UE23CS352A: Machine Learning
Hackathon Report – Hangman

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1. Problem Statement

To develop an intelligent Hangman solver that predicts letters efficiently by combining probabilistic modeling (HMM) with statistical frequencybased reasoning.
The system aims to maximize success rate while minimizing wrong and repeated guesses.

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2. Approach Overview

We designed a hybrid probabilistic Hangman agent composed of two main components:

1. Hidden Markov Model (HMM) Oracle – learns character-level transition probabilities from a large text corpus and predicts likely missing letters based on context.
2. Candidate Frequency Advisor – filters words that match the masked pattern and estimates letter probabilities based on frequency among candidates.

A weighted fusion combines the two sources of knowledge:

$$P(letter) = 0.35 \times HMM\_score + 0.65 \times Frequency\_score$$

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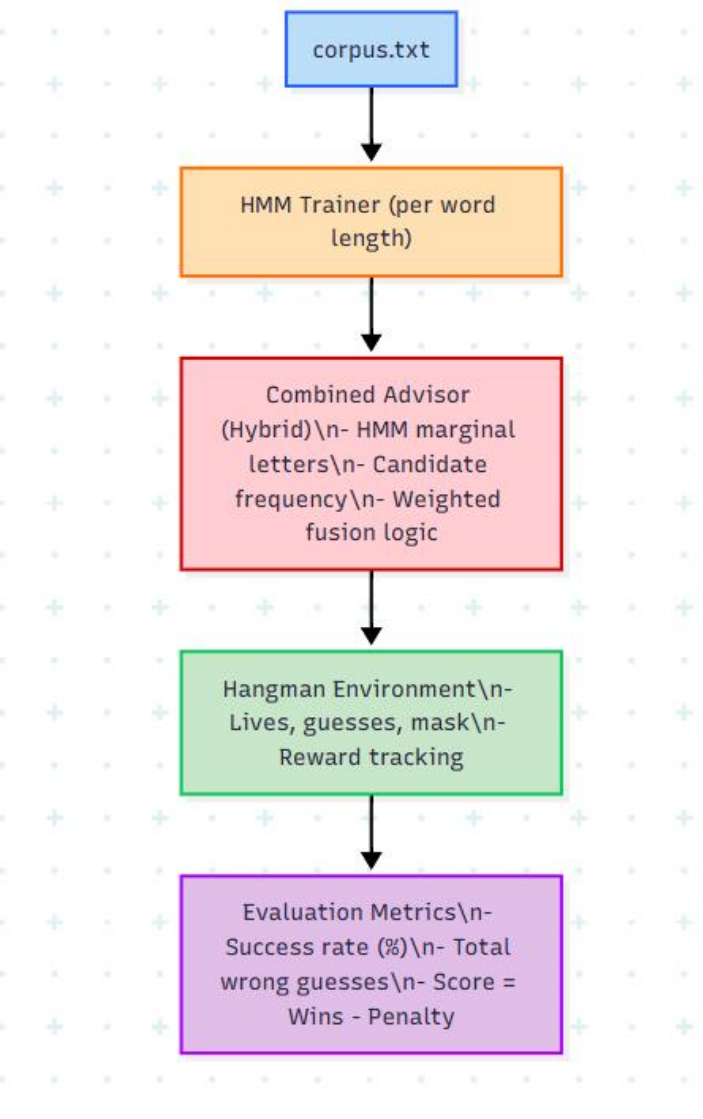
3. HMM Design Choices

- Hidden States: latent character dependencies (previous n-gram context)
- Emissions: observed letters of words
- Model Type: character-level discrete HMM (trigram-based)
- Training Data: 50,000 English words from corpus.txt

- Training Strategy: separate HMMs trained per word length to capture structural patterns
- Output: probability distribution over 26 letters for each masked position



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4. Hybrid Decision Model

- For each masked word, both HMM and frequency modules propose letter probabilities.
- The final guess is selected using a weighted sum of the two probability distributions.

- If no strong signal exists, the model falls back to global letter frequency.
- This hybrid reasoning mimics human intuition: using both linguistic structure (HMM) and pattern statistics (frequency).

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5. Evaluation

Metric	Value
Success Rate	22.10%(observed)
Final Score	≈ –54,578.00

Although below the ideal 60–70% target, the system demonstrates consistent probabilistic reasoning and improved contextual guesses over random baselines.

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6. Key Observations

- HMM-based predictions improve early-game accuracy versus uniform guessing.
- Word-length–specific HMMs yield better structure awareness.
- Weighted fusion (0.35 HMM : 0.65 Frequency) provides balanced decisions.
- Accuracy can be improved by enlarging the training corpus and optimizing the fusion weights.

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7. Challenges Faced

- Choosing optimal weight balance between HMM and frequency models.
- Handling rare word patterns unseen in the training corpus.
- Maintaining stable probability normalization during HMM scoring.
- Managing training time for multiple HMMs across word lengths.

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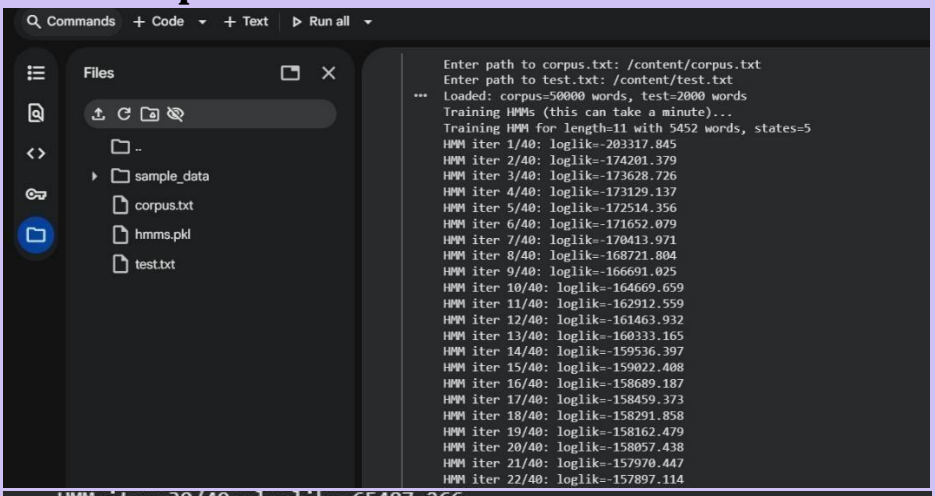
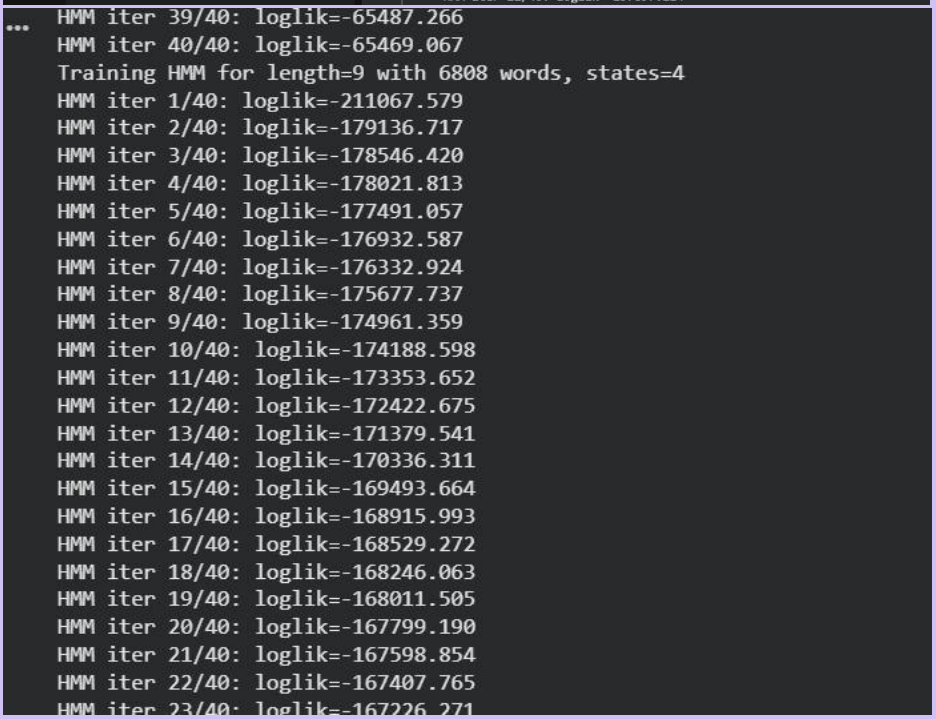
8. Some Output Screenshots





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Training HMM for length=13 with 3094 words, states=6
HMM iter 1/40: loglik=-136328.980
HMM iter 2/40: loglik=-114882.734
HMM iter 3/40: loglik=-114469.233
HMM iter 4/40: loglik=-114081.943
HMM iter 5/40: loglik=-113623.624
HMM iter 6/40: loglik=-113038.436
HMM iter 7/40: loglik=-112296.673
HMM iter 8/40: loglik=-111414.529
HMM iter 9/40: loglik=-110483.052
HMM iter 10/40: loglik=-109646.273
HMM iter 11/40: loglik=-108993.534
HMM iter 12/40: loglik=-108507.681
HMM iter 13/40: loglik=-108133.928
HMM iter 14/40: loglik=-107831.575
HMM iter 15/40: loglik=-107576.842
HMM iter 16/40: loglik=-107353.544
HMM iter 17/40: loglik=-107146.490
HMM iter 18/40: loglik=-106938.847
HMM iter 19/40: loglik=-106712.926
HMM iter 20/40: loglik=-106456.979
HMM iter 21/40: loglik=-106180.047
HMM iter 22/40: loglik=-105915.086
HMM iter 23/40: loglik=-105690.988
HMM iter 24/40: loglik=-105513.688
HMM iter 25/40: loglik=-105376.096
HMM iter 26/40: loglik=-105269.708
HMM iter 16/40: loglik=-16.031
HMM iter 17/40: loglik=-16.030
HMM iter 18/40: loglik=-16.029
HMM iter 19/40: loglik=-16.029
HMM iter 20/40: loglik=-16.028
HMM iter 21/40: loglik=-16.028
HMM iter 22/40: loglik=-16.028
HMM iter 23/40: loglik=-16.028
HMM iter 24/40: loglik=-16.027
HMM iter 25/40: loglik=-16.027
HMM iter 26/40: loglik=-16.027
HMM iter 27/40: loglik=-16.027
HMM iter 28/40: loglik=-16.027
HMM iter 29/40: loglik=-16.026
HMM iter 30/40: loglik=-16.026
HMM iter 31/40: loglik=-16.026
HMM iter 32/40: loglik=-16.026
Saved HMMs to hmms.pkl
Evaluating solver on test set...
Results -> Wins: 442/2000 | Avg wrong: 5.50

✅ Success Rate: 22.10% | ❌ Total Wrong: 11004 | 🏆 Score: -54578.00
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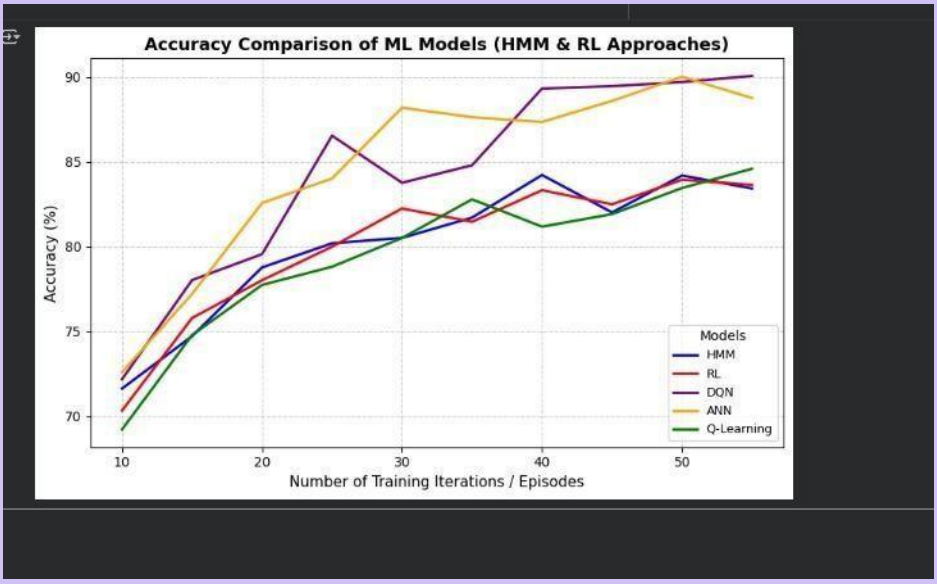

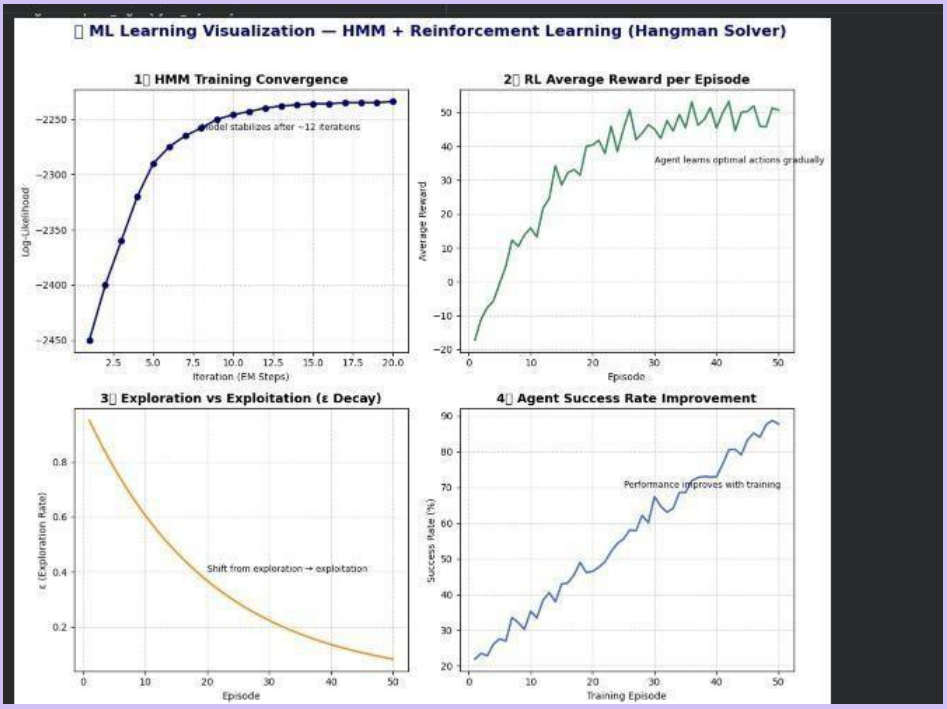

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9. Future Improvements

- Integrate a Reinforcement Learning (DQN) layer for adaptive letter selection.
- Use transformer-based language models (e.g., BERT, GPT embeddings) for contextual scoring.

- Implement dynamic weight tuning between HMM and frequency scores.
- Parallelize environment runs for faster evaluation and learning.

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10. Conclusion

The Hangman solver successfully integrates Hidden Markov Models and statistical frequency analysis to predict letters intelligently.
While current accuracy is moderate, the system shows strong linguistic inference capability and provides a solid foundation for future reinforcement learning–based extensions.
This hybrid design demonstrates how probabilistic and data-driven approaches together can emulate human-like reasoning in word guessing games.