Internship Defense

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Contents

MCTS algorithm discovery

- Much research in AI games uses MCTS
- Problem known in advance: Customize MCTS in a problem-driven way
- Why not automatize this task?

  ⇒ Monte Carlo search algorithm discovery, for finite-horizon fully-observable deterministic sequential decision-making problems

  For example:
  - Sudoku puzzles
  - *Pyramid* card game
  - ...

Grammar & algorithm space

- Generate a rich space of MCTS algorithms thanks to search components
  - `simulate`
  - `repeat`
  - `step`
  - ...
- Space cardinality grows combinatorially with length and # of search comp.
- Multi-armed bandit approach to get a collection of well-performing algorithms

Multi-armed bandit model

Bandit in this context

- Machine with multiple arms
- Pulling an arm has a budget cost and gives some reward
- Finite budget

Multi-armed bandit model

Model description

Here,

- Arm = algorithm execution
- Reward = this algorithm execution reward
- We want the best arm to be the algorithm with the best mean reward

  i.e. the algorithm performing the best on average

Multi-armed bandit model

Model flaws

- Discrete
  One cannot pull half an arm!
- Big cardinality
  Existing methods not really adapted to big cardinality with finite budget
- They used UCB policy with $100 \times$ #AlgoSpace steps
  Length up to 5 $\rightarrow$ #AlgoSpace $= 3155$: this method is not easily scalable

Multi-armed bandit model

An alternative approach

Design an alternative to standard UCB arm space exploration

- This is the best arm identification problem
- Get info. about pulled arms so far, select next arm accordingly

  ⇒ Perform some kind of information transfer from a (set of) arm(s) to another

  ⇒ This internship was about this problem

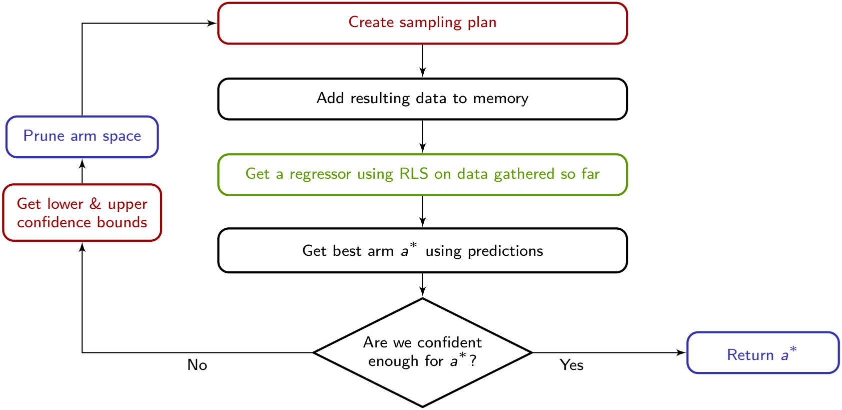
Basic idea

- Maximize the "distance" between the pulled arms and the next pull

  Get maximal information $\rightarrow$ Reduce required samples amount!

- Many challenges in this "simple" idea

Best arm identification algorithm



From the idea to the theoretical implementation

Create sampling plan

- G-optimal experiment design
  - Concerned with the variance of predictions
  - Get allocation vector γ s.t. information is, in some way, maximized
    (Erratum — Report says we maximize $J(\gamma)$. That is incorrect, we *minimize* $J(\gamma)$).
- Simple rounding procedure
  - "Translate" γ into a sequence of arms to pull

From the idea to the theoretical implementation

Get a regressor using RLS on data gathered so far

- Predictions?
  - Regressor θ
  - Features Φ
  - $r_a = \langle \phi_a, \theta \rangle = \left\langle \phi_a, \hat{\theta} \right\rangle + \eta$

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  - In fact, we just need features to compute $\hat{r}_a = \left\langle \phi_a, \hat{\theta} \right\rangle$
  - Features dual: kernels

$$n \text{ arms } (\ldots) \Rightarrow \exists \hat{\alpha} \in \mathbb{R}^{n \times 1} :$$

$$\left\langle \phi_a, \hat{\theta} \right\rangle = \left\langle \phi_a, \sum_{t=1}^{n} \hat{\alpha}_t \phi_a \right\rangle = \sum_{t=1}^{n} \hat{\alpha}_t \underbrace{\langle \phi_a, \phi_{a_t} \rangle}_{K(a, a_t)}$$

From the idea to the theoretical implementation

Get a regressor using RLS on data gathered so far

— Kernels —

The kernel “mimics” the inner product of two feature vectors

From the idea to the theoretical implementation

Get a regressor using RLS on data gathered so far

— Kernels —

The kernel "mimics" the inner product of two feature vectors

Estimating θ ⟷ Estimating α

Estimating θ	Estimating α
↓	↓
Based on features	Based on kernel
↓	↓
$\boxed{\text{Get } \hat{\theta} \rightarrow \text{Get } \hat{r}_a}$	$\boxed{\text{Get } \hat{\alpha} \rightarrow \text{Get } \hat{r}_a}$

From the idea to the theoretical implementation

Get a regressor using RLS on data gathered so far

— Kernels —

The kernel “mimics” the inner product of two feature vectors

Estimating θ ↔ Estimating α

Based on features | Based on kernel

Get $\hat{\theta}$ $\rightarrow$ Get $\hat{r}_a$ | Get $\hat{\alpha}$ $\rightarrow$ Get $\hat{r}_a$

From the idea to the theoretical implementation

Get a regressor using RLS on data gathered so far

— Regularization parameter λ —

- Auto tuning of λ given dataset

  $\Rightarrow$ Minimize $e(\lambda) = \frac{1}{n}\sum_{i=1}^{n}(f_{D_{-i},\lambda}(a_i) - r_i)^2$

- Naïve approach:
  1. Get $\hat{\alpha}$ — $O(n^3)$ (1 matrix inversion)
  2. Do it for n different datasets — $O(n)$

     $\Rightarrow$ If M evaluations of $e(\lambda)$, total complexity of $O(Mn^4)$!

- Kernelized generalized cross-validation

  $\Rightarrow$ If M evaluations of $e(\lambda)$, achievable total complexity of $O(n^3 + Mn^2)$

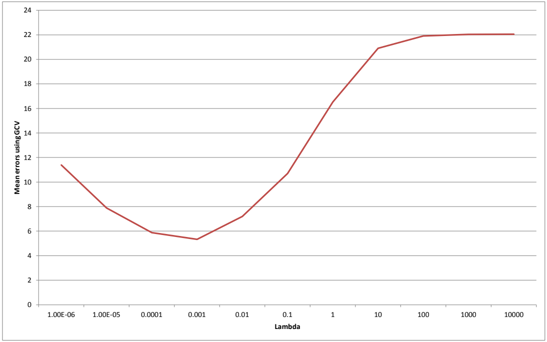
From the idea to the theoretical implementation

Get a regressor using RLS on data gathered so far

— Regularization parameter λ —

Example

Mean error when predicting the mean reward of an algorithm



From the idea to the theoretical implementation

Get lower & upper confidence bounds

- Theorem developed by **Abbasi-Yadkori et al. (2011)**
- Extension to the kernel case by **Abbasi-Yadkori (2012)**
- Given some assumptions on the model, allows to compute the (symmetrical) bounds

From the idea to the theoretical implementation

Prune arm space

- Discard all arms whose upper bound is smaller than the lower bound on a^*
- Illustration [on the board]

Conclusion

Wrap up: Sudoku 16×16

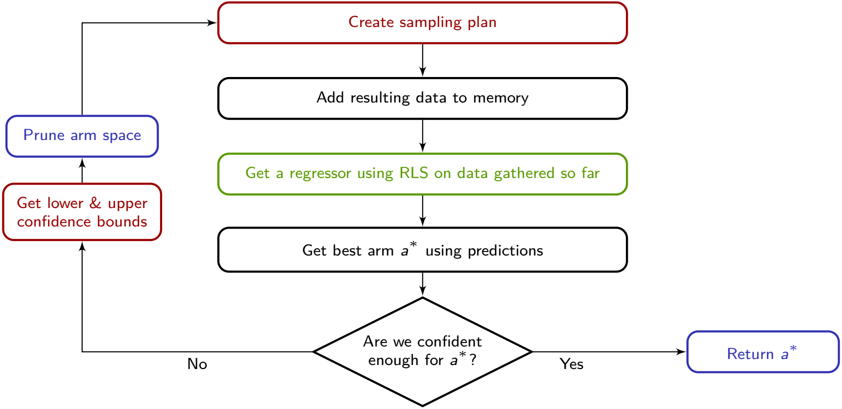
Maybe a little wrap-up example?

Data

- Problem: 16×16 Sudoku, $\frac{1}{3}$ prefilled grid
- About 3200 algorithms
- 2 rounds with sampling plans consisting of sequences of n_1 and n_2 algorithms

Conclusion

Wrap up: Sudoku 16×16



Conclusion

This internship in a nutshell

- 1 month of preparation
  - Implement MCTS algorithms generation & execution
  - C++ was used
  - 1 week to implement, more than 3 weeks to debug
- 2 months in RLAI lab
  - Create a dataset thanks to *Westgrid* network
  - Design, implement and check correctness of each parts of this new approach
  - Sadly not enough time to do significant comparisons
- Half a month to complete and re-read report

Conclusion

Thank you for your attention

Special thanks to my mentors for making this internship possible.