

Fido: A Universal Robot Control System using Reinforcement Learning with Limited Feedback

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Control System Objectives

Fido was created to fulfill the following goals:

- **Trainability:** Allow both human and autonomous training rather than reprogramming
- **Universality:** Run on any robot, even without prior knowledge of the host

These goals were achieved through the training of artificial neural networks with a wire-fitted moving least squares interpolator following the Q-learning reinforcement algorithm and an action selection policy that utilizes a Boltzmann distribution of probability.

Implementation

Fido was programmed in C++, with no external dependencies. However, the simulator does use the SFML graphics library. The hardware implementation uses the Intel Edison embedded platform, a 3D printed chassis and a differential drive system.

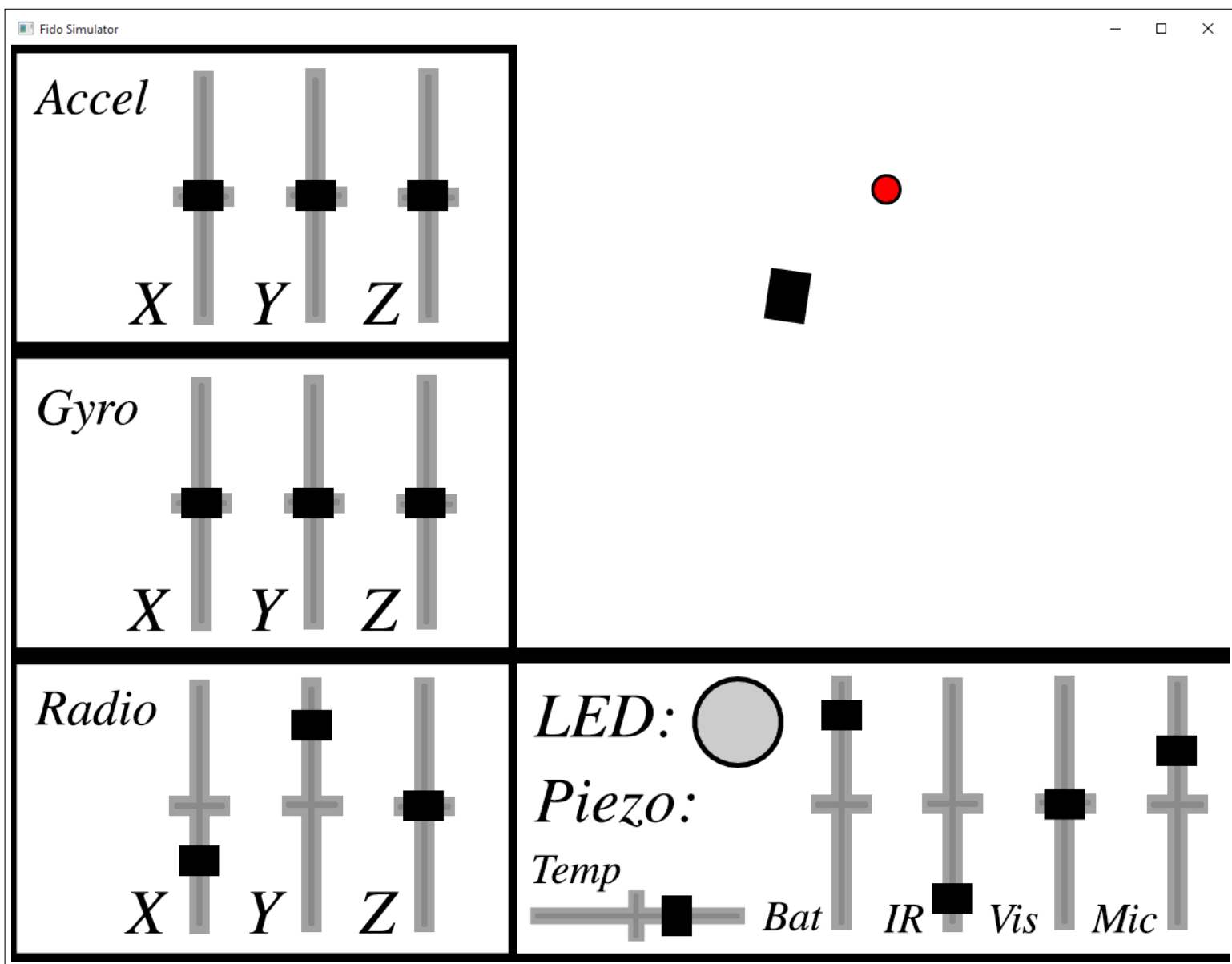


Figure 1: Fido Simulator Graphical User Interface

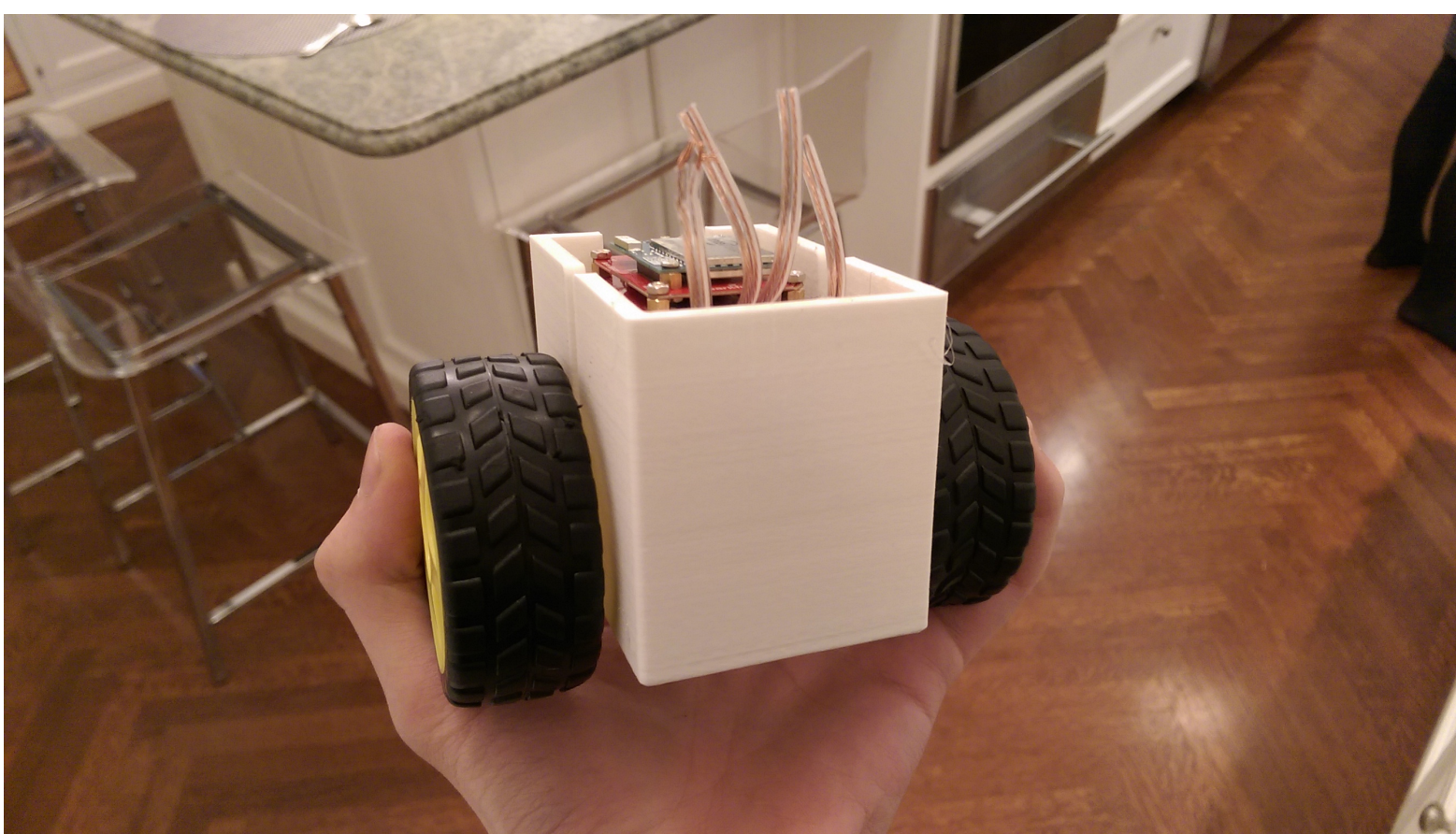


Figure 2: Fido Hardware Implementation

Learning Algorithm

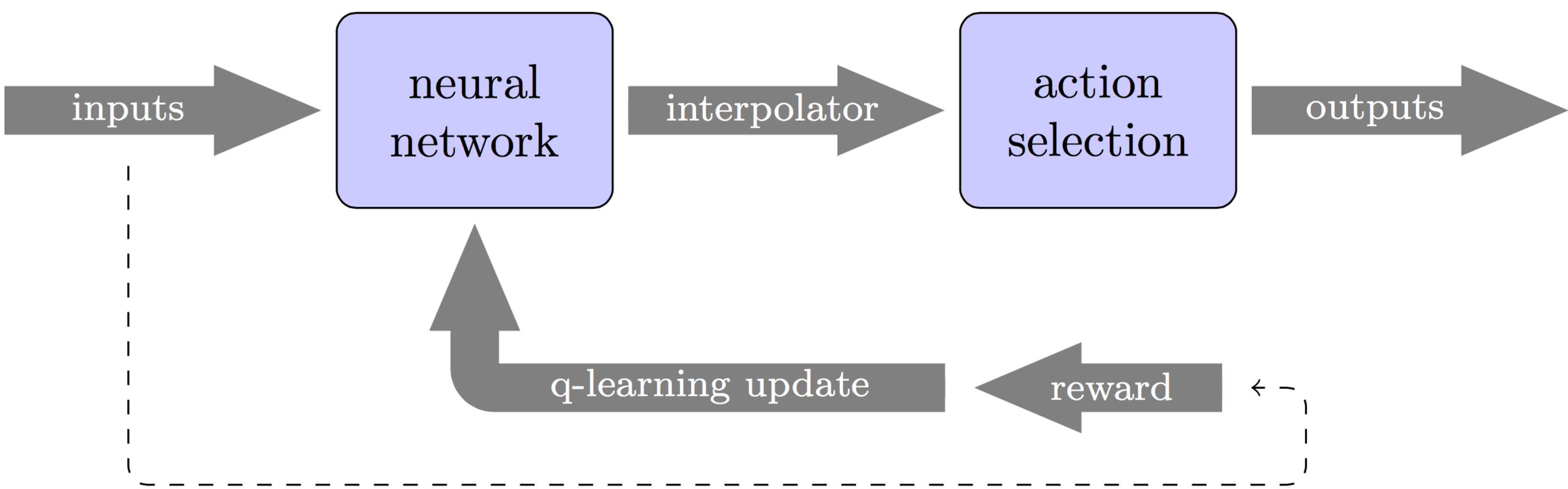


Figure 3: Control System Diagram

The following materials were required to complete the research:

- Curabitur pellentesque dignissim
- Eu facilisis est tempus quis
- Duis porta consequat lorem
- Eu facilisis est tempus quis

The materials were prepared according to the steps outlined below:

- 1 Curabitur pellentesque dignissim
- 2 Eu facilisis est tempus quis
- 3 Duis porta consequat lorem
- 4 Curabitur pellentesque dignissim

Reinforcement Learning

Action Selection Policy

Boltzmann stuff

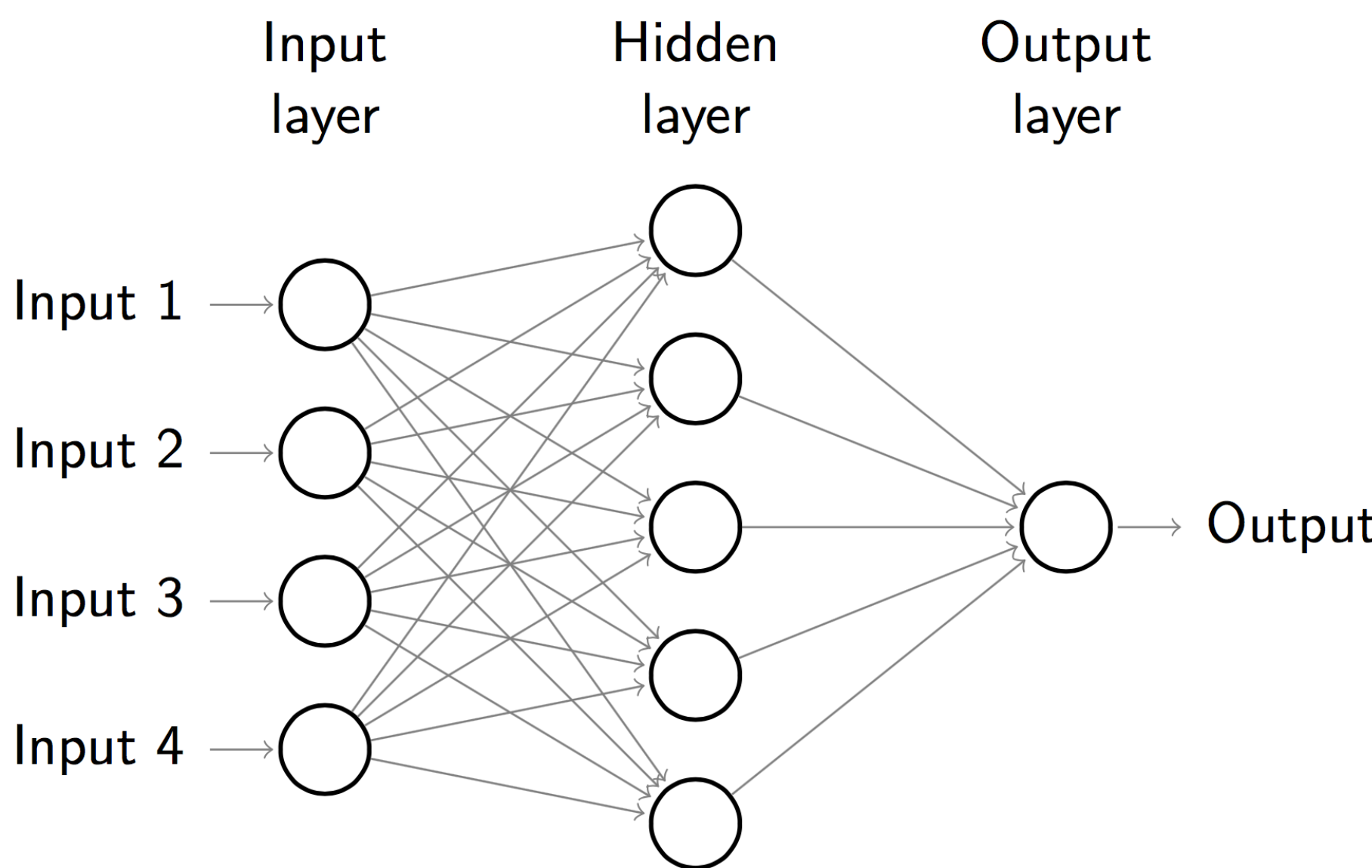


Figure 4: Single Output Feed-forward Neural Network

Future Development

Nunc tempus venenatis facilisis. **Curabitur suscipit** consequat eros non porttitor. Sed a massa dolor, id ornare enim. Fusce quis massa dictum tortor **tincidunt mattis**. Donec quam est, lobortis quis pretium at, laoreet scelerisque lacus. Nam quis odio enim, in molestie libero. Vivamus cursus mi at *nulla elementum sollicitudin*.

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Acknowledgements

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Results