DLP Final project

Asynchronous TSP transformer

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Outline

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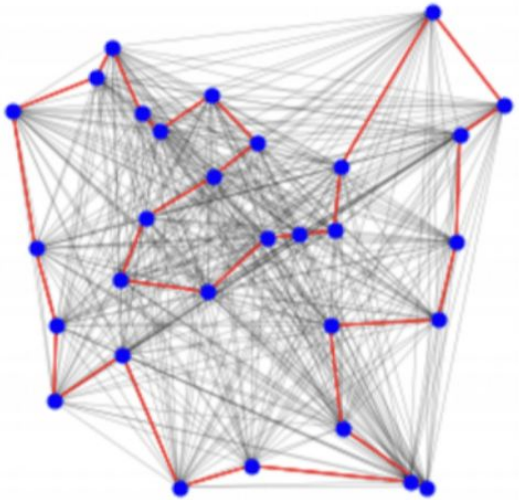
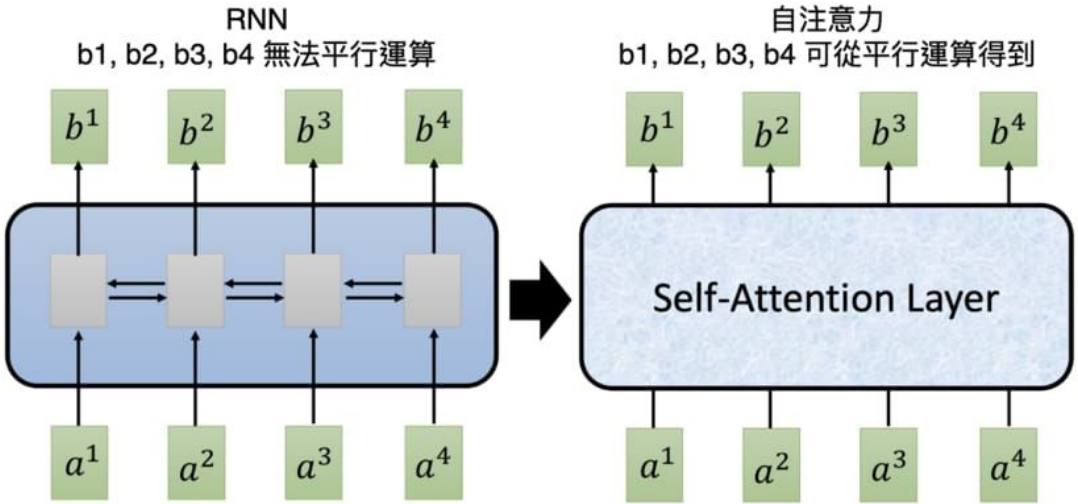
Introduction

TSP

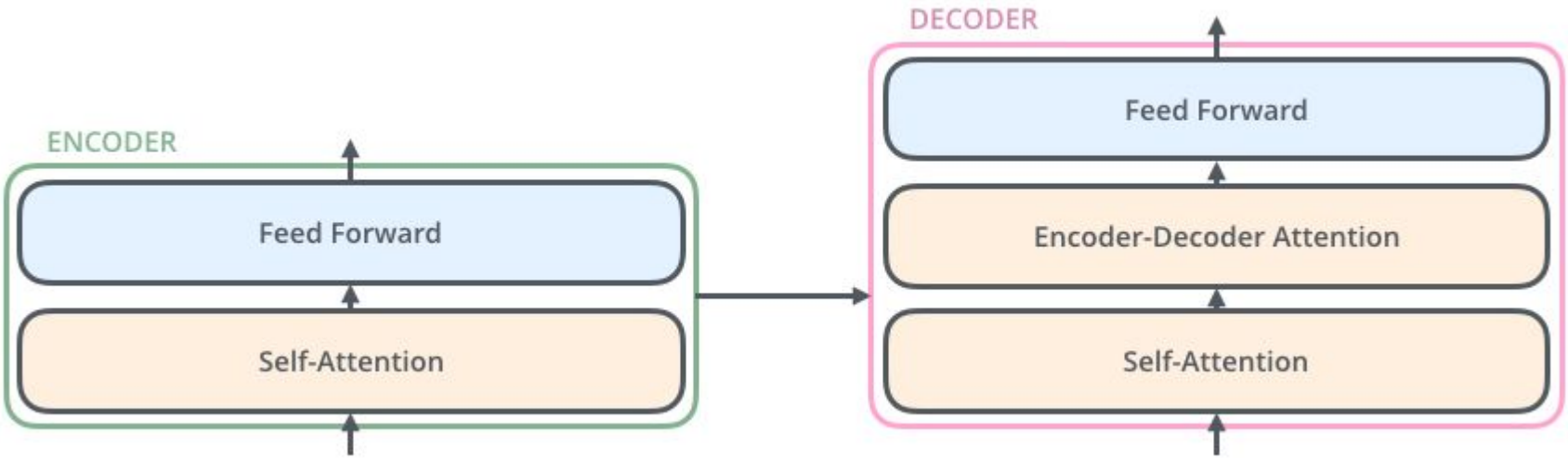
Given a list of cities and the distances between each pair of cities,what is the shortest possible path that visits each city exactly once and returns to the origin city?



Self-Attention

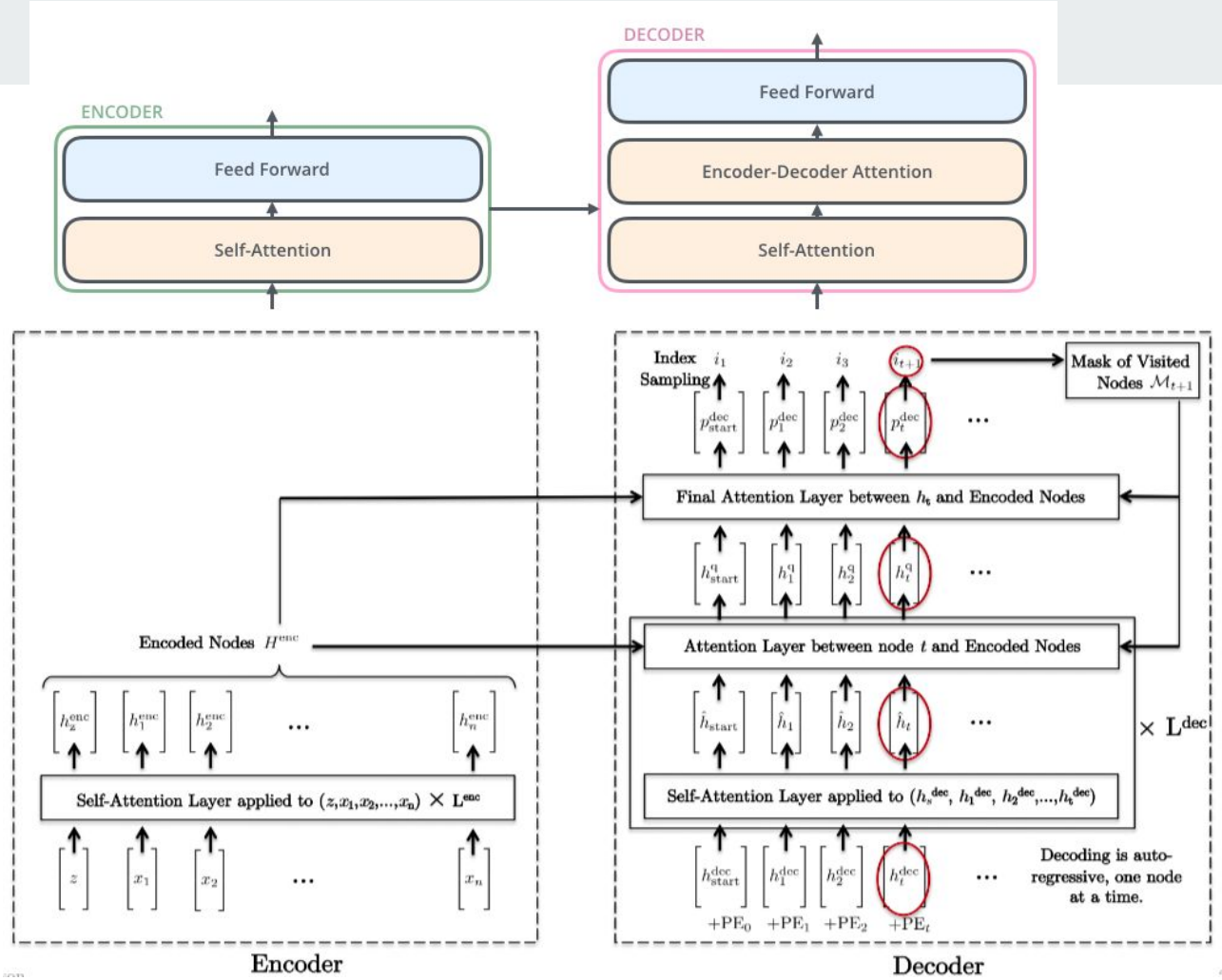


Transformer

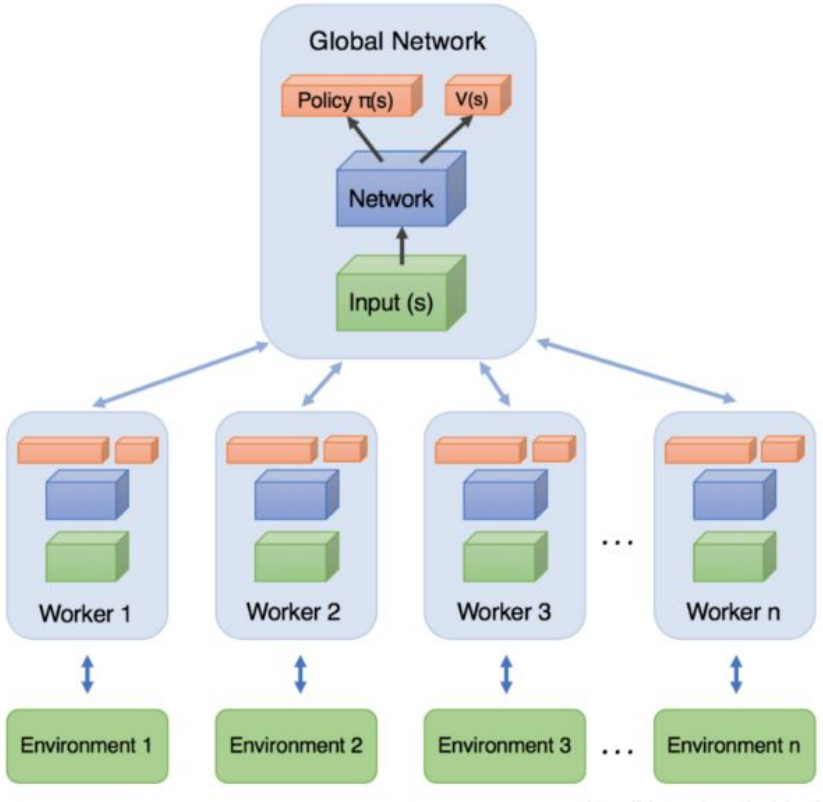


1. Encoder 為輸入序列裡的每個詞彙 產生初始的 repr.（即詞向量），以空圈表示
2. 利用自注意力機制將序列中所有詞彙的語義資訊各自匯總成每個詞彙的 repr.，以實圈表示
3. Encoder 重複 N 次自注意力機制，讓每個詞彙的 repr. 彼此持續修正以完整納入上下文語義
4. Decoder 在生成每個法文字時也運用了自注意力機制，關注自己之前已生成的元素，將其語義也納入之後生成的元素
5. 在自注意力機制後，Decoder 接著利用注意力機制關注 Encoder 的所有輸出並將其資訊納入當前生成元素的 repr.
6. Decoder 重複步驟 4, 5 以讓當前元素完整包含整體語義

Method


ENCODER
Feed Forward
Self-Attention
DECODER
Feed Forward
Encoder-Decoder Attention
Self-Attention
Index Sampling
Mask of Visited Nodes $\mathcal{M}_{t+1}$
Final Attention Layer between h_t and Encoded Nodes
Encoded Nodes H^{enc}
Attention Layer between node t and Encoded Nodes
Self-Attention Layer applied to $(z, x_1, x_2, ..., x_n) \times L^{enc}$
Self-Attention Layer applied to $(h_s^{dec}, h_1^{dec}, h_2^{dec}, ..., h_t^{dec})$
$\times L^{dec}$
Decoding is auto-regressive, one node at a time.
$+PE_0$ $+PE_1$ $+PE_2$ $+PE_t$
Encoder
Decoder

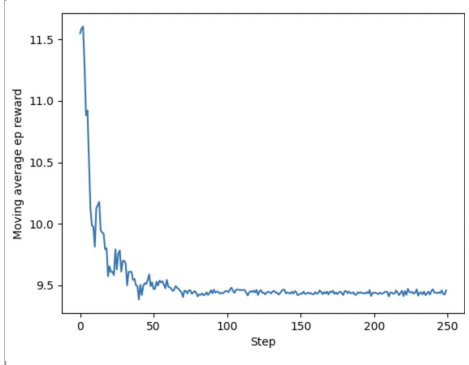
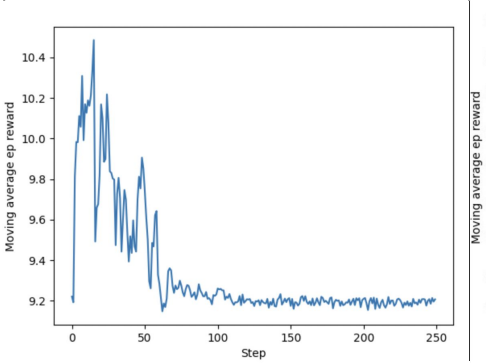
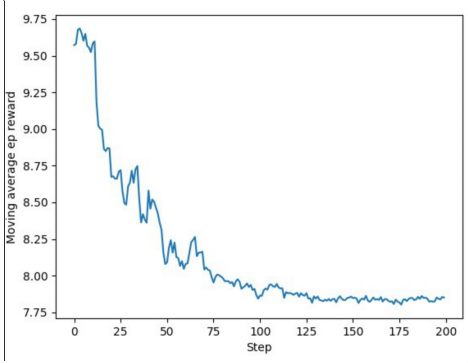
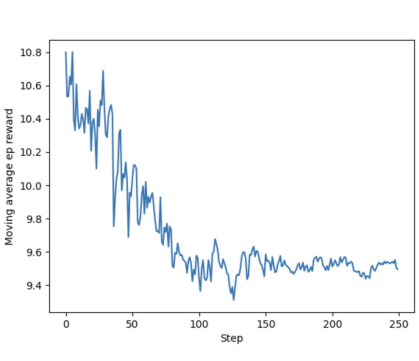
Asynchronous



Experiments

https://arxiv.org/pdf/2103.03012.pdf

baseline 600 epoch	L_train: 5.939, L_base: 5.905, L_test: 5.906, gap_train(%): 4.335
1 worker batch size:128	L_train: 9.432, L_base: 9.387, L_test: 9.391, gap_train(%): 65.701
2 worker batch size:128	L_train: 9.214, L_base: 9.175, L_test: 9.161, gap_train(%): 61.874
4 worker batch size:128	L_train: 7.859, L_base: 7.847, L_test: 7.867, gap_train(%): 38.073
8 worker batch size:64	L_train: 8.679, L_base: 8.169, L_test: 8.202, gap_train(%): 52.469,

1 worker batch size:128	2 worker batch size:128	4 worker batch size:128	8 worker batch size:64
			
7.9	7.4	6.4	6.8

Running time

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Epoch: 601, epoch time: 2.279min, tot time: 1.009day,
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Epoch: 256, epoch time: 2.183min, tot time: 0.100day,
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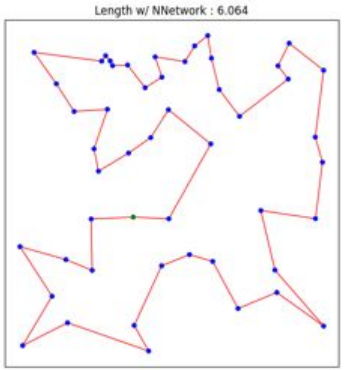

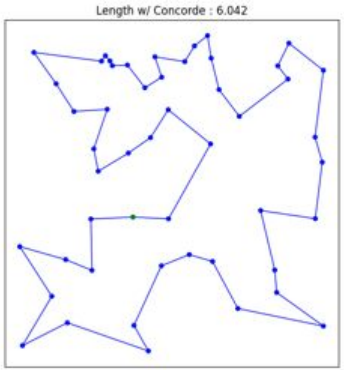

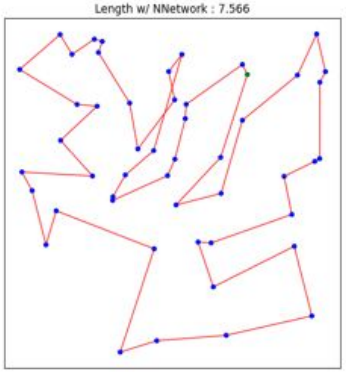

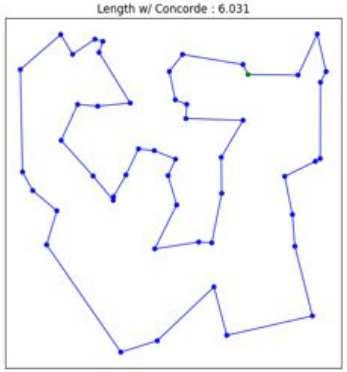

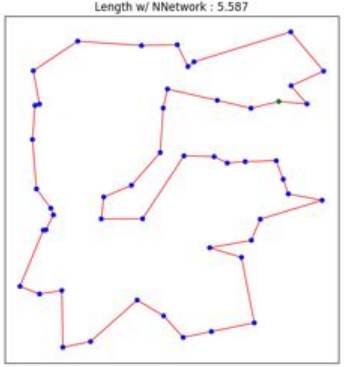

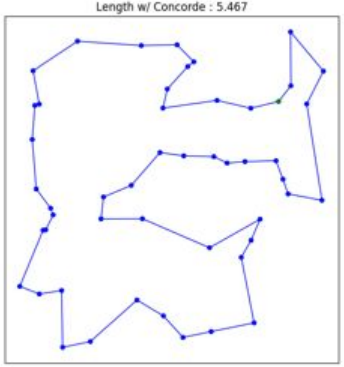

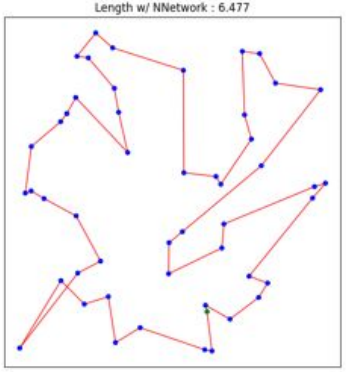

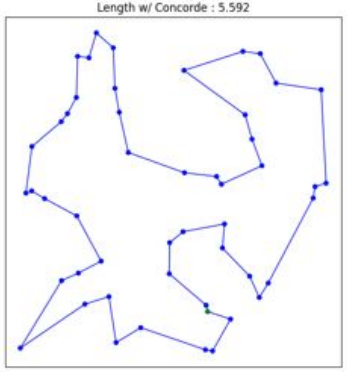

TSP transformer

synchronous TSP transformer

Conclusion

提高worker的數量，會有比較低的tour length。

訓練的速度也變快，但離baseline還有很多改善的空間，結果上是失敗的。

使用Regularization 方法使這個模型有比較好的收斂效果。

訓練的epoch跟batchsize 都會影響很大，原作者使用10000與 2500

Future research

加入 PPO

加入所謂的type-aware

Reference

https://arxiv.org/pdf/2103.03012.pdf

https://arxiv.org/pdf/1912.02958.pdf

https://distill.pub/2021/gnn-intro/