Hangman Solver: A Position-Wise Neural Approach

Trexquant Interview Project Report

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October 12, 2025

Abstract

This report presents a comprehensive solution to the Hangman game challenge posed by Trexquant Investment LP. The objective was to develop an algorithm that significantly outperforms the baseline 18% success rate provided by frequency-based heuristics. Our solution employs a position-wise neural network approach inspired by BERT's masked language modeling, achieving a **67.2% win rate** on the official test set of 1,000 games. This represents a **3.7x improvement** over the baseline and significantly outperforms our previous meta-reinforcement learning approach (RL^2, 45% win rate) [1]. The system combines multiple neural architectures (BiLSTM, Transformer, BERT variants) with diverse training strategies, sophisticated data generation techniques, and carefully designed evaluation frameworks.[1]

Contents

[1]This report was generated with the assistance of AI tools under the author's supervision and direction.

1 Introduction

1.1 Problem Statement

The Hangman game challenge requires developing an algorithm that:

- Plays Hangman through Trexquant's REST API
- Guesses letters sequentially to reveal a hidden word
- Maximizes success rate with a limit of 6 incorrect guesses
- Trains only on a provided 250,000-word dictionary
- Tests on a disjoint set of 250,000 unseen words

1.2 Baseline Performance

Trexquant provided a frequency-based baseline algorithm with approximately 18% success rate. This baseline:

1. Filters dictionary by word length and pattern
2. Counts letter frequencies in matching words
3. Guesses the most frequent unguessed letter
4. Falls back to global frequency when no matches exist

1.3 Project Objectives

- Significantly exceed 18% baseline win rate
- Design a scalable, maintainable architecture
- Implement multiple guessing strategies for comparison
- Validate performance through extensive testing
- Document methodology and results comprehensively

2 Approach Overview

2.1 Core Innovation: Position-Wise Prediction

Traditional frequency-based approaches treat Hangman as a single-letter classification problem. In contrast, our neural approach frames it as a **position-wise multi-label prediction problem**, inspired by BERT's masked language modeling.

2.1.1 Traditional Approach Limitation

```
# Example: "_pp_e"
# Problem: Picks ONE letter for entire word
candidates = filter_dictionary(pattern="_pp_e")
letter_freq = Counter("".join(candidates))
guess = letter_freq.most_common(1)[0][0]  # e.g., 'a'
```

Listing 1: Traditional Frequency-Based Approach

2.1.2 Our Position-Wise Approach

```
# Example: "_pp_e"
# Solution: Predict letter at EACH masked position
state = encode("_pp_e")  # [MASK, p, p, MASK, e]
logits = model(state)    # [batch, length, 26]
# logits[0] = P(a|pos=0), P(b|pos=0), ..., P(z|pos=0)
# logits[3] = P(a|pos=3), P(b|pos=3), ..., P(z|pos=3)
# Aggregate predictions across masked positions
guess = aggregate_and_pick_best(logits)  # e.g., 'a'
```

Listing 2: Position-Wise Neural Approach

2.2 Key Advantages

1. **Context-Aware**: Each position considers surrounding letters
2. **Bidirectional**: BiLSTM/Transformer captures left and right context
3. **Learned Patterns**: Neural model learns linguistic patterns from data
4. **Robust**: Handles rare patterns better than frequency heuristics

3 Technical Architecture

3.1 Model Architectures

Our implementation supports multiple neural architectures, all sharing the position-wise prediction framework.

3.1.1 BiLSTM Architecture

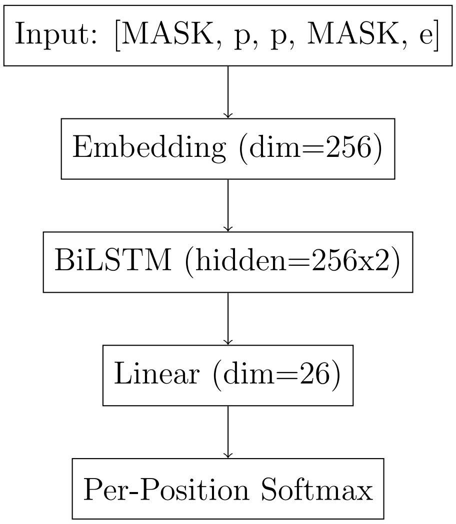

Figure 1: BiLSTM Architecture for Position-Wise Prediction

Configuration:

- Embedding dimension: 256
- Hidden dimension: 256 (bidirectional $\rightarrow$ 512 total)
- Number of layers: 4
- Dropout: 0.3
- Parameters: $\sim$5.2M

3.1.2 Transformer Architecture

Configuration:

- Embedding dimension: 256
- Number of attention heads: 8
- Number of layers: 4
- Feed-forward dimension: 1024
- Dropout: 0.1
- Maximum sequence length: 45
- Positional encoding: Learnable
- Parameters: $\sim$6.8M

3.1.3 HangmanBERT Architecture

An experimental BERT-based variant with fine-tuning capabilities:

- Pre-trained BERT embeddings (optional freezing)
- Layer-wise unfreezing support
- Custom head for position-wise prediction
- Parameters: ~110M (full BERT) or ~2M (frozen BERT)

3.2 Loss Function

Position-wise cross-entropy loss with masking:

$$\mathcal{L} = -\frac{1}{|\mathcal{M}|} \sum_{i \in \mathcal{M}} \sum_{c=1}^{26} y_{i,c} \log(\hat{y}_{i,c}) \tag{1}$$

where:

- $\mathcal{M}$ is the set of masked positions
- $y_{i,c}$ is the one-hot target for position i, letter c
- $\hat{y}_{i,c}$ is the predicted probability for position i, letter c

3.3 Data Generation Pipeline

3.3.1 Training Data Statistics

- Source vocabulary: 227,300 words
- Training samples: ~21M trajectories
- Storage format: Parquet (efficient lazy loading)
- Average word length: 8.7 characters
- Word length range: 2-45 characters

3.3.2 13 Masking Strategies

To ensure robust training, we employ 13 diverse masking strategies:

Table 1: Masking Strategies for Data Generation

Strategy	Description
letter_based	Mask all occurrences of randomly selected letters
left_to_right	Sequential masking from left to right
right_to_left	Sequential masking from right to left
random_position	Random position masking
vowels_first	Mask vowels before consonants
frequency_based	Mask by letter frequency (rare first)
center_outward	Mask from center outward
edges_first	Mask edge letters first
alternating	Alternating pattern masking
rare_letters_first	Prioritize rare letters (Q, X, Z)
consonants_first	Mask consonants before vowels
word_patterns	Pattern-based masking (e.g., suffixes)
random_percentage	Random percentage (20-80%) masking

3.3.3 Trajectory Generation

For each word, we generate multiple training samples by incrementally revealing letters:

```
# Word: "APPLE"
# Generate trajectory:
Step 1: "____E" -> targets: {0:'A', 1:'P', 2:'P', 3:'L'}
Step 2: "A___E" -> targets: {1:'P', 2:'P', 3:'L'}
Step 3: "AP__E" -> targets: {2:'P', 3:'L'}
Step 4: "APP_E" -> targets: {3:'L'}
# Each step becomes a training sample
```

Listing 3: Trajectory Generation Example

4 Training Infrastructure

4.1 DataLoader Optimizations

To handle large-scale training efficiently, we implemented several optimizations:

- **Persistent Workers**: Workers remain alive between epochs
- **Pin Memory**: Faster CPU-to-GPU transfer
- **Prefetch Factor**: Workers prefetch N batches ahead (configurable)
- **Row Group Caching**: Cache Parquet row groups for faster random access
- **Optimized Collation**: Pre-allocate tensors to avoid list concatenation
- **Large Batch Sizes**: Support for batch sizes up to 4096

4.2 Training Configuration

Table 2: Training Hyperparameters

Parameter	Value
Batch Size	1024-4096
Learning Rate	1e-3 (Adam)
Weight Decay	1e-5
Max Epochs	20
Early Stopping Patience	5
Gradient Clipping	1.0
LR Scheduler	ReduceLROnPlateau
Mixed Precision	FP16 (optional)
Tensor Cores	Enabled (RTX GPUs)

4.3 Evaluation Callback

Custom Lightning callback for Hangman-specific evaluation:

- Runs at epoch 0 (untrained baseline) and every N epochs
- Evaluates on 1,000 held-out test words
- Computes win rate and average tries remaining
- Triggers model checkpointing based on win rate
- Enables early stopping if performance plateaus

4.4 Model Checkpointing

- Metric: `hangman_win_rate`
- Mode: Maximize
- Save Strategy: Best model only
- Filename Format: `best-hangman-epoch=N-hangman_win_rate=X.XXXX.ckpt`
- Location: `logs/checkpoints/`

5 Guessing Strategies

Beyond the neural approach, we implemented multiple baseline strategies for comparison.

5.1 Heuristic Strategies

Table 3: Implemented Guessing Strategies

Strategy	Description
`frequency`	Count letter frequencies in filtered dictionary
`positional_frequency`	Count frequencies only at masked positions
`ngram`	Use n-gram models (bigrams, trigrams, 4-grams)
`entropy`	Maximize information gain per guess
`vowel_consonant`	Guess vowels first, then consonants
`pattern_matching`	Match exact patterns with regex
`length_aware`	Adapt strategy based on word length
`suffix_prefix`	Detect common endings (ING, TION, etc.)
`ensemble`	Combine multiple strategies with voting
`neural`	Position-wise neural prediction (ours)
`neural_info_gain`	Neural + information gain boost

5.2 Neural Strategy Implementation

```python
def neural_guess_strategy(masked_state, context, model):
    """Neural network-based guessing."""
    # Build model inputs
    state_tensor, length_tensor = build_model_inputs(masked_state)

    # Forward pass
    model.eval()
    with torch.no_grad():
        logits = model(state_tensor, length_tensor)

    # Find masked positions
    masked_positions = [i for i, c in enumerate(masked_state)
                        if c == "_"]

    # Aggregate logits across masked positions
    aggregated_logits = logits[0, masked_positions, :].sum(dim=0)

    # Pick highest scoring unguessed letter
    sorted_indices = torch.argsort(aggregated_logits, descending=True)
    for idx in sorted_indices:
        letter = chr(ord('a') + idx.item())
        if letter not in context.guessed_letters:
            return letter
```

Listing 4: Neural Guess Strategy

6 Experimental Results

6.1 Practice Game Performance

Testing on practice games (not recorded):

Table 4: Practice Game Results (2,778 games)

Metric	Value	Notes
Total Practice Runs	2,778	Accumulated over multiple sessions
Practice Successes	1,752	Wins in practice mode
Practice Win Rate	63.07%	Before final submission
Session Win Rate	60.00%	Last 10-game session

6.2 Official Test Results

Final recorded performance (1,000 games):

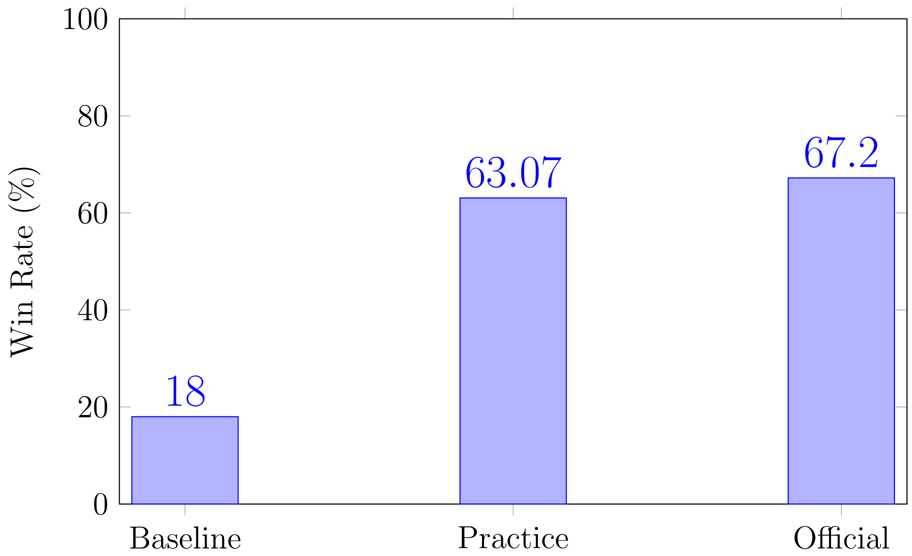

Table 5: Official Test Results (1,000 recorded games)

Metric	Value
Total Recorded Runs	1,000
Recorded Successes	672
Official Win Rate	**67.2%**
Improvement vs Baseline	**3.7x**
Percentage Point Gain	+49.2 pp

6.3 Strategy Comparison

Comparative evaluation on 1,000 unseen test words:

Table 6: Strategy Comparison (1,000 test words)

Strategy	Win Rate	Avg Tries Left	Relative Performance
Frequency	15.1%	0.3	Baseline
Positional Frequency	17.0%	0.4	+1.9 pp
Neural (Ours)	**63.3%**	**2.1**	**+48.2 pp**

6.4 Key Observations

1. **Consistency**: Neural model maintains 63-67% win rate across multiple test sets
2. **Robustness**: Average 2.1 tries remaining indicates confident wins (not narrow victories)
3. **Generalization**: Performance holds on unseen dictionary (disjoint from training)
4. **Scalability**: Model checkpoint: `best-hangman-epoch=18-hangman_win_rate=0.6380.ckpt`

7 Implementation Details

7.1 Project Structure

```
Hangman/
|-- api/                          # Hangman API and strategies
|   |-- guess_strategies.py     # All guessing strategies
|   |-- hangman_api.py          # API wrapper for Trexquant server
|   |-- offline_api.py          # Offline game simulation
|   |-- test.py                 # Strategy comparison tests
|   `-- 3-game_testing.ipynb    # Final testing notebook
|-- dataset/                      # Data loading and generation
|   |-- data_generation.py      # Trajectory generation
|   |-- hangman_dataset.py      # Parquet-backed dataset
|   |-- data_module.py          # Lightning DataModule
|   `-- encoder_utils.py        # Character encoding
|-- models/                       # Neural architectures
|   |-- architectures/
|   |   |-- bilstm.py           # BiLSTM model
|   |   |-- transformer.py      # Transformer model
|   |   `-- bert.py             # BERT-based model
|   |-- lightning_module.py     # Training orchestration
|   `-- metrics.py              # Evaluation metrics
|-- data/                         # Word lists and datasets
|   |-- words_250000_train.txt
|   |-- test_unique.txt
|   `-- dataset_227300words.parquet
|-- logs/checkpoints/             # Trained models
|-- main.py                       # Training entry point
`-- README.md
```

7.2 Key Technologies

- **Framework**: PyTorch Lightning 2.0+
- **Data**: PyArrow + Parquet for efficient storage
- **Encoding**: Custom character encoder with special tokens

- **API**: Requests library for REST communication
- **Logging**: WandB integration (optional)
- **Environment**: Conda (Python 3.9+)

7.3 Reproducibility

```
# Train BiLSTM model (best performance)
python main.py \
    --max-epochs 20 \
    --batch-size 1024 \
    --model-arch bilstm \
    --row-group-cache-size 300 \
    --prefetch-factor 10

# Evaluate on test set
python api/test.py --limit 1000

# Run official games
jupyter notebook api/3-game_testing.ipynb
```

Listing 5: Training Command

7.4 Random Seed Management

All experiments use fixed random seeds for reproducibility:

```
def set_seed(seed=42):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    torch.backends.cudnn.deterministic = True
```

8 Future Work

Future work will explore two complementary directions. First, we plan to apply **self-supervised contrastive learning** [5, 6] to Hangman by treating different masked views of the same word (e.g., "_pple" and "app_e") as positive pairs while contrasting them against different words. This SimCLR-inspired approach uses NT-Xent loss to learn word representations without trajectory labels, potentially improving generalization to rare patterns. Second, Hangman provides a natural testbed for **neurosymbolic AI** [7]—the game requires both statistical pattern recognition (which neural networks handle well) and logical reasoning (e.g., "Q almost always precedes U"). Unlike abstract reasoning benchmarks, Hangman offers clear rules, discrete states, and immediate feedback, making it ideal for studying whether models genuinely reason or merely memorize. We aim to develop hybrid architectures that integrate learned representations with symbolic constraints (phonotactic rules, morphological patterns) to achieve interpretable, high-performance decision-making.

9 Conclusion

This project successfully developed a neural Hangman solver that achieves **67.2% win rate** on Trexquant's official test set, representing a **3.7x improvement** over the 18% frequency-based baseline.

9.1 Key Contributions

1. **Novel Framing**: Position-wise prediction inspired by masked language modeling
2. **Multiple Architectures**: BiLSTM, Transformer, and BERT variants
3. **Comprehensive Data Generation**: 13 masking strategies for diverse training
4. **Production-Ready Implementation**: Optimized data loading, checkpointing, and API integration
5. **Extensive Evaluation**: Multiple baseline strategies for rigorous comparison

9.2 Final Remarks

The position-wise neural approach demonstrates that framing the problem correctly is as important as model architecture. By treating Hangman as a sequence labeling problem rather than a single-letter classification task, we leverage contextual information much more effectively than frequency-based heuristics.

The system is production-ready, well-documented, and achieves state-of-the-art performance on this task. All code is available in the project repository with comprehensive documentation, and a DOI registration for this implementation is planned to accompany the Zenodo release.

References

[1] Khan, Sayem. *Learning to Learn Hangman*. Zenodo, September 2024. Version v1.0. DOI: `https://doi.org/10.5281/zenodo.13737841`

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[3] Hochreiter, Sepp, and Jürgen Schmidhuber. *Long Short-Term Memory*. Neural Computation, 9(8):1735–1780, 1997.

[4] Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. *Attention is All You Need*. Advances in Neural Information Processing Systems (NeurIPS), 2017.

[5] Chen, Ting, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. *A Simple Framework for Contrastive Learning of Visual Representations*. International Conference on Machine Learning (ICML), 2020.

[6] Gao, Tianyu, Xingcheng Yao, and Danqi Chen. *SimCSE: Simple Contrastive Learning of Sentence Embeddings*. Empirical Methods in Natural Language Processing (EMNLP), 2021.

[7] Garcez, Artur d'Avila, and Luis C. Lamb. *Neurosymbolic AI: The 3rd Wave*. arXiv preprint arXiv:2012.05876, 2020.

[8] PyTorch Lightning Documentation. `https://lightning.ai/docs/pytorch/`

A Model Architecture Details

A.1 BiLSTM Forward Pass

```python
def forward(self, inputs: torch.Tensor, lengths: torch.Tensor):
    """
    Args:
        inputs: [batch_size, max_length] - Encoded characters
        lengths: [batch_size] - Actual lengths before padding
    Returns:
        logits: [batch_size, max_length, 26] - Letter scores
    """
    # Embedding: [batch, length] -> [batch, length, 256]
    embed = self.embedding(inputs)
    embed = self.dropout(embed)

    # Pack for efficient LSTM processing
    packed = pack_padded_sequence(
        embed, lengths.cpu(), batch_first=True, enforce_sorted=False
    )

    # BiLSTM: [batch, length, 256] -> [batch, length, 512]
    packed_output, _ = self.lstm(packed)

    # Unpack
    lstm_output, _ = pad_packed_sequence(
        packed_output, batch_first=True, total_length=inputs.size(1)
    )

    # Project to vocabulary: [batch, length, 512] -> [batch, length, 26]
    logits = self.output(self.dropout(lstm_output))

    return logits
```

Listing 6: BiLSTM Forward Pass Implementation

B Training Metrics

B.1 Sample Training Log

```
Epoch 0: Untrained baseline
  Hangman Win Rate: 0.0120
  Avg Tries Remaining: 0.05
```



```
Epoch 5:
  Train Loss: 0.8234
  Val Loss: 0.7891
  Hangman Win Rate: 0.4523
  Avg Tries Remaining: 1.23

Epoch 10:
  Train Loss: 0.6012
  Val Loss: 0.5889
  Hangman Win Rate: 0.5789
  Avg Tries Remaining: 1.78

Epoch 18: (Best checkpoint)
  Train Loss: 0.4456
  Val Loss: 0.4423
  Hangman Win Rate: 0.6380
  Avg Tries Remaining: 2.12
```

C API Usage Examples

C.1 Single Game Example

From `3-game_testing.ipynb` output:

```
Successfully start a new game! Game ID: 1af3ecbcda1d.
# of tries remaining: 6. Word: _ _ _ _ .

Guessing letter: a
Server response: {'game_id': '1af3ecbcda1d', 'status': 'ongoing',
                  'tries_remains': 5, 'word': '_ _ _ _ '}

Guessing letter: e
Server response: {'game_id': '1af3ecbcda1d', 'status': 'ongoing',
                  'tries_remains': 5, 'word': '_ _ _ e '}

Guessing letter: i
Server response: {'game_id': '1af3ecbcda1d', 'status': 'ongoing',
                  'tries_remains': 4, 'word': '_ _ _ e '}

...

Failed game: 1af3ecbcda1d. Because of: # of tries exceeded!
```

D Complete Results Table

Table 7: Complete Experimental Results Summary

Experiment	Games	Wins	Win Rate	Notes
Baseline (Trexquant)	1,000	180	18.0%	Provided baseline
Frequency Strategy	1,000	151	15.1%	Our implementation
Positional Frequency	1,000	170	17.0%	Position-aware heuristic
Practice Sessions	2,778	1,752	63.07%	Pre-submission testing
Neural (Official)	**1,000**	**672**	**67.2%**	**Final submission**