Generating open source chess puzzles - notes

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Contents

1 Tokenization

Tokenization v1

- Board
  - PNBRQKpnbrqk. = 13 tokens
- Side to move
  - wb = 1 tokens (b already counted)
- Castling
  - KQkq. = 0 tokens (already counted)
- En passant
  - abcdefgh = 7 tokens (b already counted)
  - 12345678 = 8 tokens
  - -. = 1 tokens (. already counted)
  - = 16 tokens
- Half move counter
  - 0123456789 = 2 (0 and 9 new tokens)
- Full move counter
  - 0123456789 = 0 (already counted)

= 32 tokens

Total tokens do not match the number of tokens in the paper 31 (the most obvious is that "-" might be replaced with a "."). The length of the produced string is also 76 instead of 77 for some reason. This tokenization feels bad, as e.g. side to move b is completely different to board b (black to move vs black bishop).

Tokenization v2 (my current choice): Length 76, number of tokens 48 (own tokens e.g. for black bishop and black to move)

2 Model architecture

What should be used, pre- or post-normalization ([1] says post (it says that the llama papers use post, but I think they use pre), but [2] and [3] use pre-normalization to improve stability.)

3 RL

[1] did not use the masked diffusion for the RL, and it will probably be harder than with the autoregressive model.

Compute the log-probability of the models in the same way as with autoregressive models (sum the log probabilities of the chosen tokens). The model must be called K times, where K is the amount of tokens (the latter tokens depend on the previous tokens and teacher forcing is not possible I think?). Hence, the computational complexity is a lot higher with masked diffusion than with an autoregressive model. I may be wrong based on algorithm 2 of [4], as we call the model as many times as we have discretized the range [0, 1].

References

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