Adaptive Computation Time for Recurrent Neural Network

Alex Graves

Outline

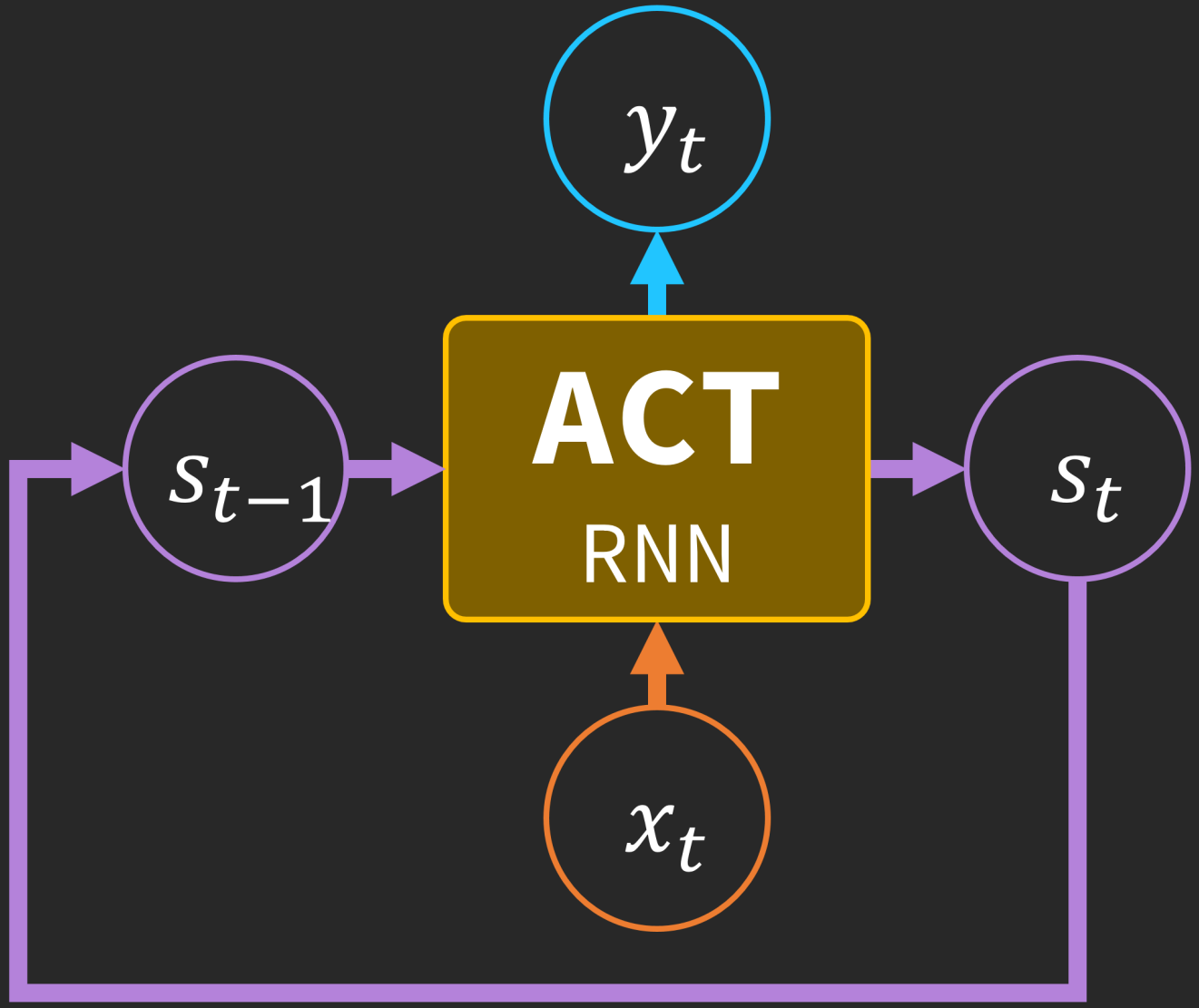
- Introduction
- Methodology
- Experiments
- Conclusion

Introduction

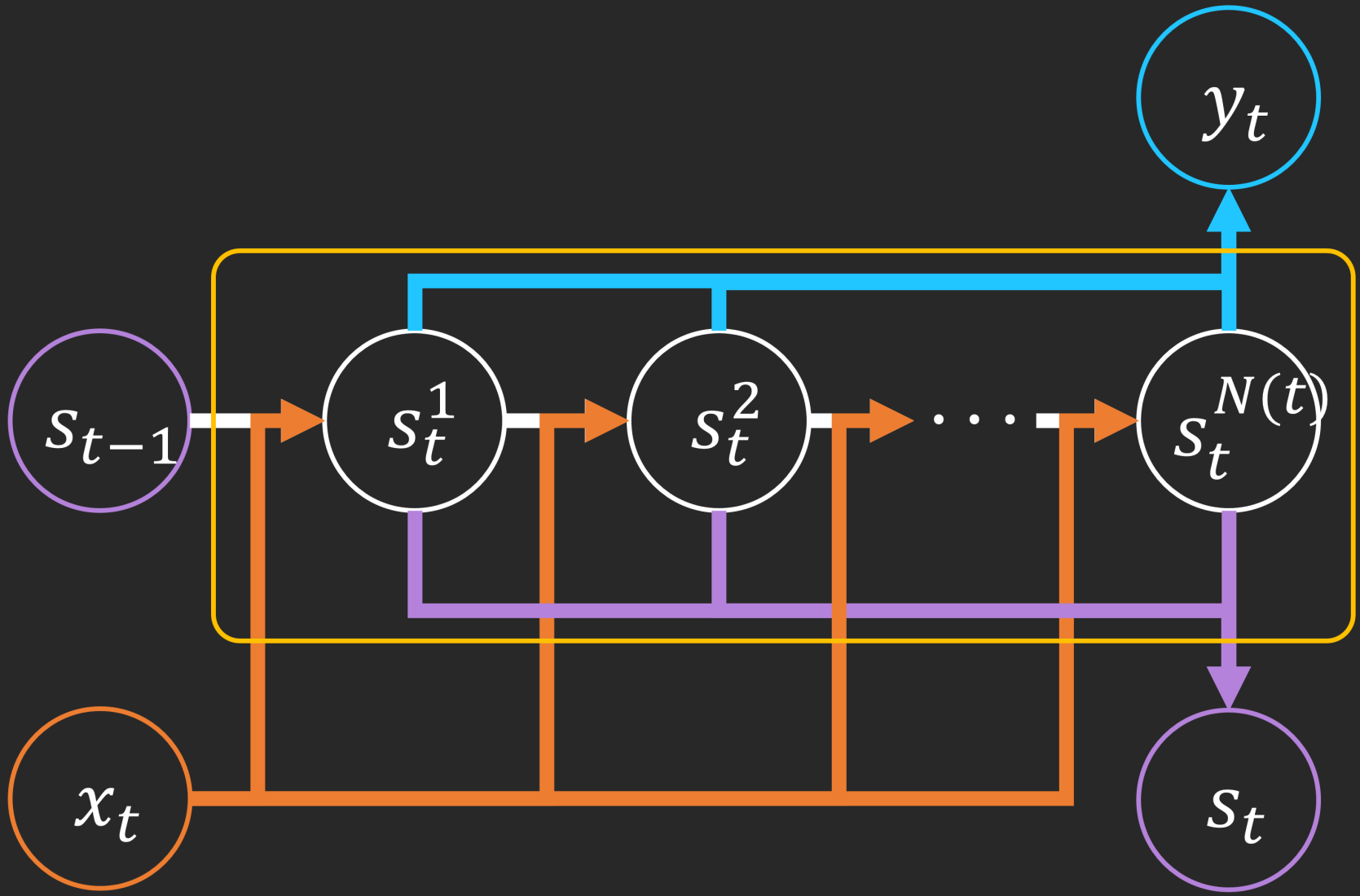
即使是在同類型的任務上，不同案例所具有的複雜度也不相同。但傳統深度學習方法卻是使用相同的計算量來處理，這明顯是不合理的。

因此，本篇論文提出了一種讓類神經網路自適應計算次數的方法，運用此方法便可在複雜度不同的案例上花費適當的計算成本，並取得良好的成果。

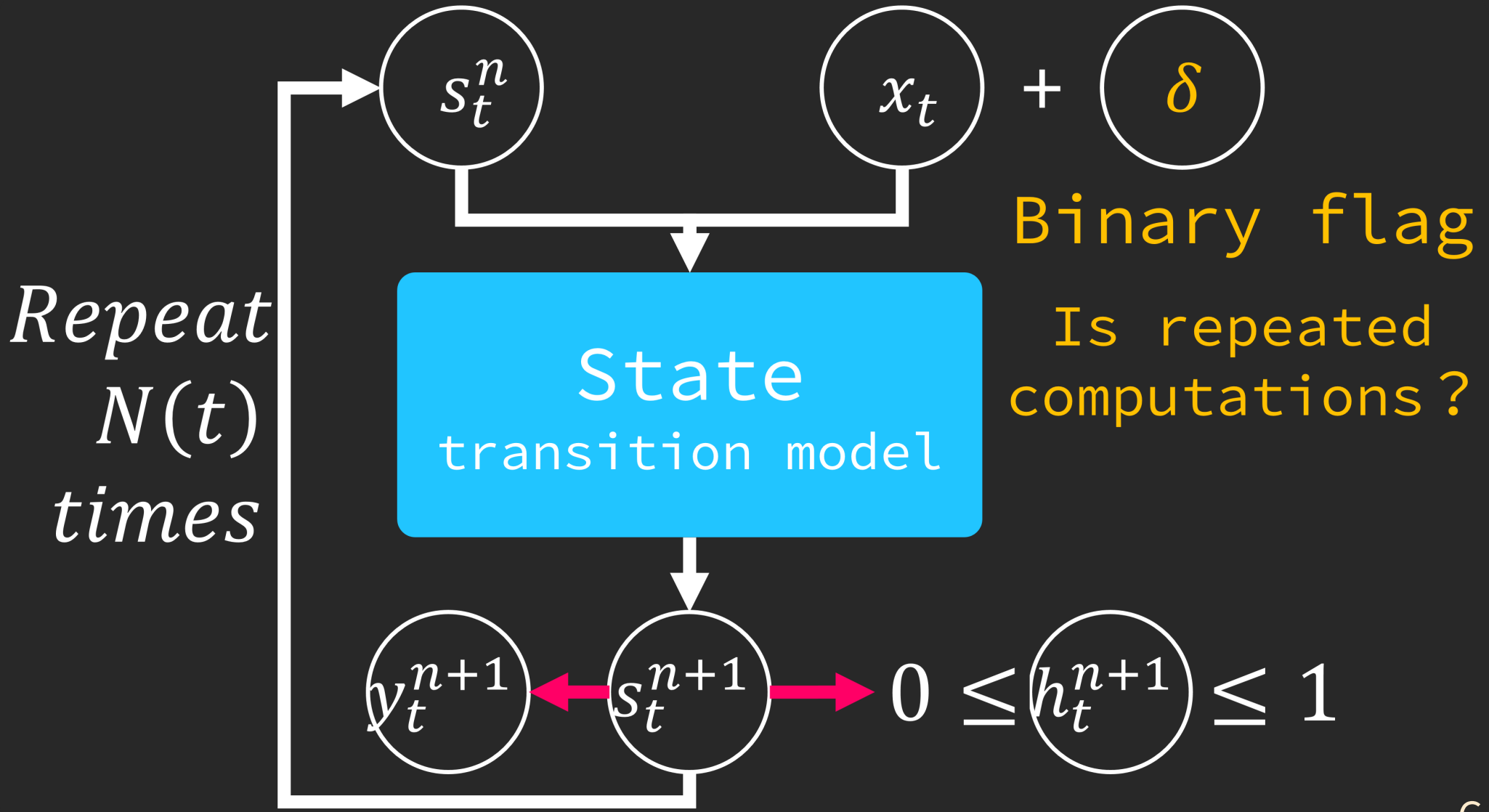
Methodology



ACT



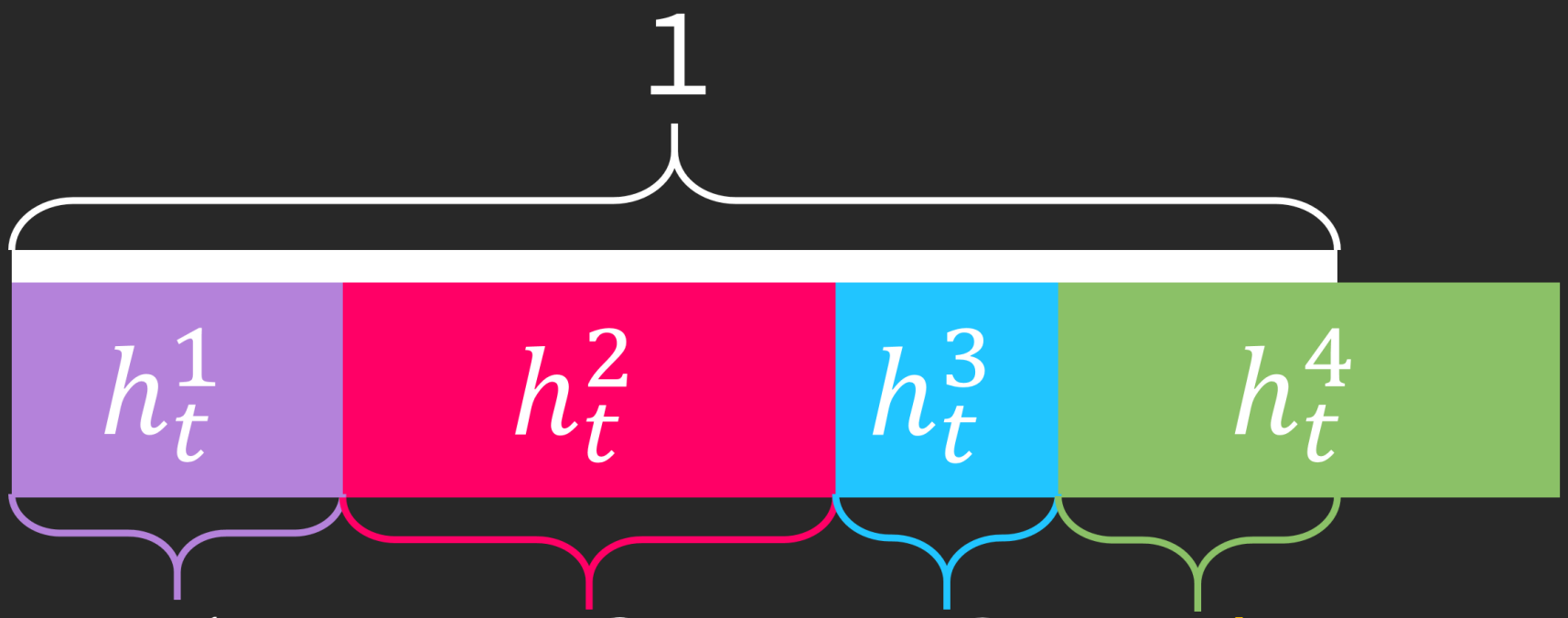
ACT


s_t^n
x_t
+
δ
Binary flag
Is repeated computations?
Repeat $N(t)$ times
State
transition model
y_t^{n+1}
s_t^{n+1}
$0 \leq h_t^{n+1} \leq 1$

Repeat Times

$$N(t): 1 < \sum_{n=1}^{N(t)} h_t^n \ and \ 1 > \sum_{n=1}^{N(t)-1} h_t^n$$

Halting Probability



$in\ this\ case\ ,\ N(t) = 4$

Remainder

$$R(t) = 1 - \sum_{n=1}^{N(t)-1} h_t^n$$

Output & State

$$y_t = \sum_{n=1}^{N(t)} p_t^n \, y_t^n$$

$$s_t = \sum_{n=1}^{N(t)} p_t^n \, s_t^n$$

Loss

$$\mathcal{L} = \mathcal{L}_{Task} + \mathcal{L}_{Ponder}$$

Ponder Loss

$$\mathcal{L}_{\mathcal{P}} = \tau \sum_{t=1}^{T} \rho_t$$

$$= \tau \sum_{t=1}^{T} [N(t) + R(t)]$$

Ponder Loss

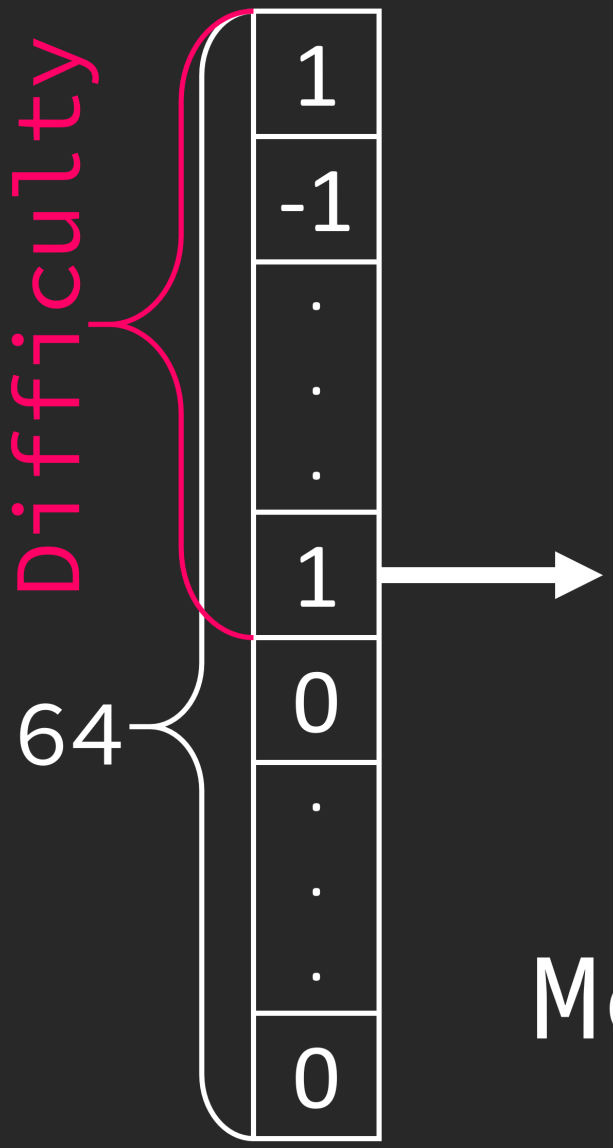
$$\mathcal{L}_{\mathcal{P}} = \tau \sum_{t=1}^{T} [N(t) + R(t)]$$

Ponder Loss

$$\mathcal{L}_{\mathcal{P}} = \tau \sum_{t=1}^{T} (1 - \sum_{n=1}^{N(t)-1} h_t^n)$$

目標：$h_t^{n<N(t)}$ 越大越好

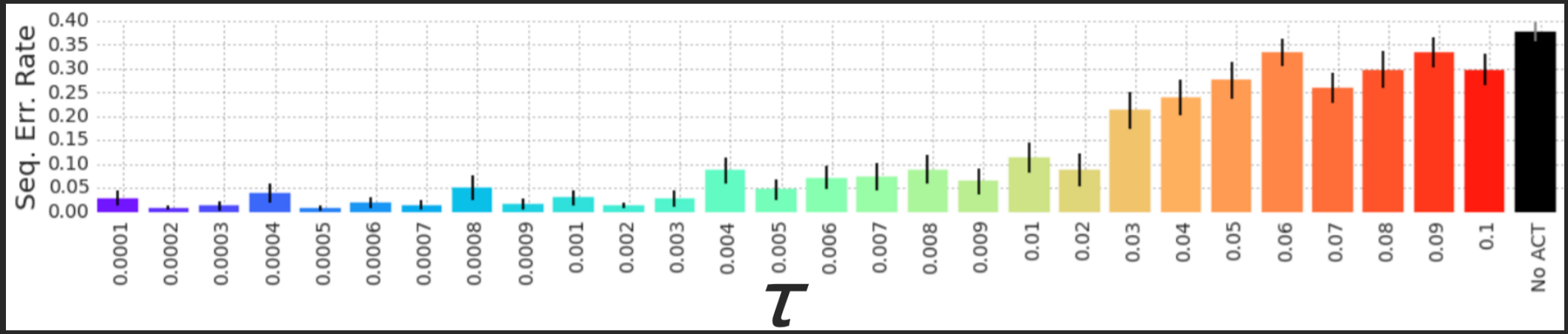
Parity



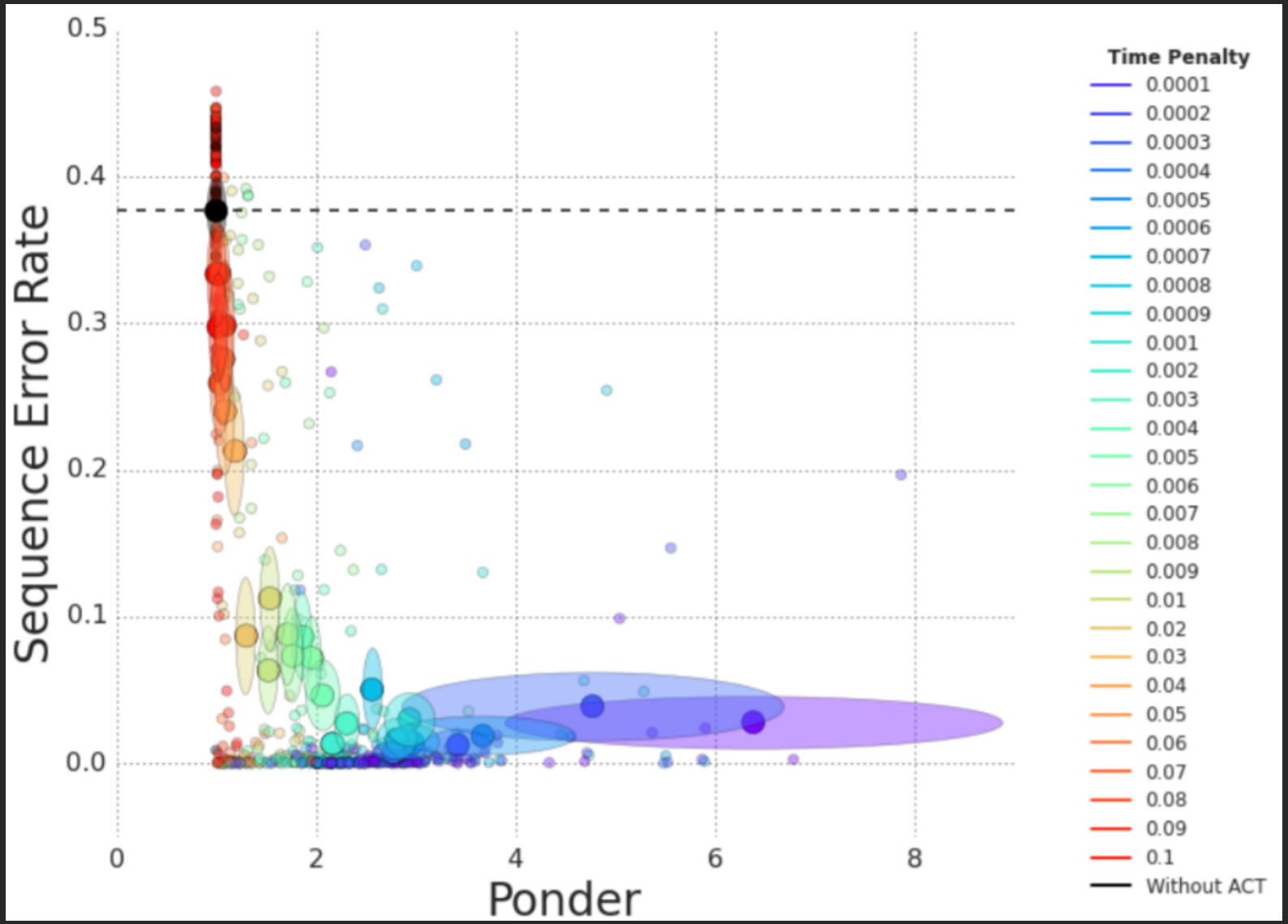
1 if odd number of ones, else *0*

Model : ANN

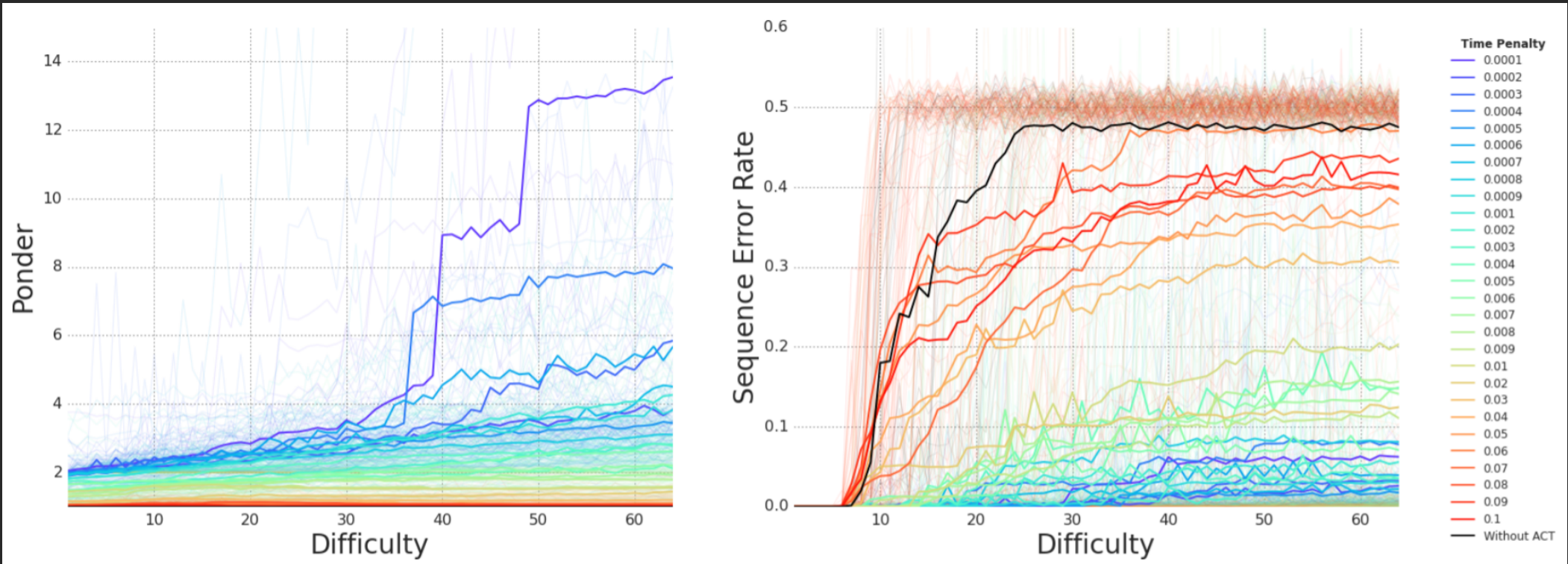
Time Penalty



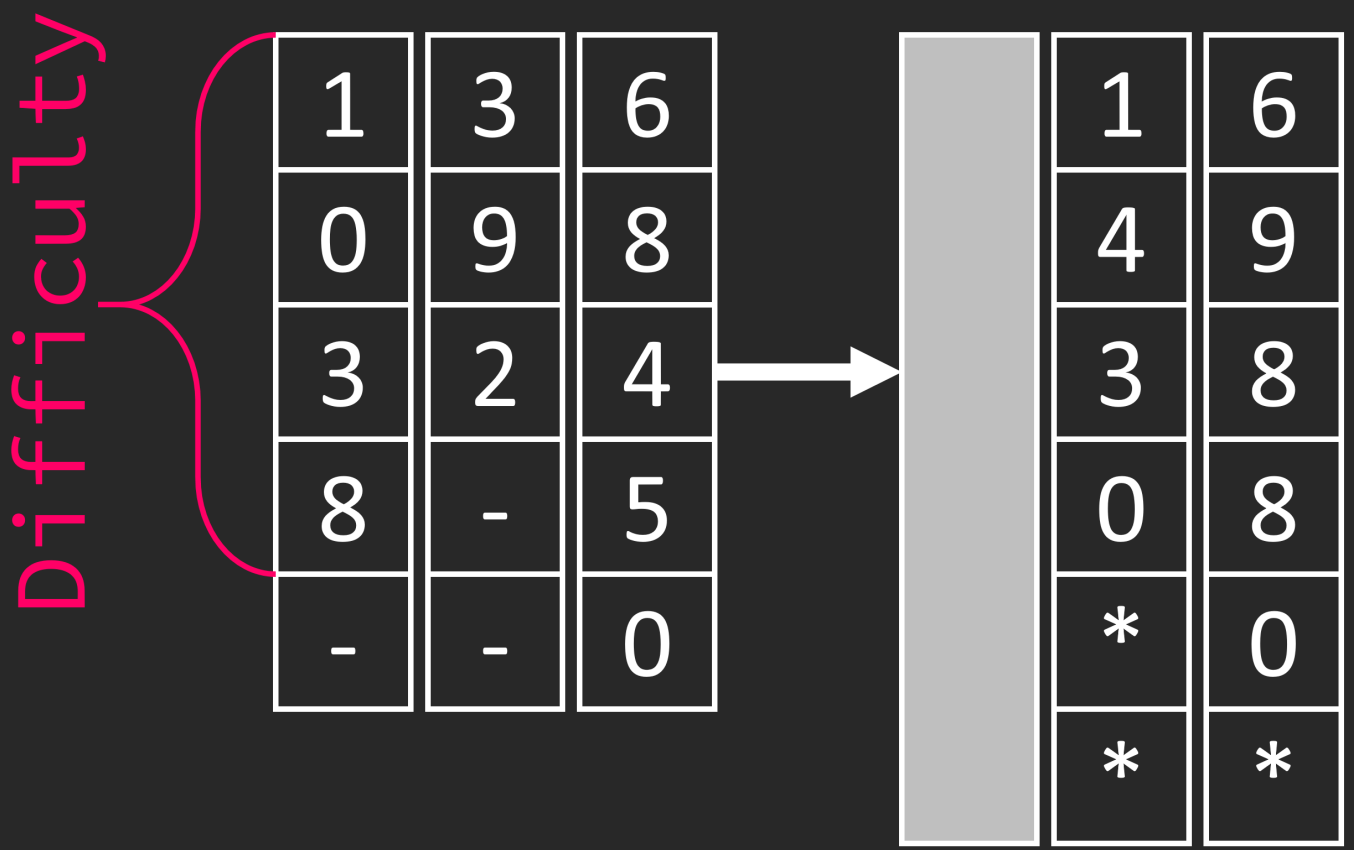
Ponder


Sequence Error Rate
0.5
0.4
0.3
0.2
0.1
0.0
0
2
4
6
8
Ponder
Time Penalty
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0.0009
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

Ponder

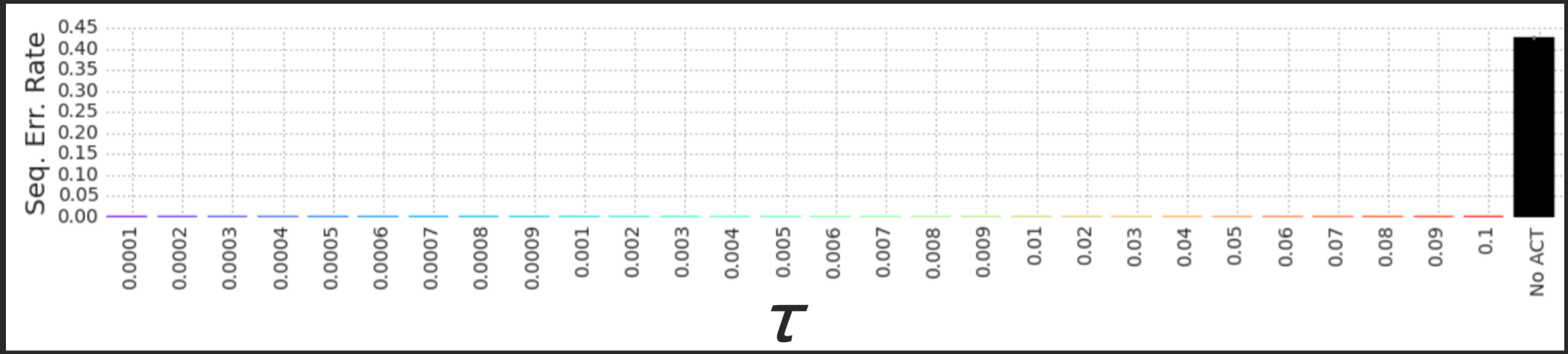

Ponder
Difficulty
Sequence Error Rate
Difficulty
Time Penalty
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0.0009
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

Addition

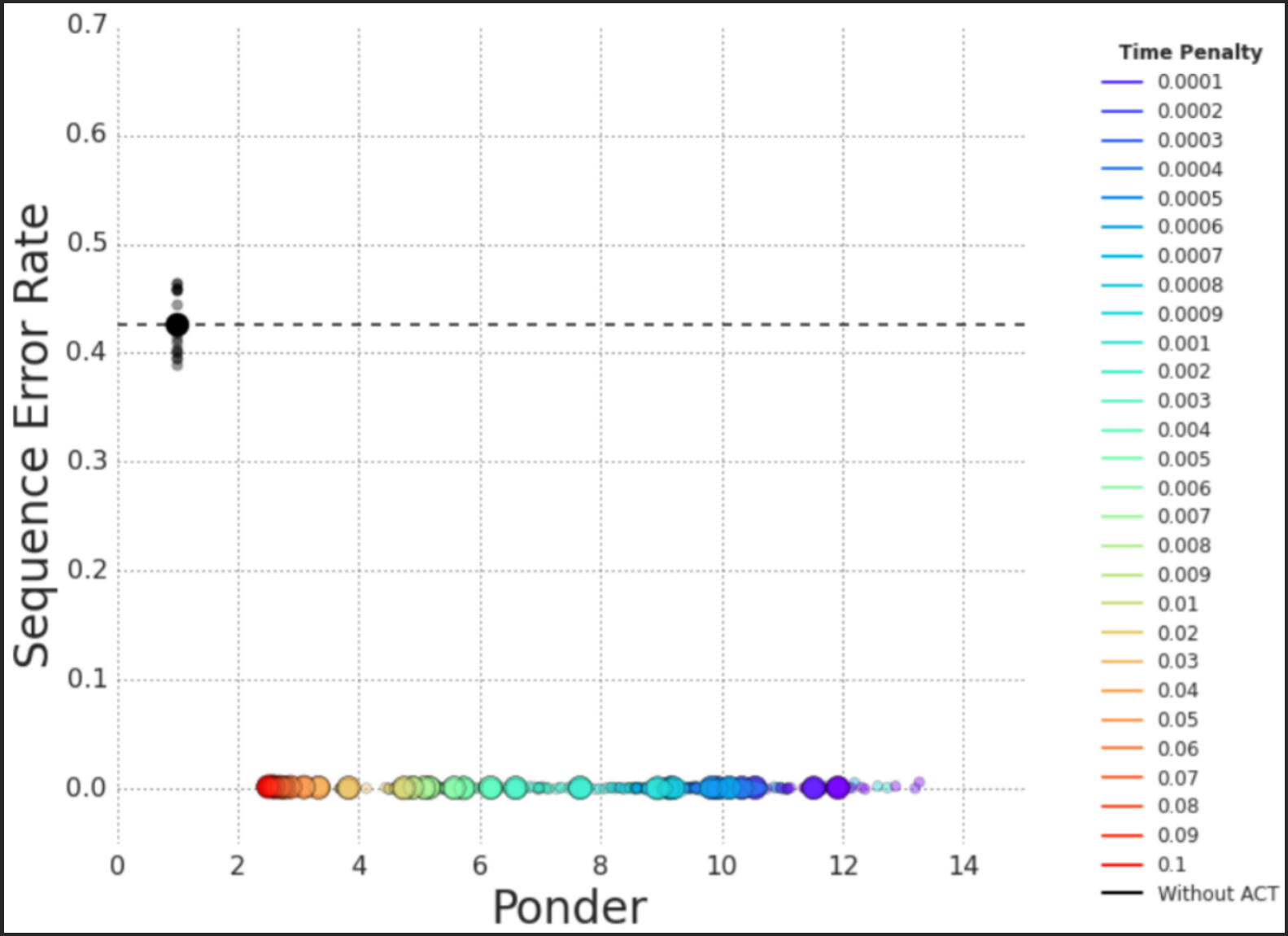


Model：LSTM

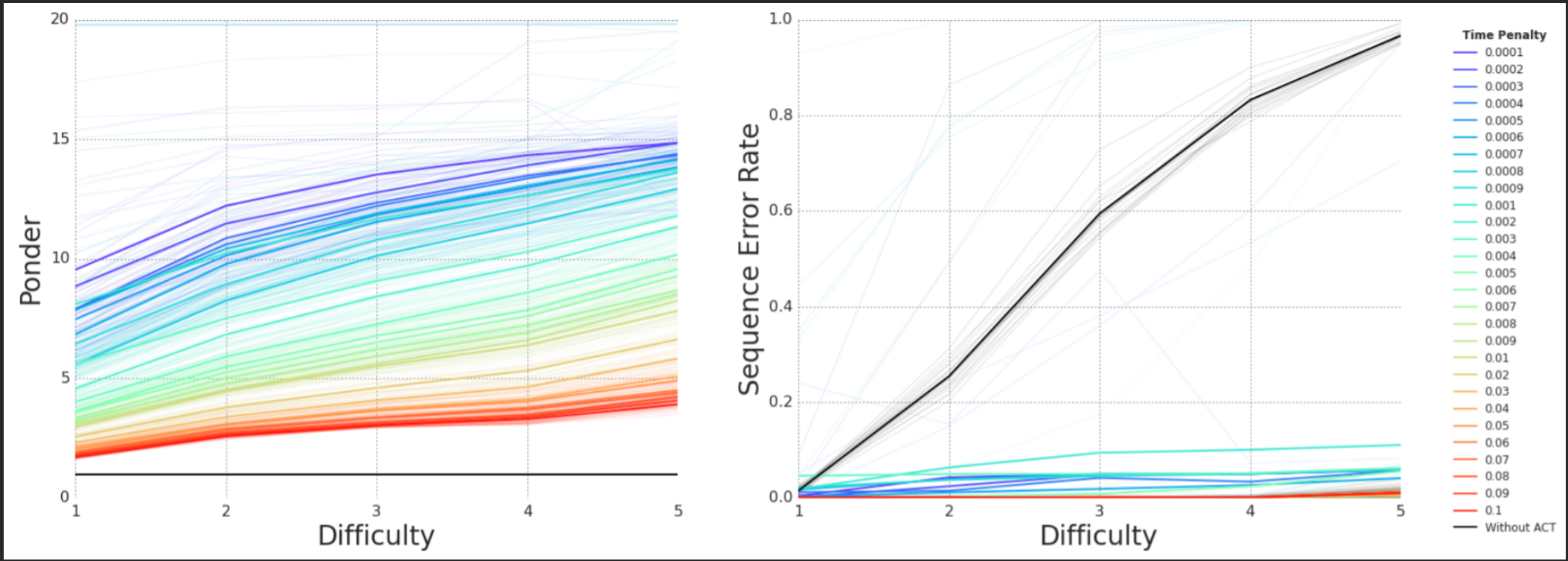
Time Penalty



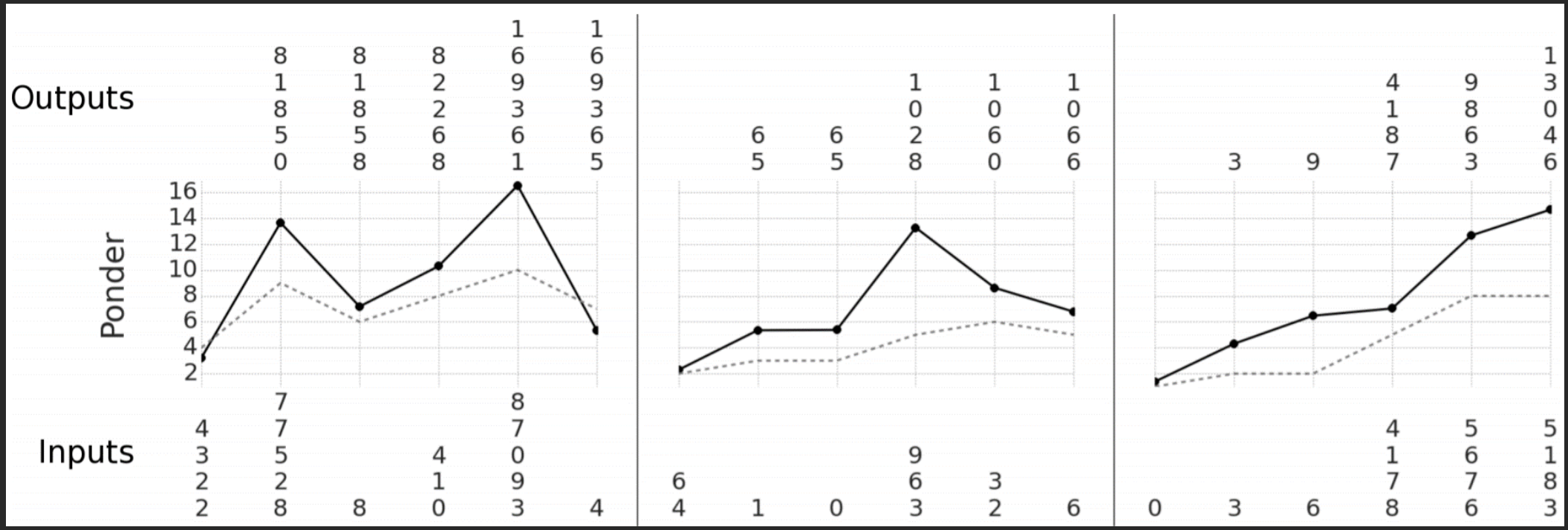
Ponder


Sequence Error Rate
Ponder
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
2
4
6
8
10
12
14
Time Penalty
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0.0009
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

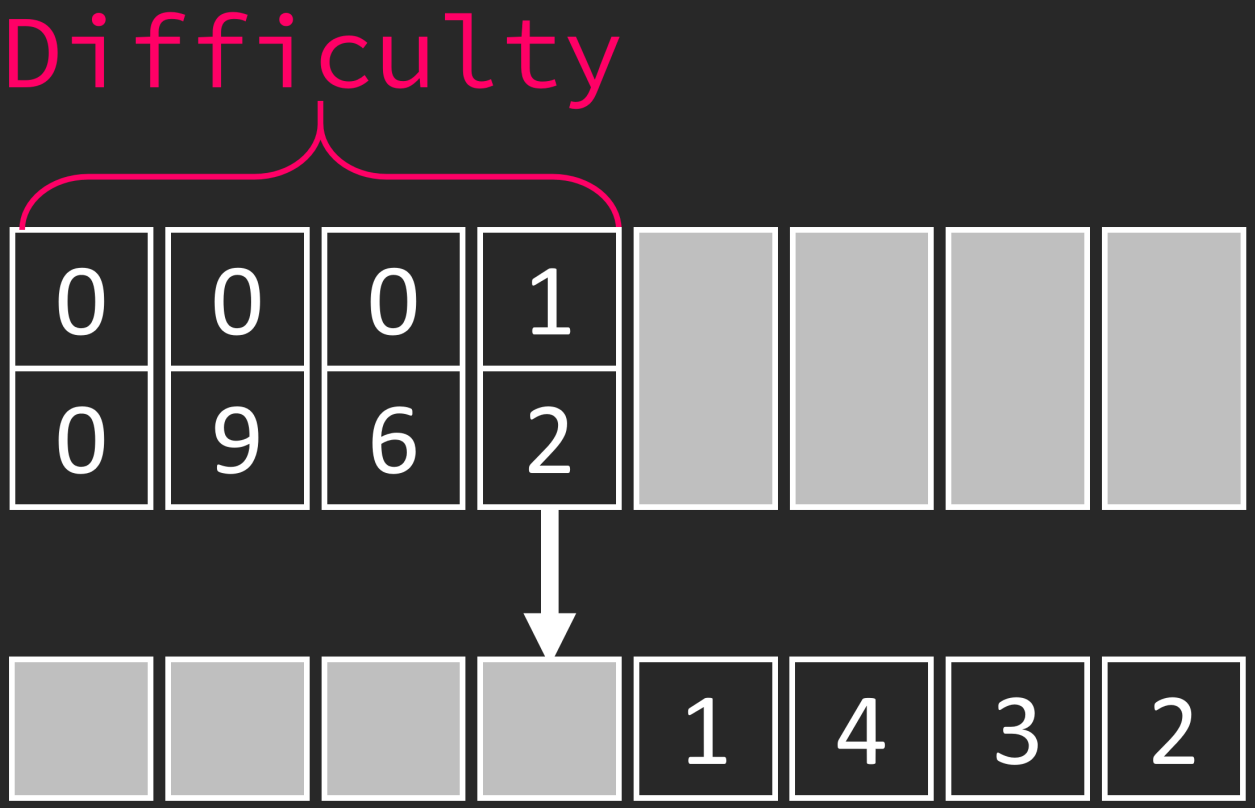
Ponder


Ponder
Difficulty
Sequence Error Rate
Difficulty
Time Penalty
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0.0009
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

Ponder

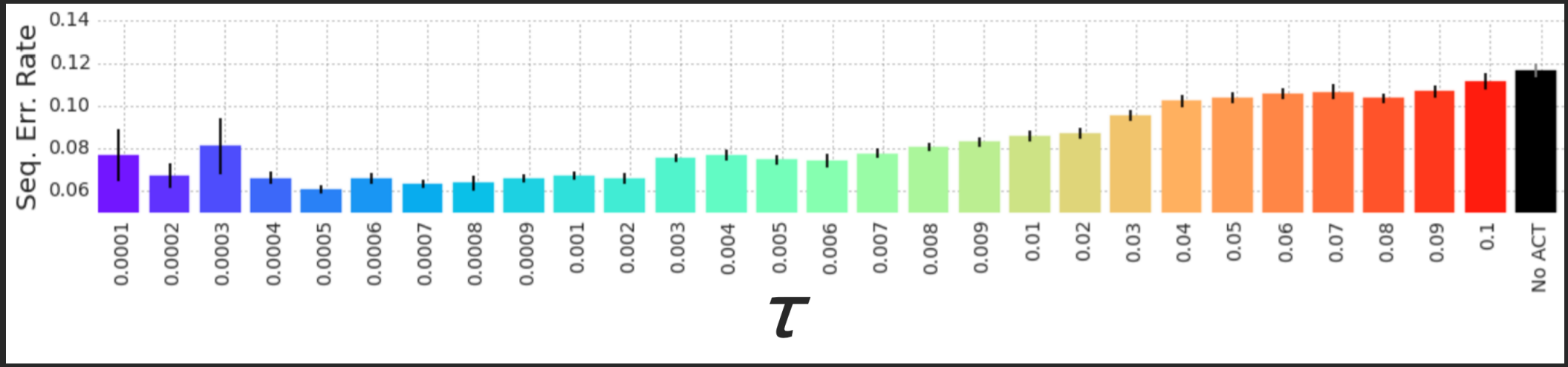

Outputs
8 8 8 16 16
1 1 2 9 9
8 8 2 3 3
5 5 6 6 6
0 8 8 1 5
Ponder
16
14
12
10
8
6
4
2
Inputs
7 8
4 7 7 5 2 8 8
4 1 0
8 7 0 9 3 4
2 2
1 0 6 5 6 5
10 10 10 2 6 0 6
9 6 3 2 6
6 4 1 0 3
3 9
4 4 1 8 7
13 9 8 6 3 0 4 6
5 5 1 4 1 7 8 6 7 8 3
0 3 6

Sort

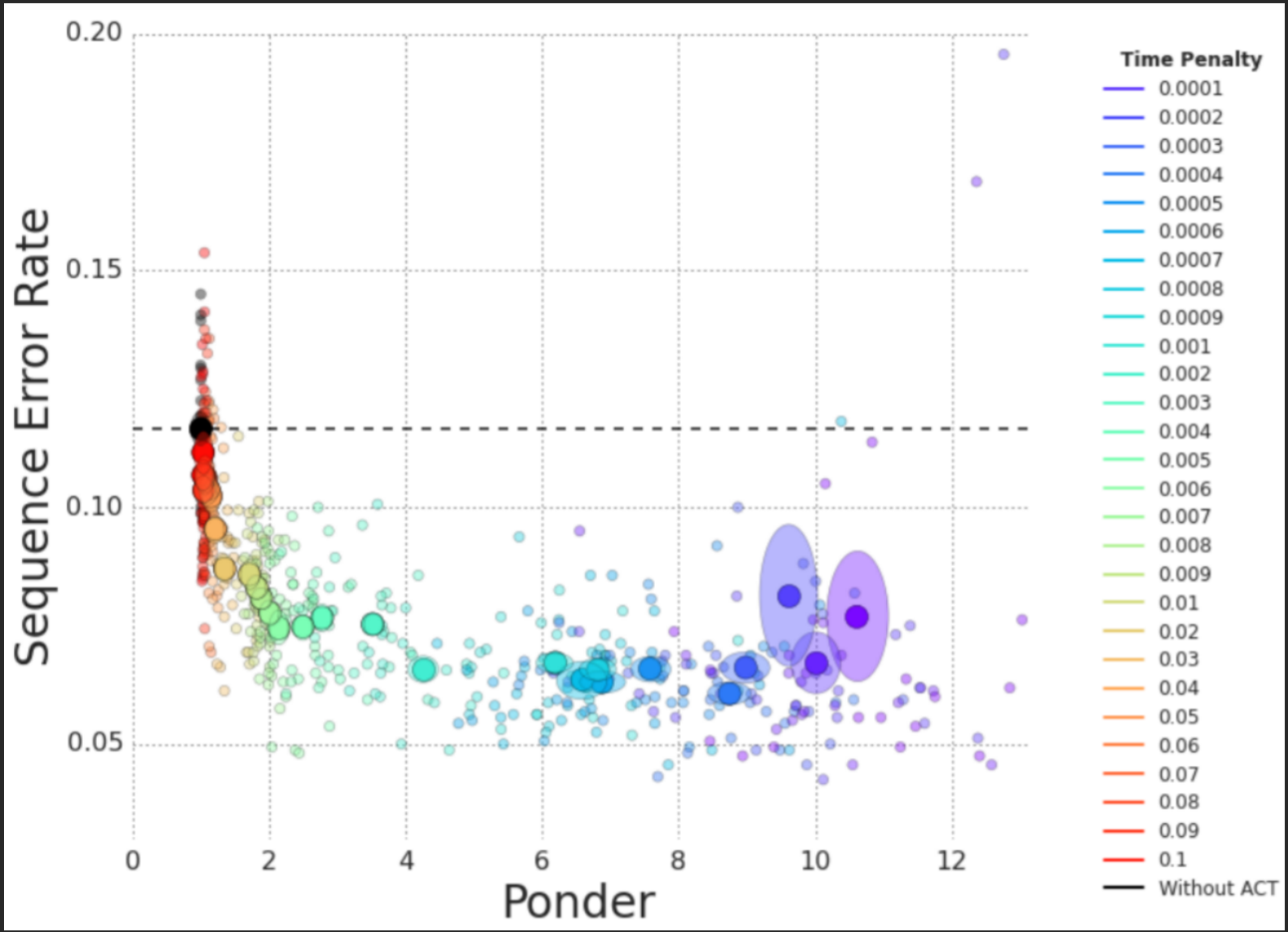


Model：LSTM

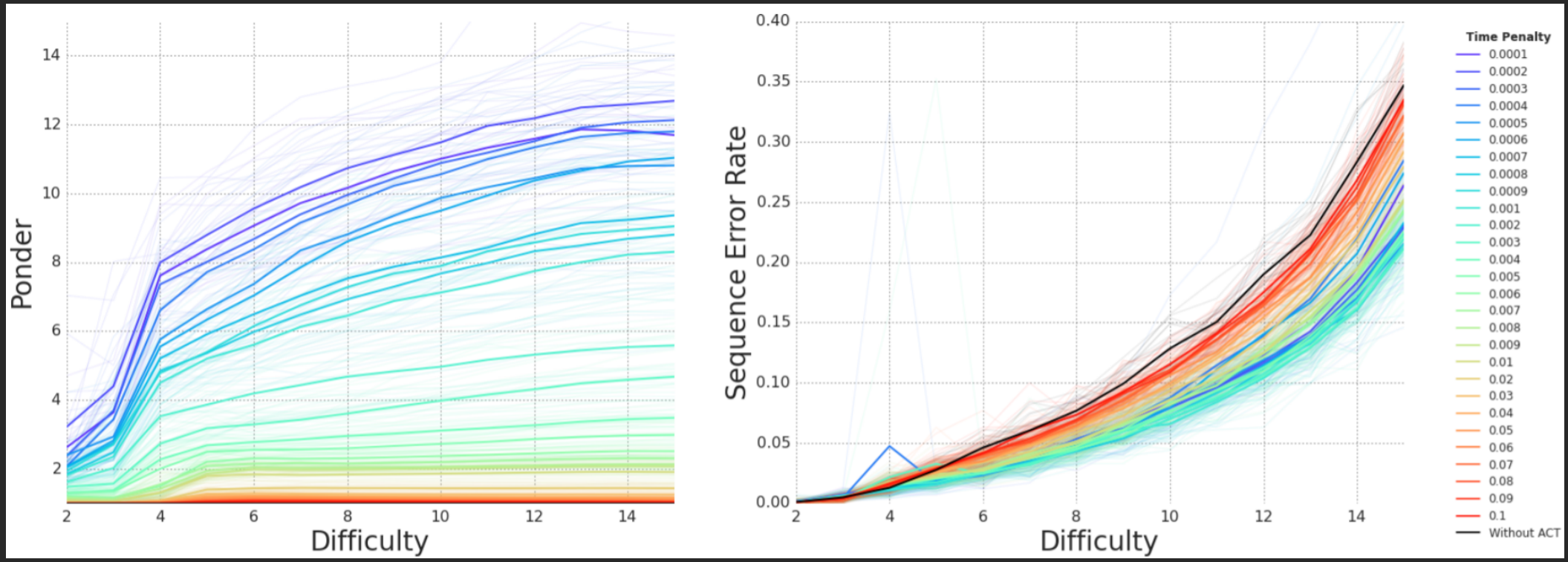
Time Penalty



Ponder


Sequence Error Rate
0.20
0.15
0.10
0.05
0
2
4
6
8
10
12
Ponder
Time Penalty
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0.0009
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

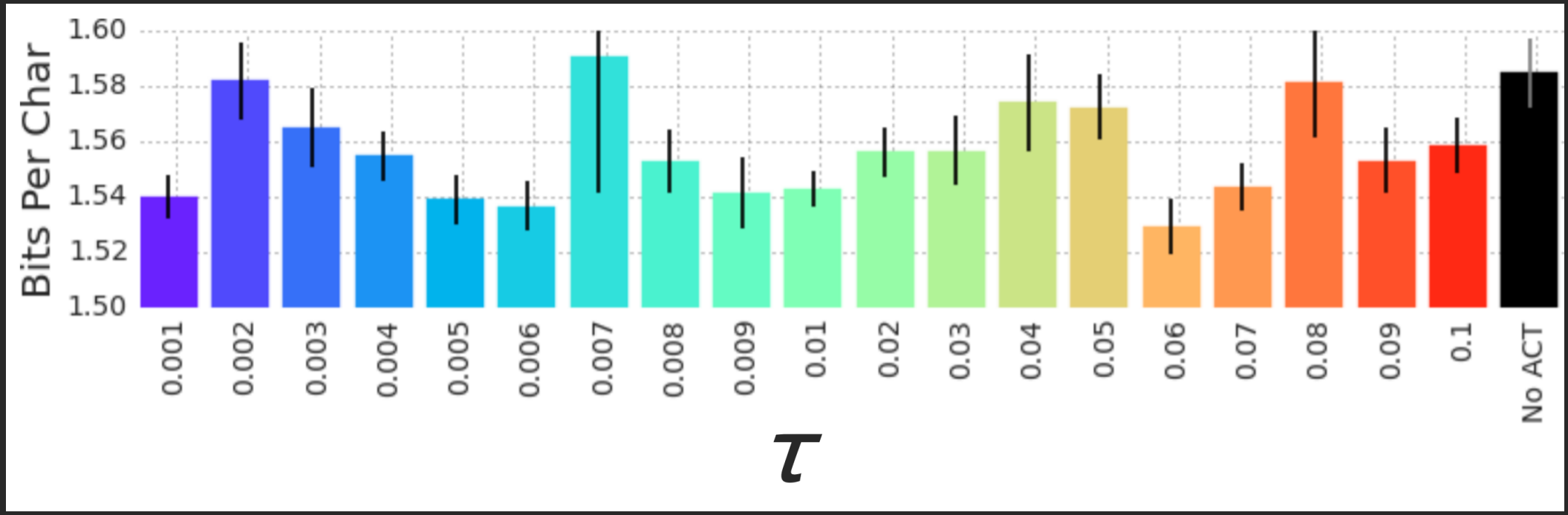
Ponder


Ponder
Difficulty
Sequence Error Rate
Difficulty
Time Penalty
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0.0009
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

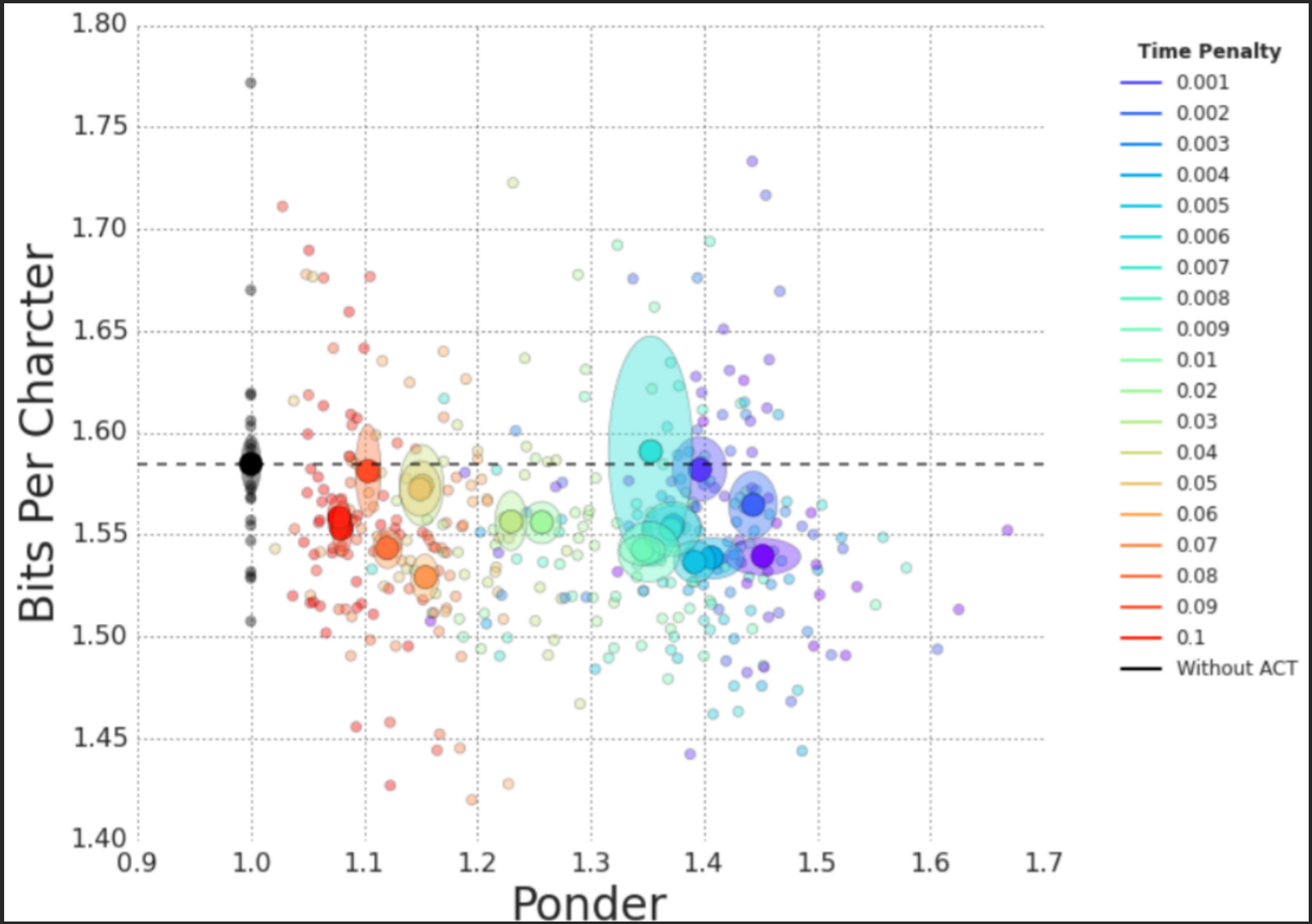
Wiki Char Pred

Model：LSTM

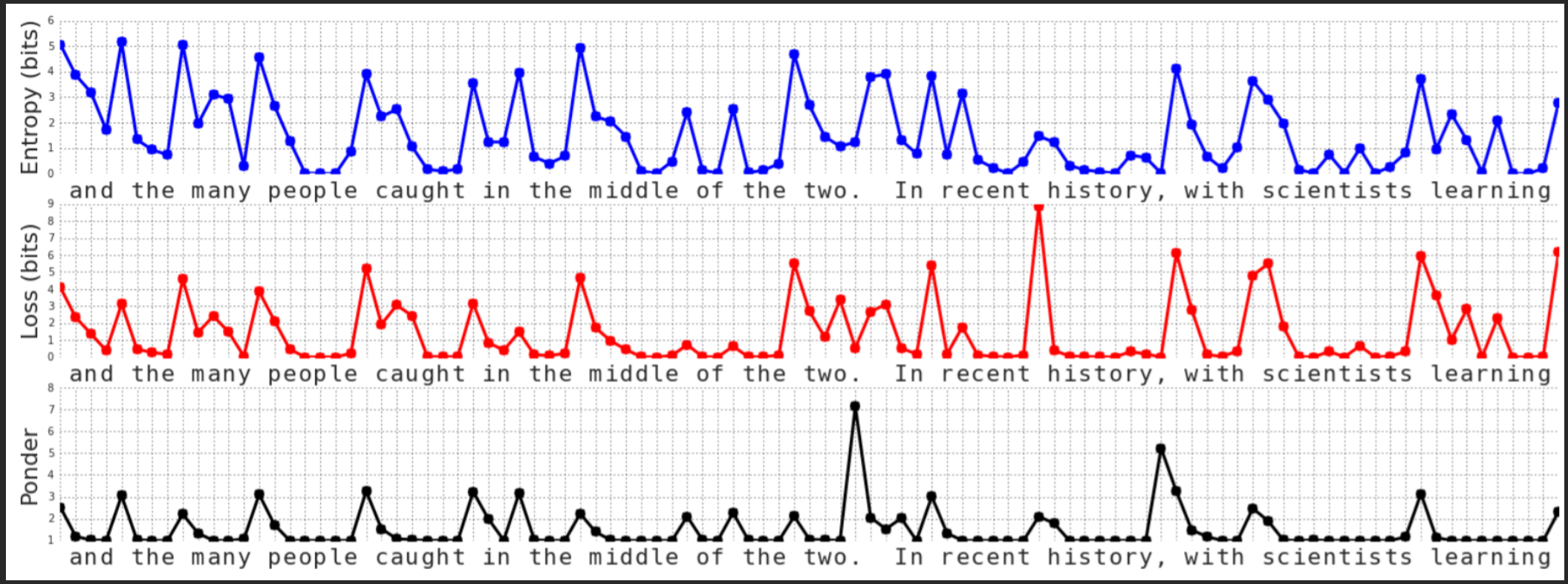
Time Penalty



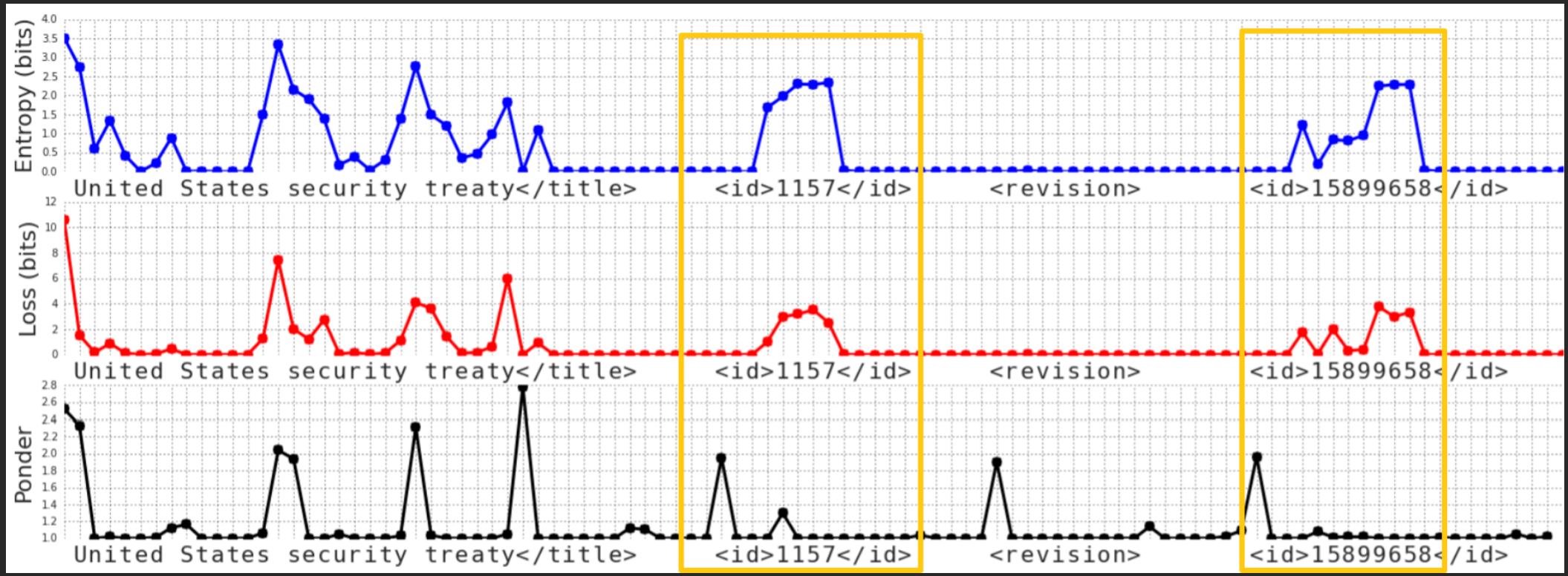
Ponder


Bits Per Charcter
Ponder
1.80
1.75
1.70
1.65
1.60
1.55
1.50
1.45
1.40
0.9
1.0
1.1
1.2
1.3
1.4
1.5
1.6
1.7
Time Penalty
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0.009
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Without ACT

Ponder


Entropy (bits)
and the many people caught in the middle of the two. In recent history, with scientists learning
Loss (bits)
and the many people caught in the middle of the two. In recent history, with scientists learning
Ponder
and the many people caught in the middle of the two. In recent history, with scientists learning

Ponder


Entropy (bits)
Loss (bits)
Ponder
United States security treaty</title>
<id>1157</id>
<revision>
<id>15899658</id>

Conclusion

- 讓模型依據問題的複雜度自行增減思考次數確實能提升效果。
- 目前的算法對於 time penalty(τ) 非常敏感，需要一個更好的方法來自動調整 time penalty。
- Ponder times 或許可以做為一種區分結構和噪聲的標準。