strategy:

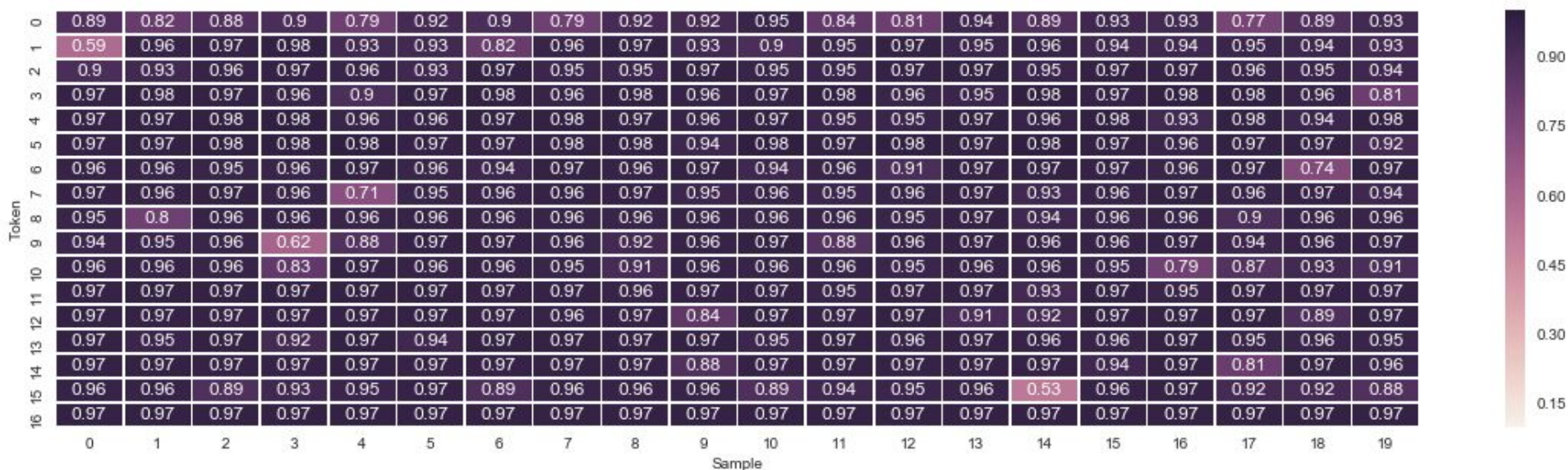


Figure A1: En sentence: the Japanese just can't get along without taking a bath every day .

Fr sentence: nous ne sont pas pris de nous faire un n' asseoir pas de la baignoire .

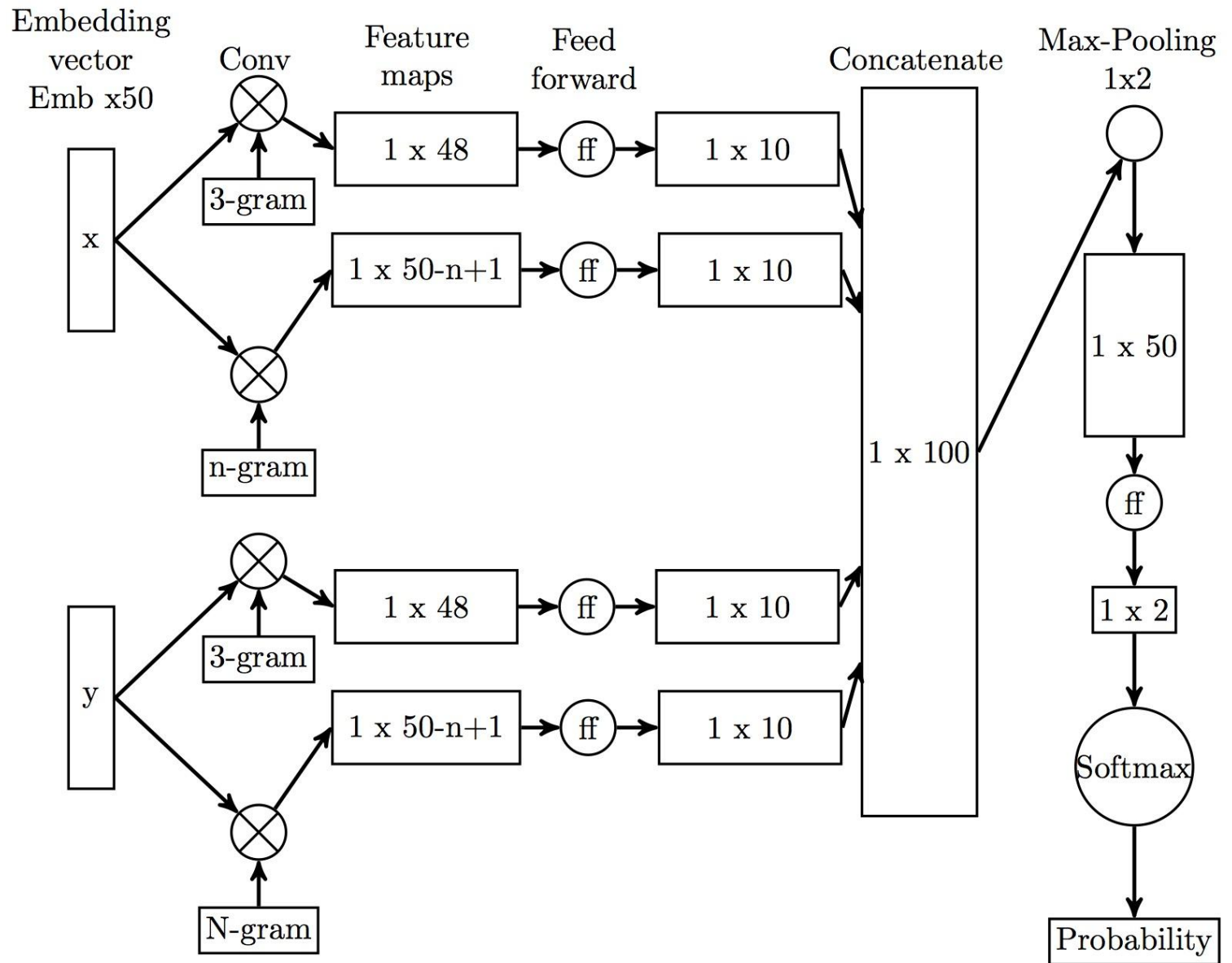


Figure 3.3: Discriminator architecture