# The unknotting number, hard unknot diagrams, and Reinforcement Learning 

Taylor Applebaum, Sam Blackwell, Alex Davies, Thomas Edlich, András Juhász, Marc Lackenby, Nenad Tomašev, and Daniel Zheng

University of Oxford

21 July 2023

## The unknotting number

- The unknotting number $u(\mathcal{D})$ of a diagram $\mathcal{D}$ of a knot $K$ is the minimal number of crossing changes required to obtain a diagram of the unknot
- $u(\mathcal{D}) \leq c(\mathcal{D}) / 2$
- $u(K):=\min \{u(\mathcal{D}): \mathcal{D}$ a diagram of $K\}$
- 6 out of 165 prime knots $K$ with $c(K) \leq 10$ and 660 out of 2978 prime knots $K$ with $c(K) \leq 12$ have unknown $u(K)$
- In comparison, smooth 4-genus $g_{4}(K)$ is known for $c(K) \leq 12$


## The knot $10_{8}$


(a) The knot 108

(b) Changing middle crossing

(c) After simplifying

- Only 25 knots in KnotInfo where $u(K)$ is known and $u(\mathcal{D})>u(K)$
- $10_{8}$ has a unique minimal diagram $\mathcal{D}$ with $u(\mathcal{D})=3$, but $u\left(10_{8}\right)=2$
- If we change the middle crossing of $10_{8}$, the resulting knot $\sigma_{2}$ has $u\left(\sigma_{2}\right)=1$, which can be seen after simplifying and changing the middle crossing
- By applying random Reidemeister moves, easy to find a diagram $\mathcal{D}^{\prime}$ of $10_{8}$ with $u\left(\mathcal{D}^{\prime}\right)=2$


## $u(K)$ versus $u(\mathcal{D})$



- Taniyama: given $K$ and $n$, there is a diagram $\mathcal{D}$ of $K$ with $u(\mathcal{D}) \geq n$
- Conjecture (Bernhard-Jablan): $\forall K$ has a minimal crossing number diagram $\mathcal{D}$ and a crossing $c$ such that changing $c$ gives a knot $K^{\prime}$ with

$$
u\left(K^{\prime}\right)=u(K)-1
$$

- Brittenham and Hermiller: At least one of $13 n 3370,12 n 288,12 n 491$, and 12 n501 violates the conjecture


## 13n3370



- 13 n3370 is the closure of the above 20 -crossing braid
- Changing the green crossing gives 11 n21 that has $u(11 n 21)=1$
- So $u(13 n 3370) \leq 2$, but hard to find a diagram $\mathcal{D}$ with $u(\mathcal{D})=2$ using random Reidemeister moves


## The Gordian distance

- Godrian graph G: vertices knots, edge if two knots are related by a crossing change
- Gordian distance $d\left(K, K^{\prime}\right)$ of $K$ and $K^{\prime}$ is the distance of $K$ and $K^{\prime}$ in $G$
- Baader: If $d\left(K, K^{\prime}\right)=2$, then $\exists$ infinitely many $K^{\prime \prime}$ such that $d\left(K, K^{\prime \prime}\right)=d\left(K^{\prime}, K^{\prime \prime}\right)=1$



## Computing the unknotting number

- Computing $u(\mathcal{D})$ is exponential in $c(\mathcal{D})$
- No algorithm known to compute $u(K)$
- Can often get a good upper bound on $u(K)$ by simplifying, changing a crossing such that the crossing number is minimal after simplifying and repeating
- $g_{4}(K) \leq u(K)$, so $\frac{|\sigma(K)|}{2}, \frac{|s(K)|}{2},|\tau(K)|,|\nu( \pm K)|$ give computable lower bounds
- We know $u(K)$ if upper and lower bounds agree; e.g.,

$$
u\left(T_{p, q}\right)=\frac{(p-1)(q-1)}{2}
$$

## Additivity of the unknotting number

- Conjecture: $u\left(K \# K^{\prime}\right)=u(K)+u\left(K^{\prime}\right)$
- Scharlemann: $u\left(K \# K^{\prime}\right) \geq 2$ if $K, K^{\prime} \neq U$
- Alishahi-Eftekhari: $u\left(K \# T_{p, q}\right) \geq p-1$ if $p<q$
- If, for example, $\operatorname{sgn}(\sigma(K))=\operatorname{sgn}\left(\sigma\left(K^{\prime}\right)\right)$ and $u(K)=\frac{|\sigma(K)|}{2}$ and $u\left(K^{\prime}\right)=\frac{\left|\sigma\left(K^{\prime}\right)\right|}{2}$, then $u\left(K \# K^{\prime}\right)=u(K)+u\left(K^{\prime}\right)$
- Unknown whether $u\left(T_{2,3} \#-T_{2,5}\right)=u\left(T_{2,3}\right)+u\left(T_{2,5}\right)$
- Strong conjecture: in every collection of unknotting crossing arcs for $K \# K^{\prime}$, there is one that can be isotoped into $K$ or $K^{\prime}$


Figure: A crossing arc and the corresponding crossing change

## Machine Learning

- Supervised Learning (SL): Given labelled data, learn a function that predicts the label, while minimising the error
- Can be classification (spam filter) or regression (predicting house prices, linear regression)
- Artificial Neural Network (ANN): A composition of affine maps and non-linearities. Trained using Stochastic Gradient Descent.
- Reinforcement Learning (RL): An agent learns to perform actions to maximise a reward (chess, Go, self-driving car, robot)
- Can be phrased as a Markov decision problem


## Markov decision problems

- Markov decision problem: tuple $\left(S, A, P_{a}, R_{a}\right)$, where
- S: set of states (e.g., a knot diagram $\mathcal{D}$ )
- $A_{s}$ : set of actions available from $s \in S$ (changing a crossing)
- $P_{a}\left(s, s^{\prime}\right)$ : the probability that $a \in A_{s}$ leads to $s^{\prime} \in S$ (0 or 1 for a crossing change)
- $R_{a}\left(s, s^{\prime}\right)$ : immediate reward after transitioning from $s$ to $s^{\prime}$ via action a (1 (or 0 ) if $s^{\prime}$ is a diagram of $U$ and 0 (or -1 ) otherwise)
- Policy $\pi$ : potentially probabilistic mapping from $S$ to $A$
- Objective: Choose $\pi$ to maximise the state value function

$$
V^{\pi}(s):=E\left(\sum_{t=0}^{\infty} \gamma^{t} R_{\pi\left(s_{t}\right)}\left(s_{t}, s_{t+1}\right)\right)
$$

where $s_{0}=s, s_{t+1} \sim P_{\pi\left(s_{t}\right)}\left(s_{t}, s_{t+1}\right)$, and $\gamma \in[0,1]$ discount factor

## Q-learning

- Goal: Learn state-action value $Q(s, a)$, which is the expected reward if action $a$ is taken in state $s$
- At time $t$, agent selects action $a_{t}$, observes reward $r_{t}$, and enters state $s_{t+1}$
- Initialise $Q$ and update via Bellman equation:

$$
Q^{\text {new }}\left(s_{t}, a_{t}\right):=Q\left(s_{t}, a_{t}\right)+\alpha\left(r_{t}+\gamma \max _{a \in A_{s_{t+1}}} Q\left(s_{t+1}, a\right)-Q\left(s_{t}, a_{t}\right)\right),
$$

where $\alpha \in(0,1]$ learning rate (step size)

- Selecting an action: exploration vs. exploitation
- $\varepsilon$-greedy policy: with probability $\varepsilon$, choose random action, with probability $1-\varepsilon$, perform action $a_{t}$ with maximal $Q\left(s_{t}, a_{t}\right)$
- Deep Q-learning: ANN $f: \mathbb{R}^{S} \rightarrow \mathbb{R}^{A}$, where $f\left(e_{s}\right) \cdot e_{a}=Q(s, a)$ for $s \in S$ and $a \in A_{s}$. Weights updated via Bellman equation


## Importance Weighted Actor-Learner (IMPALA)



Figure 1. Left: Single Learner. Each actor generates trajectories and sends them via a queue to the learner. Before starting the next trajectory, actor retrieves the latest policy parameters from learner. Right: Multiple Synchronous Learners. Policy parameters are distributed across multiple learners that work synchronously.

- IMPALA [Espeholt et. al]: Distributed agent for parallelisation
- Learns policy $\pi$ and value function $V^{\pi}$ via stochastic gradient ascent
- Set of actors repeatedly generate trajectories of experience
- One or more learners use experience to learn $\pi$
- Policy of actors lags behind learner's


## Imitation Learning

- An agent tries to learn a policy that mimics expert behaviour
- No reward function
- Behavioural Cloning: using SL, map environment observations to (optimal) actions taken by the expert
- Adversarial Imitation [Ho and Ermon] is a minimax game between two AI models (Generative Adversarial Nets): the agent policy model produces actions to attain the highest rewards from a reward model using RL that indicates how expert-like an action is, while the reward model attempts to distinguish the agent policy behaviour from expert behaviour


## Supervised Learning and unknotting

- We trained a Random Forest classifier and an ANN (SL) to predict $u(\mathcal{D})$ from Alexander, Jones, writhe, and longitudinal translation (10k random diagram of 3-25 crossings, $80 \%$ accuracy, baseline 50\%)
- In some diagrams, every crossing is in an unknotting set, in others, only small percentage
- We trained an SL agent to predict whether a crossing is in an unknotting set (100k random diagrams of $11-30$ crossings, $85 \%$ accuracy, baseline $50 \%$ )
- Imitation learning: Behavioural Cloning trained on brute-forced unknotting trajectories


## Reinforcement Learning and unknotting

- Goal: train an RL agent that performs crossing changes in a fixed diagram $\mathcal{D}$ to unknot it, giving an upper bound on $u(\mathcal{D})$
- Mostly used IMPALA agent
- Can determine $u(\mathcal{D})$ even when $c(\mathcal{D}) \approx 200$, when brute-forcing is not possible
- Representation: Knot invariants of diagram and all diagrams obtained by changing one crossing (diagrams hard to feed into ANN)


## Features

- Using Alexander and Jones polynomial (coefficients, evaluations incl. derivatives, min and max degree), we got almost the same accuracy as with all features
- Other invariants either failed to compute for significant percentage of knots ( $\geq 20 \%$ ) or slow to compute for 100 -crossing knots (HFK)
- Sum of absolute values of coefficients of $\Delta_{K}$ improves performance
- Jones + Alexander $>$ Alexander only (esp. when forcing inter-component crossing changes for connected sums)
- $V_{K}$ conjectured to detect unknot, $\Delta_{K}$ does not (algebraic unknotting number)
- One step lookahead: Agent computes Alexander/Jones polynomial of all knots obtained by changing one crossing as features
- Jones polynomial seems to contain yet unobserved unknotting information


## Braids



- Jones polynomial computation exponential time. Polynomial-time algorithm exists for braids if we fix the braid index
- Slice-Bennequin inequality: $|w(\beta)|-n(\beta)+1 \leq 2 u(\widehat{\beta}) \leq c(\widehat{\beta})+1-n(\beta)$
- Better mixing of the components than overlay by inserting identity braid words into connected sums (inter-component crossings in red)
- We trained an IMPALA agent that performed well
- Also experimented with a transformer on braid words


## Additivity of $u$ and RL

- Obtained $u(K)$ for 31 k random knots ( $10-60$ crossings) and 26 k QP knots (10-50 crossings) with $|\sigma(K)| \gg 0$, where upper bounds from RL agent and lower bounds from HFK coincide
- Searched for potential counterexamples to the additivity of $u$ by overlaying summands with known $u$ and, in some cases (100k), performing random Reidemeister moves (stochasticity vs. learning to find unknotting crossing arcs)
- Summands either from KnotInfo with known $u$, torus knots, or from the above 57k knots (random + QP)
- Limit of our $\mathrm{RL} \approx 200$ crossings, so too much mixing was not always feasible
- Have not found a counterexample to $u\left(K \# K^{\prime}\right)=u(K)+u\left(K^{\prime}\right)$


## Strong conjecture

- Strong conjecture: in every collection of unknotting arcs for $K \# K^{\prime}$, there is one that can be isotoped into $K$ or $K^{\prime}$
- Inter-component crossing change: results in a knot that is not a connected sum; e.g., not hyperbolic
- Agent performed several inter-component crossing changes
- Counterexamples to the strong conjecture by undoing all in-component crossing changes


## A counterexample to the strong conjecture



Figure: Unknotted by 13, 14, 48, 50

## Strong counterexample



## Theorem

Suppose that the prime knots $K_{1}$ and $K_{2}$ in $S^{3}$ are not 2-bridge. Then there is a diagram of $K_{1} \# K_{2}$ and a set $C$ of unknotting crossings of size $u\left(K_{1}\right)+u\left(K_{2}\right)$ such that changing any crossing in C results in a prime knot.

## New unknotting numbers assuming additivity of $u$

- If we assume $u$ is additive and consider knots appearing along minimal unknotting trajectories of connected sums, we obtain the unknotting number of 43 knots $K$ with $c(K) \leq 12$ that were unknown
- In all these examples, $u(K)$ was equal to the KnotInfo upper bound
- 39 of these knots $K$ have a crossing change in their Knotlnfo diagram $\mathcal{D}$ that results in a connected sum $K_{0} \# K_{1}$ with $u(\mathcal{D})=u\left(K_{0}\right)+u\left(K_{1}\right)-1$
- We have found by hand a diagram for 12a981 where two crossing changes yield a diagram $\mathcal{D}$ of $T_{2,7} \#-T_{2,5}$ with $u(\mathcal{D})=u\left(T_{2,7}\right)+u\left(T_{2,5}\right)-2$
- Remaining 3 knots: 12a898, 12a917, 12a999


12a981

## Hard unknot diagrams



Figure 8. A 28 -crossing diagram $D_{28}$ of the unknot requiring three extra crossings.

- We say that a diagram of the unknot is hard if, in any sequence of Reidemeister moves to the trivial diagram, the crossing number has to first increase before it decreases
- 11 hard unknot diagrams and 2 special infinite families from the literature [Burton, Chang, Löffler, Mesmay, Maria, Schleimer, Sedgwick, Spreer. Hard diagrams of the unknot., Exp. Math., 2023]
- Tried to construct using Generative Adversarial Network (setter/solver)


## Hard unknot diagrams


(a) simplify('level') hard

(b) simplify('global') hard

- While running the unknotting agent, we have found $\approx 5.9 \mathrm{M}$ unknot diagrams that SnapPy could not simplify using simplify('level') (random R3 moves + R1 and R2)
- Out of 5.9 M (between 9 and 75 crossings), verified that $\geq 2.46 \mathrm{M}$ are hard and not related by R3 moves
- 2121 diagrams survive even 25 simplify('global') attempts: also picks up a strand and puts it elsewhere (pass move) to reduce $c(K)$
- Potential counterexamples to unknotting algorithm candidates


## Thank you for your attention...

## Any questions?



Figure: A 42-crossing hard unknot diagram with 6225 R3-equivalent diagrams that we have not been able to simplify by calling SnapPy's 'global' heuristic 100 times.

> Differential and
> Low-Dimensional Topology

ANDRÅS JUHÅSZ


London Mathematical Society
Student Texts 104

