Hangman with LLMs

Training Google's CANINE transformer to play Hangman

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https://github.com/vsa1920/Hangman-with-Transformers

HANGMAN: A Word Guessing Game

Hangman is a popular word-guessing game:

1. Player 1 typically chooses a word that Player 2 has to guess. All the letters are concealed at the start of the game.
2. Player 2 then has to guess the letters of the hidden word, one letter at a time. All its positions are revealed if the guessed letter is in the word.
3. If a guessed letter is not in the word, Player 2 exhausts one failed try. If the player guesses the word before guessing the wrong N times, they win; otherwise, they lose.
   (typically $N = 6$ or 7)

How hard is Hangman?

Number of letters	Optimal calling order
1	A I
2	A O E I U M B H
3	A E O I U Y H B C K
4	A E O I U Y S B F
5	S E A O I U Y H
6	E A I O U S Y
7	E I A O U S
8	E I A O U
9	E I A O U
10	E I O A U
11	E I O A D
12	E I O A F
13	I E O A
14	I E O
15	I E A
16	I E H
17	I E R
18	I E A
19	I E A
20	I E

Figure: Calling Order for the first letter according to word length
Image courtesy - Datagenetics

Formulating the problem

Hangman: Actions and States

Applying the rules of Hangman (H), it can be modeled as taking an action (a_t: guessing 1 of the 26 letters in the English Alphabet), given a Hangman game state (s_t: Guessed letters and the state of the hidden word)

$$H(a_t, s_t) = s_{t+1}$$

Encoding the Hangman Game States

We want to model the game states to feed it to our Transformer model:

$s_t =$ [CLS] <GUESSED_LETTERS> [SEP] <HANGMAN_STATE> [SEP]

Example:

Actual word: b i r t h d a y; Guessed letters: e, a, i, s; State: _ i _ _ _ _ a _
$s_t =$ [CLS] eias [SEP] [MASK] i [MASK] [MASK] [MASK] [MASK] a [MASK] [SEP]

Machine Learning Task

How do we model the decision that our agent takes at each step? It turns out there is more than 1 way to do so.

1. Multi-label Classification Task:
   - Label consists of every hidden letter that hasn't been guessed.
   - Model can simultaneously guess letters!
   - Not too restrictive. Well defined? Hard to train?
2. Multi-class Classification Task:
   - Guess the most likely or the most frequent letter.
   - Make a distribution of the likelihood by normalizing the counts.
   - A 1-1 mapping between labels and states. Easier to train?

$$[l(s_t)]_i = \frac{\sum_j \delta_j \cdot I_{x_j = x_i}}{\sum_i \sum_j \delta_j \cdot I_{x_j = x_i}}$$

where x_i is the i-th letter of the alphabet, and x_j is the letter at the j-th position of the word

Data Generation

We have chosen the right way to label the data. The number of Hangman states in a Hangman game is huge!

$||\Omega|| \sim 2^k \cdot \binom{26-k}{N} \cdot N!$

k : Number of unique letters in the word)

N: Number of allowed wrong tries

How do we sample efficiently?

Biased Random Sampling

Game Simulations

Learn as much as possible from each simulated game!

Biased Random Sampling (p)

Proposed approach:

- With a probability p, sample from one of the missing letters in the word
- The rest of the time, sample randomly from any of the letters that haven't been guessed
- p is a hyperparameter to be tuned. We find $p = 0.4$ works well!

Model Selection: Google's CANINE

- Our states have character-level information stored in them
- Intuitively, we need a character-level language model that can model the conditional distribution of letters in English words!
- CANINE: [Clark et al., 2022]

Training our Transformer from scratch!

The model does not benefit from transfer learning of sentence-level language modeling. This is why it's actually simpler to work with it from random initialization:

Training Algorithm (Pre-training)

- Preprocess a corpus of words: Random-split to train, validate, and test
- At each epoch, for each word, the training corpus is used to perform gameplay simulation through biased sampling
- The model then learns to match the output distribution as defined before for each state, using Cross-entropy loss

Pre-training Results

Our model has 50+% game-winning accuracy with 6 tries!

Self-play fine-tuning

Our model does well. But can we improve its accuracy further? Biased sampling provides a lot of simulation states, but as the model becomes better, it needs more precise data. We need more cases where we know it does poorly.

Self-play fine-tuning Algorithm - motivated by [Mary Wahl, 2017]

- Let our model navigate through the state space on its own based on its guesses
- If it guesses correctly, we proceed; otherwise, we calculate the loss
- Iteratively update the model to correct these mistakes by optimizing our loss

Self-play fine-tuning Results

Our model has 56% game-winning accuracy with 6 tries and 83% with 10 tries!

Future Scope and Improvements

> ***Future Scope***
>
> We have successfully trained our Hangman agent. What other cool downstream tasks can our trained model be used for?
>
> 1. Our model can be fine-tuned to be a great spell-checker and auto-complete! It can identify if a spelling is correct or not and even provide suggestions to auto-complete.
> 2. Can be an interesting decrypting tool for simple decrypting tasks!
> 3. Can help in speech recognition in filling missing partial phonemes.

Dataset Analysis

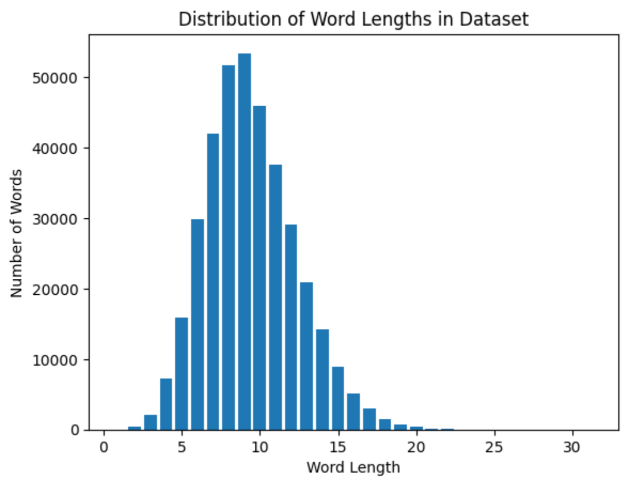


Figure: Word length distribution

Calling Order

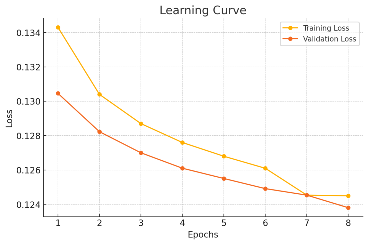
```
Length 4: ['a', 'e', 'o', 'i', 'u', 'y', 's', 'r', 'd', 't']
Length 5: ['a', 'e', 'o', 'i', 'u', 'y']
Length 6: ['e', 'a', 'o', 'i', 'u', 'y']
Length 7: ['e', 'a', 'i', 'o', 'u']
Length 8: ['e', 'a', 'i', 'o', 'u']
Length 9: ['e', 'i', 'a', 'o']
Length 10: ['e', 'i', 'o', 'a']
Length 11: ['e', 'i', 'o', 'a']
Length 12: ['e', 'i', 'o', 'a']
Length 13: ['e', 'i', 'o', 'a']
Length 14: ['i', 'e', 'o']
Length 15: ['i', 'e', 'o']
```

Figure: Calling Order of our Dataset

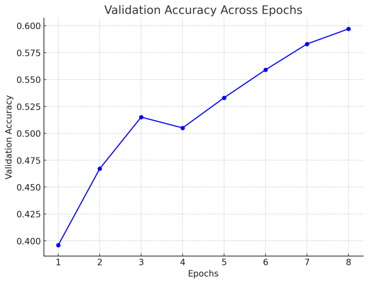
Pre-training results

Validation Accuracy

59 %



(a) Learning Curve

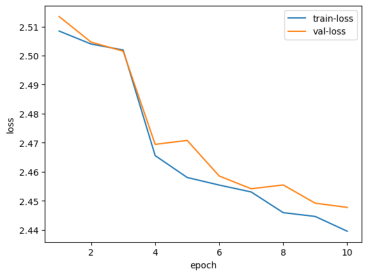


(b) Validation accuracy plot

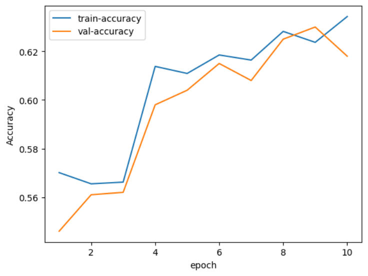
Self-play Finetuning

Validation Accuracy

63.5 %



(a) Learning Curve



(b) Accuracy plot for self-play

Model Analysis Results

> ***Validation Accuracy***
>
> 63 %

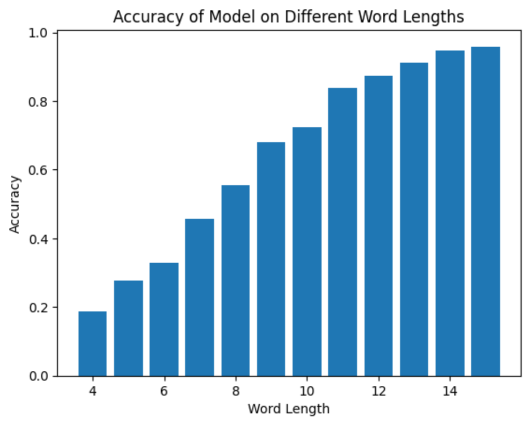


Figure: Accuracy vs word length

Comparison with a baseline

	Baseline N-gram Model	**Modified CANINE Model**
6-guesses	23%	63%
10-guesses	56%	86%

Table: Test accuracy comparison between Baseline N-gram Model and Modified CANINE Model

Future Scope and Improvements

Improvements

How can we improve our model performance, reduce latency, and speed it up?

- Our model is very slow at backprops when working with single samples at a time. If we could batch them together, the fine-tuning process and iteration would achieve significant speedup.
- Parameter Efficient Fine-tuning (PEFT) is another idea worth exploring to speed up fine-tuning our model. Backpropagation would be faster even when working one sample at a time.
- More hyperparameter tuning: We have been very conservative in using Hyperparameter values, and some good enough values have worked. However, we have parameters that still require more analysis. We have a Bias rate of p and the training and fine-tuning hyperparameters such as η and λ.

References

- Clark, J. H., Garrette, D., Turc, I., and Wieting, J. (2022).
  Canine: Pre-training an efficient tokenization-free encoder for language representation.
  Transactions of the Association for Computational Linguistics, 10:73–91.
- Mary Wahl, Shaheen Gauher, F. B. U. K. Z. (2017).
  Microsoft azure: Play hangman with cntk.