(i)  $m \leftarrow \beta, m + (1 - \beta) \nabla_{\theta} J_{mini-batch}(\theta)$  $\theta \leftarrow \theta - \alpha m$ 

Using  $\beta_1$  tracks the history of the gradients by the rolling average. Controlling  $\beta_1$  on the previous State  $m_{i-1}$ , we can let the recent changes have a bit more importance than the current gradient, thus reduce the variance

(ii) Small v values will get larger updates.

This can be helpful for learning because it can get recent parameters moving more efficiently along the axes and thus expediate the convergence.

(b) (i)  $\gamma = \frac{1}{1 - Pdrop} = \frac{1}{Pkcep}$ 

Edrop [hdrop]  $i = P_{drop} \cdot 0 + (1-P_{drop}) \gamma \cdot h_i = h_i$   $\gamma = \frac{1}{1-P_{drop}}$ 

(ii) dropout is used for preventing overfitting.

2. (a)	1	•	1
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(b) O(n)

The worst case is 2·n, which is linear.

(e) Final model performance

dev UAS test UAS

88.47