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# Learning Robust Bipedal Locomotion On Tilled Farm Soils via Multistages Deep Reinforcement Learning

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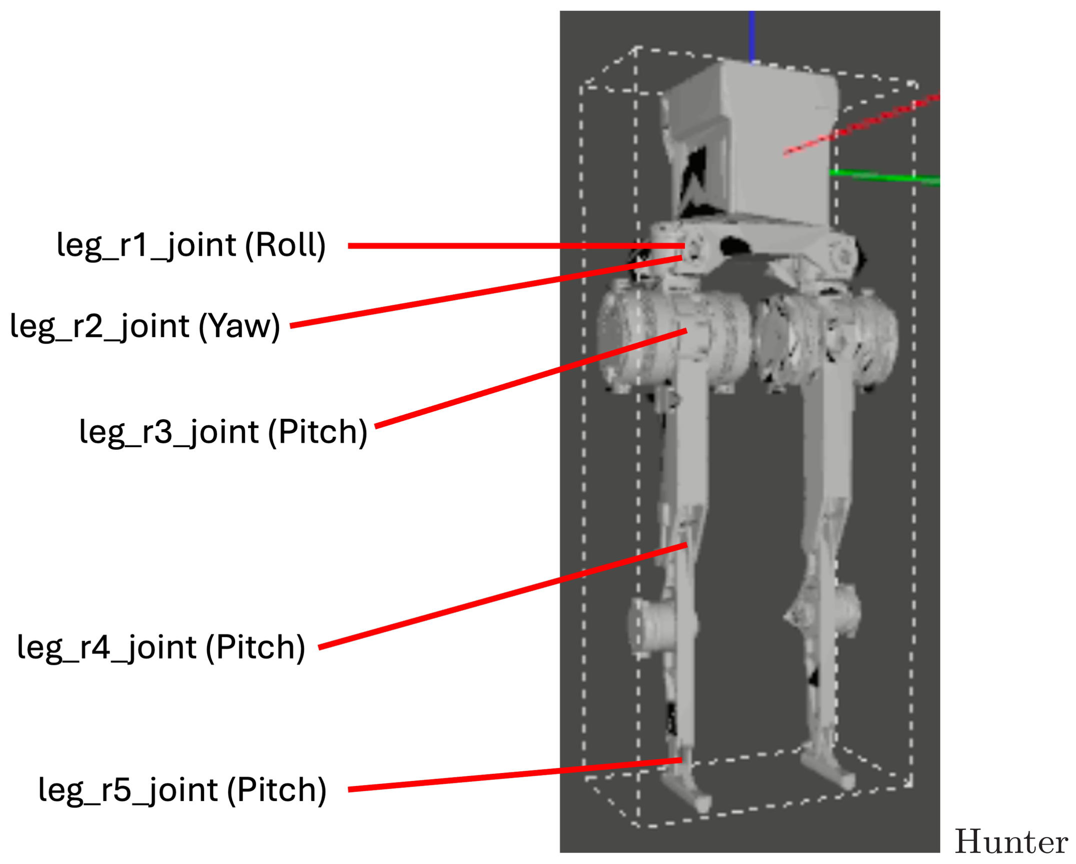
## 1. Introduction

Agricultural robotics faces significant challenges when operating in **unstructured farm environments**. Traditional bipedal robots struggle with variable soil conditions, **ranging from hard-packed earth to soft, wet to dry terrain**. This research presents a novel multistages approach using deep reinforcement learning to train a bipedal robot (Hunter) for robust locomotion across agricultural soil structures. Our three-stage curriculum progressively increases terrain complexity: plane terrain → soft soil → farm soil, enabling the robot to **develop adaptive walking strategies essential for agricultural applications**.

## 2. Robot Platform

**EC-Hunter80-V01 Specifications:**

- **DOF:** 10 (legs only)
- **Mass:** 12.7 kg
- **Height:** 0.6 m standing
- **Structure:** Bipedal with base platform
- **Actuators:** 23.7 Nm max torque




Robot Joint Configuration

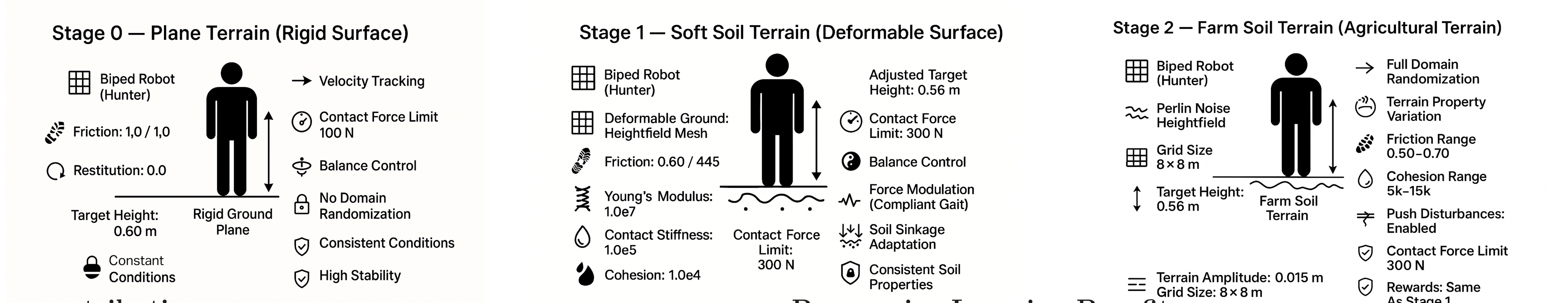
**Joint Mapping:**

- Hip: Roll, Yaw, Pitch (3 DOF/leg)
- Knee: Flexion (1 DOF/leg)
- Ankle: Dorsiflexion (1 DOF/leg)

## 3. Contribution: Three-Stage Curriculum Learning

Our approach progressively increases environmental complexity to develop robust locomotion skills:

| Stage | Environment | Terrain Properties | Domain Randomization | Reward Function | Skills Developed | Training Purpose |
|---|---|---|---|---|---|---|
| **Stage 0** | Plane Terrain (Rigid surface) | • Mesh: plane • Friction: 1.0/1.0 • Restitution: 0.0 • High stability | None • Push disturbances • No parameter variation • Consistent conditions | Standard locomotion rewards • Target height: 0.6m • Contact force limit: 100N | • Basic bipedal gait • Joint coordination • Velocity tracking • Balance control | Foundation stage for loading pretrained models • Establishes baseline walking patterns |
| **Stage 1** | Soft Soil (Deformable surface) | • Mesh: heightfield • Young's modulus: 1.0e7 • Contact stiffness: 1.0e5 • Cohesion: 1.0e4 • Friction: 0.60/0.45 | None • No randomization • Consistent soil properties • Stable learning conditions | Soil-adapted rewards • Adjusted height: 0.56m • Contact force limit: 300N • Reduced penalties for slip/orientation | • Adaptive foot placement • Force modulation • Compliant surface gait • Soil sinkage adaptation | Introduces soil physics without complexity of randomization • Smooth progression from rigid to soft |
| **Stage 2** | Farm Soil (Agricultural terrain) | • Same soil physics • Terrain amplitude: 0.015 • Perlin noise generation • 8x8m terrain grid • 64x64 resolution | Full randomization • Push disturbances: disabled • Terrain property variation • Friction range: [0.50,0.70] • Cohesion range: [5k,15k] | Same as Stage 1 • Handles variability • Maintains tracking performance under uncertainty | • Robust terrain adaptation • Multi-modal locomotion • Environmental adaptation • Disturbance rejection • Parameter robustness | Maximum robustness training with all environmental variations • Prepares for real-world deployment |




**Our contributions:**

- Introduce a three-stage soil-aware curriculum (rigid → soft soil → farm soil)
- Design soil-tuned rewards and PD gains
- Demonstrate robust biped locomotion in photorealistic Isaac Sim farm-soil with push recovery-targeting agricultural robots

**Progressive Learning Benefits:**

- Stable foundation building in Stage 0
- Gradual complexity introduction prevents training instabilities
- Transfer learning between stages accelerates convergence
- Final policy generalizes across diverse soil conditions

## 4. Deep RL Architecture

**Algorithm:** Proximal Policy Optimization (PPO)
**Neural Network:**

- Actor: 512→256→128 (ELU activation)
- Critic: 512→256→128 (ELU activation)
- Output: 10D action space (joint commands)

**Key Reward Components:**

- **Tracking:** Linear/angular velocity following
- **Stability:** Orientation and height maintenance
- **Energy:** Torque and acceleration penalties
- **Contact:** Proper foot placement rewards
- **Safety:** Joint limits and collision avoidance

**Observation Space (45D):**

- Base orientation, velocity
- Joint positions, velocities
- Contact states
- Command targets

## 5. Technical Innovations

**Reward System Design:**

- Multi-objective optimization balancing performance and efficiency
- Hierarchical penalty structure prioritizing safety
- Contact-aware rewards for foot-ground interaction

**Morphology Adaptation:**

- URDF standardization for policy transfer
- Joint limit calibration matching hardware specs
- Contact sensor mapping for ground interaction

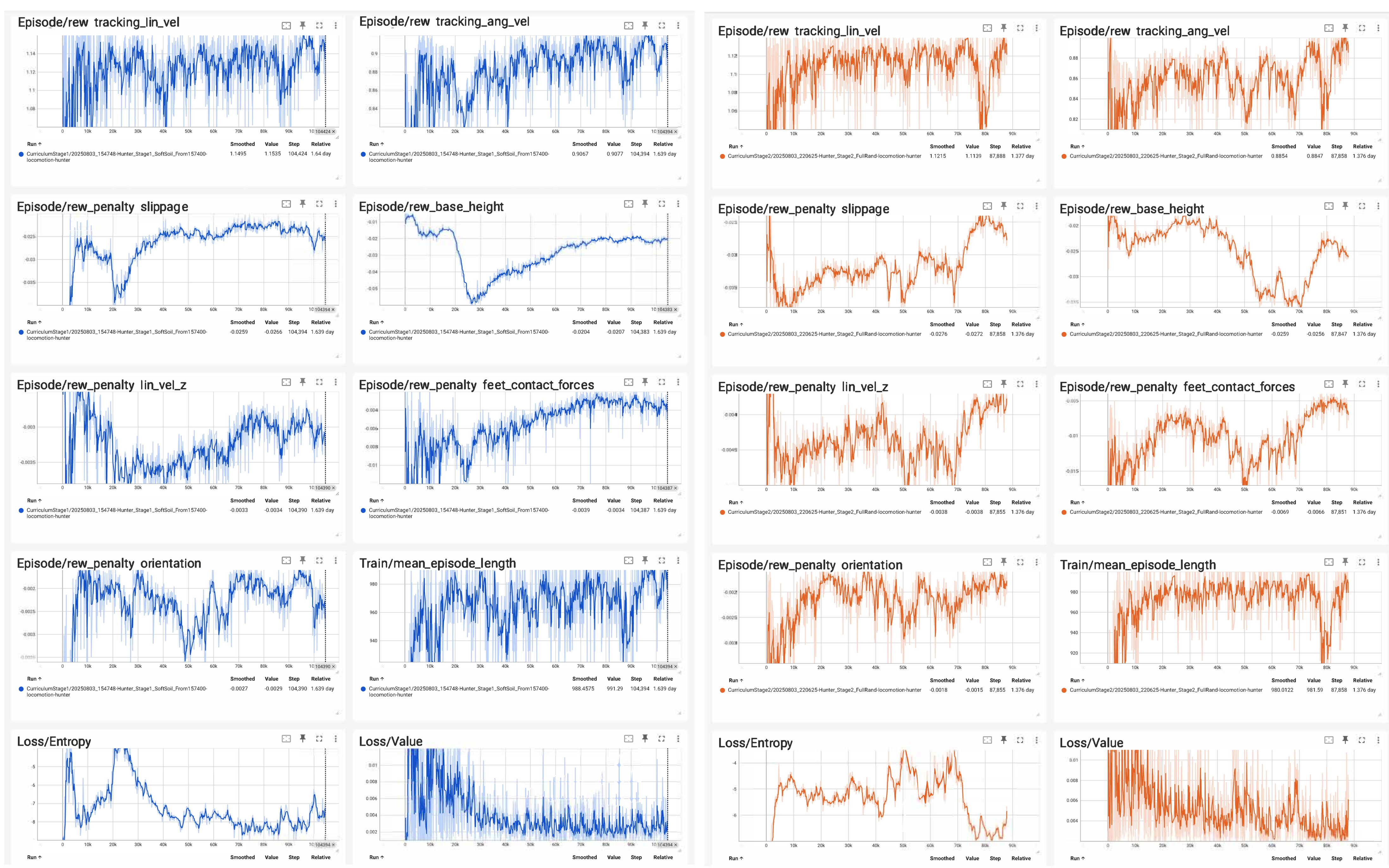
**Training Optimizations:**

- Episode timing: 50 Hz control frequency
- Batch learning: 5 epochs per iteration
- Curriculum scheduling: Progressive difficulty increase

## 6. Related Work

- **Sim-to-real legged locomotion.** Learning-based controllers achieve robust quadruped locomotion in natural terrain and drastically reduced training times via massive parallelism [1,2]. Rapid Motor Adaptation handles unseen dynamics through online adaptation [3].
- **Deformable terrain.** High-speed locomotion on soft sand using contact-aware training highlights the need to model soil compliance [4].
- **Imitation and skill priors.** Motion imitation (e.g., DeepMimic) seeds policies with natural gaits that transfer well [5].
- **Hybrid control.** Combining RL with heuristic components can improve biped stability and sim-to-real transfer [6].
- **Curriculum learning.** Structured curricula enable reliable biped learning over complex terrains [7].
- **Humanoids on compliant ground.** Recent results demonstrate robust DRL walking on HRP-5P over uneven, compliant terrain [8].

## 7. Experiments




Learning curves (left is stage 1, right is stage 2) showing rewards convergence.

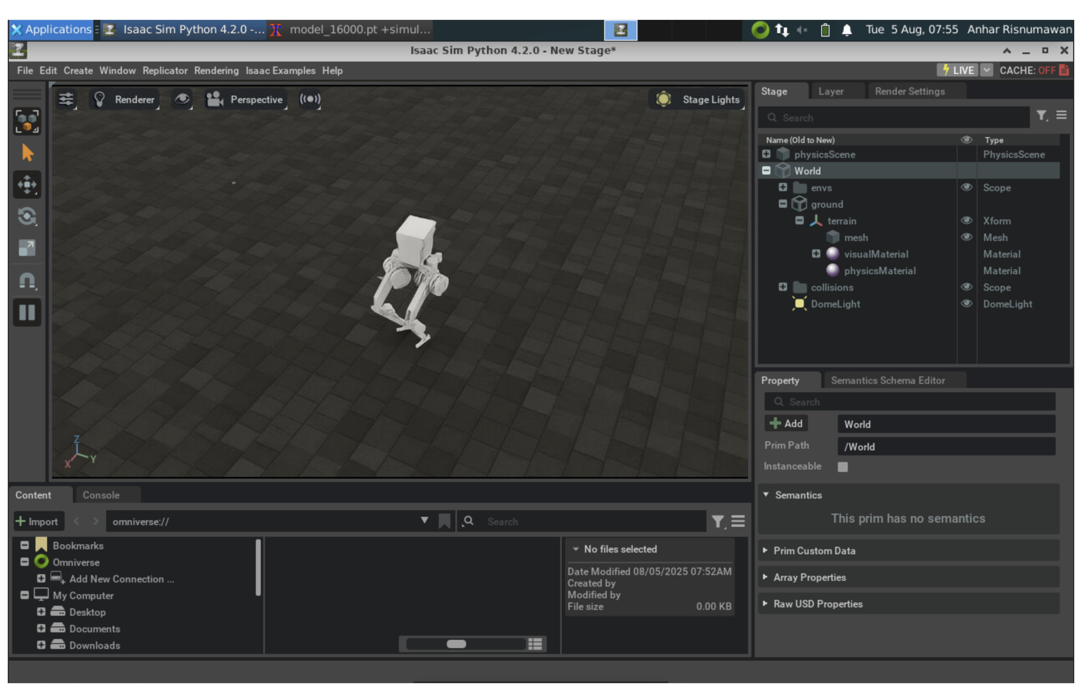
**Key Training Achievements:**

- Successful locomotion learning within $\approx 100K$ iterations
- Stable upright posture maintenance (base_height penalty minimized)
- Effective velocity tracking (tracking rewards maximized)
- Energy-efficient gait patterns (torque penalties reduced)
- Robust balance control under external disturbances (0.5 m/s push resistance)

**Performance Metrics:**

- Walking speed: ±0.5 m/s target tracking
- Episode length: 20 seconds (1000 control steps at 50 Hz)
- Success rate: >90% episode completion
- Balance recovery: Maintains stability under lateral pushes

## 8. Soil Adaptation Capabilities



Hunter robot navigating across different soil environments: plane terrain → soft soil → farm soil

**Stage 2 - Farm Soil Locomotion:**

- Integration of plane terrain skills with soft soil adaptations
- Robust performance across wet to dry agricultural soil conditions
- Possible applicability for farming operations and crop monitoring

## 9. Conclusions & Future Work

**Conclusions:**

1. Demonstrated multistages learning for agricultural soil locomotion
2. Successful deep RL training of Hunter biped
3. Comprehensive reward system for bipedal stability

**Future Directions:**

- Real hardware deployment and validation
- Long-duration autonomous field operations

## 10. References

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