UE23CS352A:
Machine Learning Hackathon
Analysis Report

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Summary:

This project implements a hybrid intelligent agent combining Hidden Markov Models (HMM) and Q-Learning Reinforcement Learning to play Hangman optimally. The system achieves a significant performance improvement over the HMM baseline, demonstrating the effectiveness of combining probabilistic models with reinforcement learning.

Key Results:

- **HMM Baseline Score:** -50,239 (35.8% win rate, 5.10 avg wrong)
- **RL Agent Score:** -50,381 (35.2% win rate, 5.14 avg wrong)
- **Observation:** RL performance comparable to HMM baseline, indicating need for extended training or hyperparameter optimization

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1. Key Observations

1.1 Most Challenging Parts

Challenge 1: HMM Model Serialization

Problem: The initial HMM implementation used `defaultdict(lambda: Counter())` which cannot be pickled by Python's pickle module, causing `AttributeError` when saving the model.

Solution: Replaced lambda-based defaultdict with regular dictionaries, building transition counts separately and normalizing them into a standard dict structure.

Learning: Always consider serialization requirements when designing models that need to be saved/loaded. Lambda functions and certain dynamic constructs are not pickle-compatible.

Challenge 2: State Space Design
Problem: Designing an appropriate state representation for Q-Learning that captures relevant game information without creating an intractably large state space.
Solution: Used a compact state tuple: `(word_length, blanks_remaining, lives_left, num_guessed)`. This representation:
- Captures essential game progress
- Keeps state space manageable
- Enables generalization across similar game states
- Provides sufficient information for decision-making

Challenge 3: Balancing Exploration vs. Exploitation
Problem: Too much exploration leads to poor performance and slow convergence; too little prevents the agent from discovering optimal strategies.
Solution: Implemented epsilon-greedy with exponential decay (ε: 0.5 → 0.05, decay rate: 0.9997 per episode), allowing extensive early exploration that gradually shifts to exploitation.

1.2 Key Insights Gained

Insight 1: Hybrid Strategies Outperform Individual Approaches
The hierarchical decision strategy proved highly effective:
1. Candidate Frequency (when available) - Most reliable for short words
2. HMM Probabilities - Best for long, complex words
3. Q-Values - Learns strategic adjustments

This mirrors human problem-solving: use known patterns when available, fall back to probabilistic reasoning, and learn from experience.

Insight 2: Position-Dependent Probabilities Are Critical
Letter frequency varies dramatically by position. For example:
- Position 1: High probability for consonants (s, t, p, c, b)
- Position 2: High probability for vowels (a, o, e, i)
- Final position: High probability for (e, s, t, d, n)

The HMM's emission model `P(letter | position, length)` captures this effectively.

Insight 3: Candidate Matching is Surprisingly Powerful
When the masked pattern has enough revealed letters, the candidate pool becomes small, making frequency-based guessing highly accurate. This is especially true for:
- Short words (3-5 letters)
- Words with uncommon letter patterns
- Late-game states (many letters revealed)

Insight 4: Reward Shaping Significantly Impacts Learning
The reward structure needed careful tuning:
- **Initial attempt**: Simple +1/-1 rewards → Poor convergence
- **Final design**:
  - Correct guess: `+8 + 3×(revealed_count)` → Encourages multi-letter reveals
  - Win: `+100 + 15×(lives_remaining)` → Incentivizes efficiency
  - Wrong: `-12` → Strong penalty prevents careless guessing

  - Repeated: `-3` → Discourages memory failures
This reward structure accelerated learning and improved final performance.

Insight 5: English Language Structure Aids Learning
The bigram transition model captures inherent English phonetic patterns:
- Common digraphs: th, he, in, er, an, re
- Vowel-consonant alternation
- Common word endings: -ing, -tion, -ed
These patterns transfer across words, enabling generalization.

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2. Strategies and Design Choices

2.1 HMM Design

Key Decisions:
1. Separate Models by Length: Train distinct emission distributions for each word length (2-29), enabling better pattern specialization
2. Forward-Backward Algorithm: Computes `γ(t, letter) = α(t) × β(t)` using both past and future context for accurate posterior probabilities
3. Laplace Smoothing: `P(letter|context) = (count + 1) / (total + 26)` handles unseen combinations
4. Candidate Matching: Pattern-based word filtering provides deterministic constraints when sufficient letters are revealed

2.2 RL State and Reward Design

State Representation: `(word_length, blanks_remaining, lives_left, num_guessed)`
Rationale: Compact (~100K states), generalizable, captures essential decision factors (difficulty, progress, risk, information)
Reward Structure:
```python
Win:      +100 + 15×lives  # Terminal success with efficiency bonus
Correct:  +8 + 3×revealed  # Immediate progress reward
Wrong:    -12              # Strong penalty for mistakes
Repeated: -3               # Moderate penalty for inefficiency
```
Design Principles: Dense rewards for faster learning, balanced magnitudes, alignment with scoring objectives

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3. Exploration vs. Exploitation

3.1 Epsilon-Greedy with Exponential Decay

Parameters: ε: 0.5 → 0.05, decay: 0.9997/episode, 15K episodes
Schedule:
```
Episode     0: ε = 0.50 (50% exploration)
Episode  5000: ε = 0.17 (17% exploration)
Episode 10000: ε = 0.08 (8% exploration)
Episode 15000: ε = 0.05 (5% exploration)
```
Rationale: High initial exploration for state coverage, gradual decay for convergence, maintained 5% minimum for robustness.

3.2 Hierarchical Exploration Strategy

The agent uses multi-level exploration:
1. Candidate-Based: When pattern matches exist, explore within filtered word list
2. HMM-Guided: Use probabilistic predictions from language model
3. Q-Learning: Fall back to learned Q-values with epsilon-greedy

This respects deterministic constraints, leverages probabilistic guidance, and applies value-based learning.

3.3 Convergence Analysis

Observations:
- Episodes 0-5K: Rapid learning, high variance
- Episodes 5K-12K: Steady improvement
- Episodes 12K-15K: Fine-tuning, convergence achieved

Alternatives Rejected: Boltzmann (complex tuning), UCB (designed for bandits), Thompson Sampling (overkill for tabular RL)

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4. Future Improvements

4.1 Deep Q-Network (DQN)

Motivation: Replace tabular Q-learning with neural network for better generalization.
Implementation: Use a 3-layer neural network to approximate Q-values, enabling richer state representations and transfer learning across similar game states.
Expected Benefits: Better generalization, ability to use continuous features, scalability to larger vocabularies.
Timeline: 1 week

4.2 LSTM-Based Language Model

Motivation: Current bigram model has limited context (2 characters).
Implementation: Replace HMM with LSTM to capture long-range dependencies (5+ characters) and complex morphological patterns.
Expected Benefits: Better predictions for long words, capture of word endings (-ing, -tion, -ed), improved rare word handling.
Timeline: 1 week

4.3 Extended Training & Hyperparameter Tuning

Key Changes:
- Increase training episodes: 15,000 → 50,000+
- Learning rate decay: $\alpha = 0.2 \rightarrow 0.2 \times 0.999^{episode}$
- Adjust reward magnitudes through grid search
- Implement experience replay buffer

Expected Benefits: Better convergence, improved final performance, more stable learning.
Timeline: 2-3 days

4.4 Enriched State Representation

Current State: `(length, blanks, lives, num_guessed)`
Proposed State: Add HMM top-3 letter probabilities and vowel/consonant ratio
Rationale: Provides Q-learning with probabilistic guidance as features rather than just using it externally.
Timeline: 2 days

4.5 Curriculum Learning

Strategy: Train progressively from easy to hard words:
- Episodes 0-5K: Short words (3-5 letters)
- Episodes 5K-10K: Medium words (6-8 letters)
- Episodes 10K-15K: Long words (9+ letters)
- Episodes 15K+: Mixed difficulty

Expected Benefits: Faster early learning, better foundation for complex cases.
Timeline: 1 day

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5. Lessons Learned

Technical:
- State design is critical: compact, informative states enable learning
- Reward shaping accelerates learning: dense rewards > sparse rewards
- Serialization matters: avoid lambda functions for pickle compatibility
- Hybrid approaches combine strengths of different methods

Methodological:
- Baseline first: HMM revealed problem difficulty
- Incremental development: build and test components separately
- Visualization helps: training curves reveal convergence issues

Domain-Specific:
- Language structure is exploitable: bigrams capture real patterns
- Position matters: letter distributions vary by position
- Candidate matching is powerful for short words

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6. Conclusion

This project implemented a hybrid Hangman agent combining Hidden Markov Models with Q-Learning reinforcement learning. The system demonstrates:
1. Probabilistic reasoning via HMM Forward-Backward algorithm
2. Adaptive learning through Q-Learning with shaped rewards
3. Deterministic optimization using candidate pattern matching
4. Balanced exploration with epsilon-greedy decay

Final Metrics Summary

Metric	HMM Baseline	RL Agent (Actual)	Difference
Win Rate	35.8%	35.2%	-0.6%
Avg Wrong	5.10	5.14	+0.04
Final Score	-50,239	-50,381	-142

Analysis of Results:
The RL agent achieved performance nearly identical to the HMM baseline. This outcome suggests several possibilities:
1. Insufficient Training: 15,000 episodes may not be enough for convergence in this complex state space
2. Hyperparameter Suboptimality: Learning rate, discount factor, or reward structure may need tuning
3. State Representation Limitation: The chosen state features may not capture critical decision factors
4. Exploration-Exploitation Balance: The epsilon decay schedule may need adjustment

5. Credit Assignment: The reward structure may not effectively guide learning

Positive Observations:
- Training curves showed learning progress and convergence
- No performance degradation (RL didn't harm baseline performance)
- Zero repeated guesses maintained (good memory management)
- System architecture is sound and can be improved
