# Learning Rate Tuning: Warm-up & Linear Decay

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### **Previous Methods**

#### SGD

• 가장 기본적인 방법

$$\theta \leftarrow \theta - \gamma \nabla_{\theta} \mathcal{L}(\theta)$$

- Learning rate(LR)에 따른 성능 변화
- 학습 후반부에 LR decay 해주기도

#### Adam

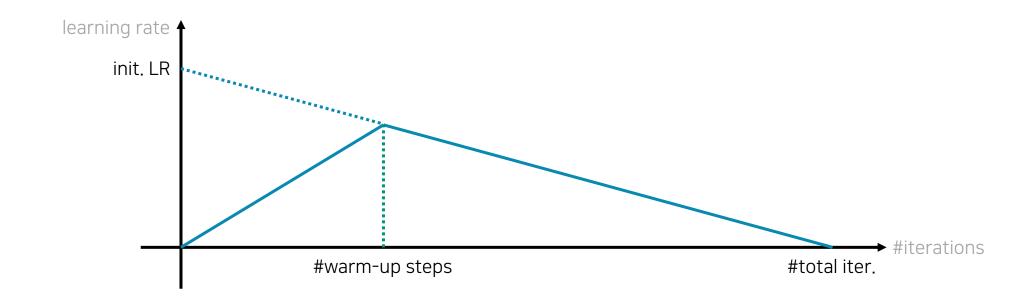
• Adaptive하게 LR을 조절

출처: [Liu et al., 2020]

- 일부 깊은 네트워크(e.g. Transformer) 에서 성능이 낮음
  - 문제는 지금은 Transformer의 세상

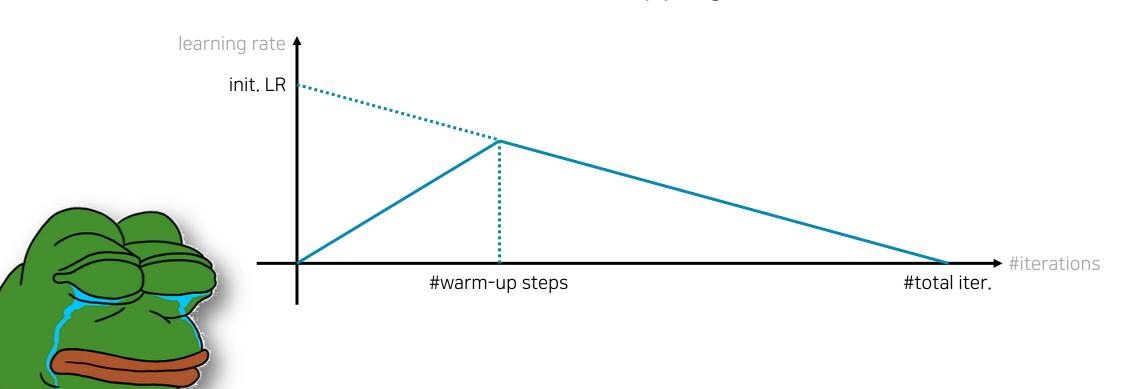
## Warm-up and Linear Decay (Noam Decay)

- Heuristic Methods
  - Control learning rate for Adam with hyper-params
- 학습 초기 불안정한 gradient를 통해 잘못된 momentum을 갖는 것을 방지



## Warm-up and Linear Decay (Noam Decay)

- 결국 Trial & Error 방식으로 Hyper-parameter 튜닝을 해야 함
  - 가장 핵심은 #warm-up steps와 #total iterations.
  - 이외에도 다양한 hyper-params: init LR, batch size
- 심지어 튜닝에 따라 SGD + Gradient Clipping이 더 나은 결과를 얻기도 함



## Rectified Adam [Liu et al., 2020]

- Adam이 잘 동작하지 않는 이유(가설)
  - Due to the lack of samples in the early stage, the adaptive learning rate has an undesirably large variance, which leads to suspicious/bad local optima. [Liu et al., 2020]

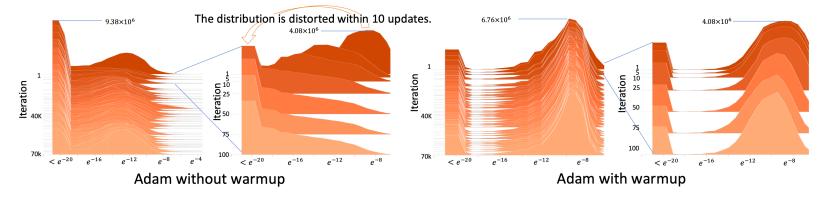


Figure 2: The absolute gradient histogram of the Transformers on the De-En IWSLT' 14 dataset during the training (stacked along the y-axis). X-axis is absolute value in the log scale and the height is the frequency. Without warmup, the gradient distribution is distorted in the first 10 steps.

- PyTorch 구현
  - https://github.com/LiyuanLucasLiu/RAdam
  - \$ pip install torch-optimizer