# Ainslee's RL Final Project Environment Design

This environment simulates a character-level spell correction task. Each episode begins with a real English word that has been corrupted using DeepWordBug. The agent sees the corrupted version and attempts to restore it to the correct (original) spelling using one-character substitutions. The environment is built to be compatible with OpenAI Gymnasium and can be used with discrete-action RL algorithms like PPO or DQN.

#### • Observation Space

- obs: a fixed-length sequence of characters (e.g., max 10), padded as needed
- Characters are integer-encoded (a=1 to z=26, PAD=0).
- Represented as a 1D NumPy array of length max\_word\_length

#### • Action Space

- Discrete space of size max\_word\_length × 26.
  - \* Each action encodes a tuple (position, new\_char), where:
    - position ∈ [0, max word length 1]
    - new\_char ∈ [0, 25], representing 'a' through 'z'
  - \* To decode:

```
position = action // 26
char_index = action % 26
new_char = chr(97 + char_index) # ASCII for 'a' is 97
```

- \* This is functionally the same as using (position, letter) directly, but flattened into a single integer for Gymnasium's Discrete(n) action space. This keeps the interface simple for standard agents that expect discrete actions.
- \* I could instead define a MultiDiscrete([max\_word\_length, 26]) action space if I'd rather keep the (position, char) tuple literal.

#### • Step Output Format

- The step(action) method returns:

obs, reward, terminated, truncated, info

- \* obs: the new word state, integer-encoded and padded
- \* reward: see reward structure below
- \* terminated: True if the agent has restored the word exactly
- \* truncated: True if max number of steps reached
- \* info: a dict with optional metadata (maybe: edit distance or original word)

### • Reward Structure

- Sparse by default:
  - \* +1.0 if the current word exactly matches the ground truth (i.e., the correct word **before** it was corrupted with DeepWordBug)
  - \* 0.0 otherwise
- Optional: negative shaping via normalized edit distance:
  - \* The agent receives -normalized\_edit\_distance(current,

## target), where:

- normalized\_edit\_distance = edit\_distance / max(len(current), len(target))
- $\cdot\,$  This penalizes edits that move the agent farther from the correct answer.
- · Encourages more efficient and targeted edits.
- \* This can be introduced if sparse rewards prove too difficult for learning.

#### • Done Condition

- terminated = True if current word == original word (i.e., correct spelling)
- truncated = True if step count  $\geq$  to max\_steps
- The episode ends when either is **True**.