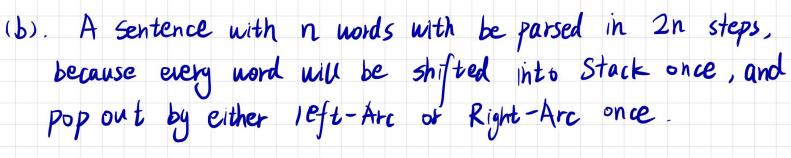
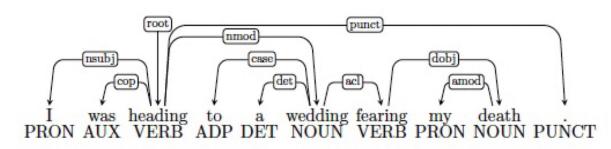
CS224n: #3: Dedendency Parsing written part 3/31/2021 at NYU-SH 1. [Machine Learning & Neural Network] (8 point) (i) the momentum is such that  $\begin{cases}
 m_{n+1} \leftarrow \beta_1 \cdot m_n + (+\beta_1) \nabla_{\theta} \int_{\text{minibatch}} (\theta) \\
 \theta_{n+1} \leftarrow \theta_n - \alpha \cdot m_{n+1}
\end{cases}$ Intuitively, using "m" stops the updates from varying too much because each min-batch only contribute/change the momentum by a factor of c1-B1), with usually &1 set to 0.9. So, if it so happens that a gradient of mini-batch deviates from the true whole-batch gradient too much, using momentum ve would still roughly be on the right track. (ii) the adaptive learning rates is such that  $\int M_{n+1} \leftarrow \beta_1 \cdot m_n + (+\beta_1) \cdot \nabla_{\theta} \int_{\text{minibatch}} (\theta)$   $\int V_{n+1} \leftarrow \beta_2 \cdot V_n + (+\beta_2) \cdot (\nabla_{\theta} \int_{\text{minibatch}} (\theta) \odot \nabla_{\theta} \int_{\text{minibatch}} (\theta)$   $\Theta_{n+1} \leftarrow \Theta_n - \alpha \odot m_{n+1} / \int_{V_{n+1}} V_{n+1}$ parameters that are ① previously very small in gradient 2 variance is stable, stay more or less same in momentum
gets larger updates. This can help handle with sparse gradient. (b) harop = T. doh where  $d \in \{0.1\}^{Dn}$  is mask vector, each entry with Parop being 0, and (- Parop) being 1. (i) to have Eparop harop ] i = hi



(C) code part (d) code part (e) code part (f)

i

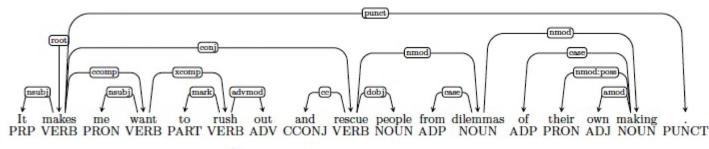
(i)



Error type: Verb Phrase Attachment Error Incorrect dependency: wedding -> fearing

Correct dependency: heading -> fearing

(iì) ii.



Error type: Coordination Attachment Error Incorrect dependency: makes -> rescue correct dependency: rush -> rescue

