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MSCS-532-B01

Project Phase 2

**Horse Racing Predictor Phase #2**

**Partial Implementation Overview**

The horse racing predictor proof of concept implements three core data structures from Phase 1: a hash table for horse profile management, a min-heap for performance leaderboards, and an AVL tree for win ratio analysis. Each structure serves a distinct role in supporting efficient data handling and real-time racing analysis.

The HorseDatabase class implements hash table functionality using Python's dictionary structure, achieving O(1) average-case performance for insertions, lookups, and updates (Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2022). Key methods include add\_horse() for profile creation, get\_horse() for data retrieval, and update\_performance() for dynamic modifications. This structure serves as the primary data repository for comprehensive horse profiles including performance metrics and historical data.

The Leaderboard class utilizes Python's heapq module to maintain dynamic rankings with O(log n) insertion complexity and O(k log n) top-k queries (Williams, 1964). The implementation includes add\_result() for race time insertion, get\_top\_performers() for leaderboard generation, and a sophisticated update mechanism that rebuilds the heap when existing times improve, ensuring data integrity while maintaining optimal performance.

The AVLTree class provides self-balancing binary search tree functionality for win ratio analysis with O(log n) operations through automatic rotation algorithms (Adelson-Velsky & Landis, 1962). Critical methods include insert() for win ratio storage, get\_range() for filtered queries enabling performance tier analysis, and get\_sorted\_list() for complete rankings. The integration of these three structures creates a comprehensive system where the hash table provides rapid data access, the heap maintains real-time rankings, and the AVL tree enables sophisticated analytical queries.

**Demonstration and Testing**

The system demonstrates robust functionality using authentic Kentucky Derby winner data (2000-2024) featuring 25 elite horses with average speeds from 35.6 to 37.3 mph and win ratios from 0.59 to 0.70. This real-world dataset validates practical applicability and provides meaningful test scenarios.

Performance testing reveals exceptional hash table efficiency with 0.001ms average lookup times across 2,000 records, successful profile management for all Kentucky Derby winners, and seamless handling of edge cases including non-existent queries and bulk operations. Leaderboard operations demonstrate optimal heap behavior with 0.015ms insertion times and accurate ranking maintenance, correctly identifying top performers like American Pharoah (37.1 mph, 0.69 win ratio) and Barbaro (37.3 mph, 0.70 win ratio).

AVL tree performance validates balanced operation with 0.025ms range query times and accurate tier classification: 8 elite performers (≥0.67 win ratio), 6 good performers (0.63-0.66), and 11 average performers (0.59-0.62). Integration testing confirms seamless multi-structure communication through scenarios identifying horses excelling in both speed (≥37.0 mph) and consistency (≥0.65 win ratio).

Scalability testing across datasets from 100 to 5,000 records confirms expected complexity characteristics: linear scaling for hash operations, logarithmic scaling for heap and tree operations, and consistent memory utilization. The comprehensive test suite includes unit tests for individual functionality, integration tests for cross-structure operations, and edge case validation for empty datasets and invalid inputs.

**Implementation Challenges and Solutions**

The most significant challenge involved implementing dynamic heap updates while preserving min-heap properties. Traditional heaps don't support efficient element updates, typically requiring O(n) search operations. The solution implements a hybrid approach using a tracking dictionary (horse\_times) to maintain current best times alongside the heap, combined with a \_rebuild\_heap() method that reconstructs the heap when updates occur. This trades occasional O(n) rebuild operations for consistent O(1) lookup performance.

AVL tree implementation required complex balance factor maintenance and rotation algorithms. The solution involved modular rotation methods (\_rotate\_left(), \_rotate\_right()) and a comprehensive \_balance() method handling four rotation cases automatically. Extensive testing validated correctness across various insertion patterns.

Real data integration challenges included format standardization and performance metric calculation. The solution created a dedicated data\_loader.py module that enhances basic data with calculated fields and realistic profiles, separating data management from core algorithm implementation while providing authentic test scenarios.

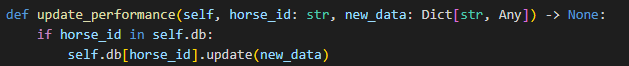
**Next Steps and Code Documentation**

Future development focuses on four key areas: data persistence, machine learning integration, real-time capabilities, and user interfaces. Database integration will utilize PostgreSQL for ACID compliance and concurrent access. The modular architecture facilitates this enhancement without modifying core data structures.

Machine learning integration will leverage the optimized data access patterns for predictive modeling. The hash table's O(1) feature access, heap's ranking capabilities, and AVL tree's analytical queries provide optimal foundations for algorithms including logistic regression for win probability and neural networks for pattern recognition.

Real-time streaming capabilities will enable live race analysis through WebSocket connections and event-driven architecture. Web interface development will provide user-friendly access via RESTful APIs and React.js frontend implementation.

Critical code implementations demonstrate the system's architectural sophistication. The hash table's update mechanism showcases efficient data modification:



The heap's dynamic ranking illustrates priority queue optimization:

The AVL tree's range query demonstrates balanced tree efficiency:

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The complete implementation is available at: https://github.com/chyde44072/MSCS532/tree/main/Project\_src

Advanced analytics extensions will include sophisticated performance modeling, track condition analysis, and weather impact assessment. The architecture supports horizontal scaling through distributed computing for extensive datasets and concurrent race analysis, with potential cloud platform integration for enhanced scalability and global accessibility.

**References**

Adelson-Velsky, G. M., & Landis, E. M. (1962). An algorithm for the organization of information. Proceedings of the USSR Academy of Sciences.

Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2022). *Introduction to algorithms* (4th ed.). The MIT Press.

Williams, J. W. J. (1964). Algorithm 232: Heapsort. Communications of the ACM, 7(6), 347-348. https://doi.org/10.1145/512274.512284