RETROFIT

ReinforcemEnT leaRning algOrithm For HIV Treatment

drugs that target HIV in at

least two different ways,

mportant to efficacy and

preventing mutational

escape





U1 variable

U2 variable

HIV can be targeted in many places throughout its life cycle.

Aims

by binding to CD4

eceptors expressed on

the T cell surface

spreading and destroying

CD4 T cells

levels become

langerously low, and HIV

can develop into AIDS

(acquired immune

deficiency syndrome)

- Leverage reinforcement learning to tackle the complex issue of HIV treatment planning
- > Train a Q-learning algorithm to model to optimize treatment efficacy value to increase CD4 cell counts
- Show how the algorithm could be extended to predict optimal HIV treatment for a certain patient

Results **Theoretically derived results from [5] Empirically derived optimal solutions using Q**learning: **CD4 Cell Counts CD4 Cell Counts** 1200 1400 1000 1200

Methods

Three differential equations describing how the concentrations of uninfected CD4 (T), infected CD4 (V), and free HIV (I) evolve with time:



- **CD4 cell count** the number of healthy immune cells found in a patient, normally >500 cells/ μ L, indicates HIV progression and severity
- **Constrained vs unconstrained agent** The constrained agent is restricted to making smaller changes in the levels of U1 and U2, whereas the unconstrained agent can make arbitrary changes to the values of U1 and U2



(1)
$$\frac{dT}{dt} = rT\left(1 - \frac{T}{T_{max}}\right) - \frac{(1 - u_1)\beta VT}{1 + \alpha V}$$

(2) $\frac{dV}{dt} = (1 - u_2)N\mu I - \gamma V$ (3) $\frac{dI}{dt} = \frac{(1 - u_1)\beta VT}{1 + \alpha V} - \mu I$

Q-Learning:

- for state, action pairs
- 2. Agent performs an action
- 1. Initialise table of values 3. Environment is updated
 - 4. Reward calculated
 - 5. Value of the state, action pair is updated

Conclusions

- Successfully trained RL agent to increase CD4 count of a patient infected with HIV
- Found levels of U1 and U2 suggested by agent resemble those found through theoretical methods
- Developed a framework for the optimization of HIV treatment plans over more complex constraints

Next Steps

- Evaluate the performance of the agent against patient profiles and medical data
- Develop the agent to give it the capacity to generate optimal treatment plans
- Make the model more patient-specific by incorporating the treatments that have unique advantages and disadvantages (e.g. Pregnancy, mental health
- struggles, treatment resistance)

Figure 6: Optimal value of U2 against time

Time (*t*)

Generalise the technique to develop treatment plans for other illnesses



References

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[2] Gibas, K.M. et al. (2022) 'Two-drug regimens for HIV treatment', The Lancet HIV, 9(12), pp. e868–e883. Available at: https://doi.org/10.1016/S2352-3018(22)00249-1. [3] HIV and AIDS Epidemic Global Statistics (no date) HIV.gov. Available at: https://www.hiv.gov/hiv-basics/overview/data-and-trends/global-statistics [4] Ogunlaran, O.M. and Oukouomi Noutchie, S.C. (2016) 'Mathematical Model for an Effective Management of HIV Infection', BioMed Research International, 2016, p. e4217548. Available at:

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