Ant Colony Optimization in Elixir

Andrea Malleo

December 11, 2021

1 Abstract

In this paper we present a distributed implementation of an Ant Colony Optimizer for the Travelling Salesman problem using the Actor Model of Concurrency. We give an overview of the system architecture and present the experiments we ran to validate the correctness of the code and compare performance against an open source serialized implementation. We find that performance compared to the serialized approach scales with the problem size, and identify key future enhancements for further speed up.

2 Introduction

Ant Colony Optimization [3] is a bio-inspired coorperative learning algorithm for finding the shortest path in a graph. Ants are simulated as software agents who independently travel along the graph, dropping pheromones in their wake that evaporate with time. These pheromones are a form of communication for other ants in the colony, as concentration of pheromones on a pathway signals recent ant traffic.

The algorithm is iterative, and each ant completes a tour every round. After each round, the solutions for each of the ants are aggregated and the optimal choice from all of the candidates is selected. Additionally the shared pheromone matrix, acting as a collective and evolving intelligence for the colony of ants, is updated to reflect new pheromone concentrations following all of the ant tours of this round. In successive rounds of the algorithm, ants bias their path toward edges with higher pheromone concentration. Since edges of greater distance take longer to travel, evaporation will lower the concentration of pheromone there and make future ants less likely to take those edges. Over successive rounds, the searches converge to some (locally) optimal solution. There have since been many enhancements to the original Any Colony algorithm, such as the Ant Colony System [2] and the Max-Min Ant System [11] which produce better convergence results. In this paper we stuck with the original, simplest approach and settled for convergence to some local minimum which empirically proved to be not too far from the global minimum.

The problem being considered here is the Travelling Salesman Problem [1], that is to find a complete tour of a fully connected graph with minimal cost.

3 Related work

The independence of the ant agents lends the algorithm to parallelization. The central point of synchronization is the pheromone matrix, which must maintain accurate values for a given round and update atomically for the next round. Many approaches have been presented that parallelize the algorithm in different ways. Pedemonte et. al [8] categorize the approaches, drawing distrinctions between a *master-slave model* with the simultaneous execution of ants providing updates to a master process maintainting the global pheromone matrix and a *parallel independent runs model* where many executions of independent ACO systems run simultaneously, further subdivided between whether or not the independent colony systems eventually coordinate with each other. There are also GPU based implementations, such as in [9].

Instead of working under the shared memory model of distributed computing, Ilie and Badica reformulate the classical algorithm using message passing in a multi-agent framework in [7]. Their work leverages existing multiagent system middleware, but the paradigm shift they introduced is built up on by Starzec et all in [10]. Here they build an actor model[6] implementation using Akka, a toolkit for building concurrent message driven applications for Scala. Their paper outlines a hierarchy of processes in their architecture, the bottom layer, representing ants, being the most ubiquitous, with each layer of managers collecting and aggragating state updates from the layer beneath it. It is this paper upon which our work is mainly based. The process architecture is largely the same, although a bit simplified as will be discussed towards the end of the Methods and in Future work. Novel to our approach is the choice of Elixir as the high level programming language for implementation. Elixir too employs the Actor computation model and thus uses message passing as a lock free form of state synchronization.

4 Methods

This section will outline the construction of this implementation by considering in turn the five Elixir process types running in the ACO system:

- the ant: responsible for graph traversals according to probablistic rules
- the graph manager: responsible for servicing requests for graph state
- the pheromone manager: responsible for servicing requests for pheromone matrix state
- the ant manager: responsible for collecting ant solutions and reporting the optimal one
- the colony manager: maintains the global optimal solution

The most ubiquitous of these processes at runtime is the ant process. At the start of each round, an ant begins at a randomly selected node. The following logic loops until a tour of the graph is completed. At the top of the loop the Ant is at some given node. The Ant requests from the Graph Manager process the set of possible edges emanating from this node (given the list of nodes already traversed in this tour) and waits for the response. If the response indicates that the tour of the ant is complete, the ant sends up its Solution Report (the order nodes it traversed and the tour cost) to both the Pheromone Manager and the Ant Manager and then transitions into the next round. Otherwise, the Edge Response will include the list of edges left and their respective costs. The ant then forms a Pheromone Request for this set of edges and sends it to the Pheromone Manager. Following a response, the Ant will compute the probability distribution over the set of edges from node i to node j as:

$$p_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\Sigma_{k \in \text{edges}}[\tau_{ik}(t)]^{\alpha}[\eta_{ik}(t)]^{\beta}}$$

where $\tau_{ij}(t)$ is the intensity of the pheromone trail on edge ij and η_{ij} is the reciprocal of the cost of edge ij. The sum in the denominator is over all eligible edges. The ant then draws an edge from this distribution and makes its move, before the cycle repeats once more.

The Graph Manager holds the graph: a dictionary with node numbers as keys, mapping to a dictionary holding key, value pairs of every other node and the cost of this edge between the two. Note that the graphs on which the Travelling Salesman Problem is run are complete, so space requirement is n^2 in the number of nodes. The Graph Manager loop simply services Edge Requests that come in, first checking to see for a completed tour, and otherwise pulling up the total set of neighbors and edge costs for a given node and dropping from this set any nodes already visited in this tour. Note that the state contained in the Graph Manager is constant and therefore valid indefinitely. As such, it needn't care about which ant is making a request or what state that ant is in.

This differs significantly from the Pheromone Manager. Recall that the end of every complete tour, the ant sends up the order of its nodes and the tour cost to the Pheromone Manager. This is so that the ant's pheromones may be sprinkled along its trail. Precisely, for ant k, the pheromone contributions to an edge ij for a given round is

$$\Delta\tau_{ij} = \begin{cases} \frac{Q}{C_k} & \text{if kth ant uses edge (i,j)} \\ 0 & \text{otherwise} \end{cases}$$

Where Q is a parameter, set to 1 here, and C_k is the cost of the tour for ant k. The Pheromone Manager must only service requests for the pheromone matrix for a given round m and simultaneously collect the completed tour reports from all of the ants in order to compute the pheromone matrix for round $m + 1$. To enforce this, Requests and Reports contains a field for the round number, and the Pheromone Manager will drop any Pheromone Requests or Solution Reports from the ants marked for a different round from the Manager's. The Pheromone Manager counts how many Solution Reports it has received in any round, and once one from each ant has come in, the pheromone matrix needs to be updated atomically for the next round.

As a time saving optimization, there are actually two pheromone matrices kept by the Manager, the first is the live one for the current round, and the second is the working matrix for the next. As tours come in, the pheromone contributions are accumulated for all of the edges in the working matrix, while the live matrix remains valid for interleaved Pheromone Requests coming in. Once it is time to transition to the next round, the live pheromone matrix is updated for each edge ij as

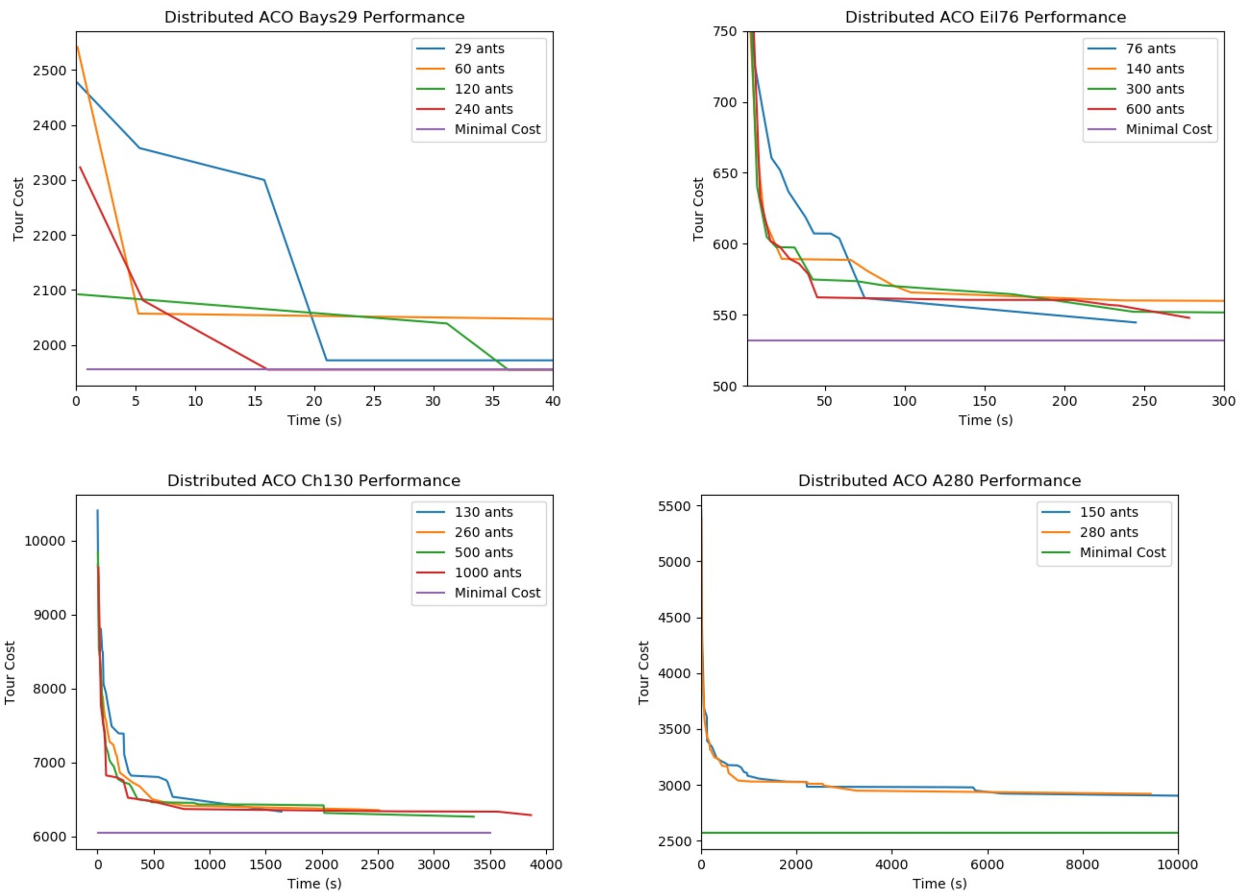
$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Sigma_{k=1}^{n}\Delta\tau_{ij}^{k}$$

where ρ represents the pheromone decay parameter and the sum is over all n ants. Note that if a Request or Solution comes in from an ant for the wrong round, it is simply dropped on the floor, and the ant will wait five seconds before resending the message. The Pheromone Manager's round increment serves as barrier that keeps the independent ant processes from progressing with too much variance.

The second process collecting Solution Reports from ants is the Ant Manager. In a similar fashion as just described, the Ant Manager only accepts Solutions indexed by the correct round, tracking the lowest cost tour received by any of the ants, and reporting the final best result up the hierarchy to the Colony Manager.

Finally there is the Colony Manager. In the current state the Colony Manager simply reports and saves each new lowest cost solution as it comes in from the Ant Manager. Future Work will address how its responsibilities might be increased.

Figure 1: Examining the performance against number of ants on graphs of size 29, 76, 130, and 280



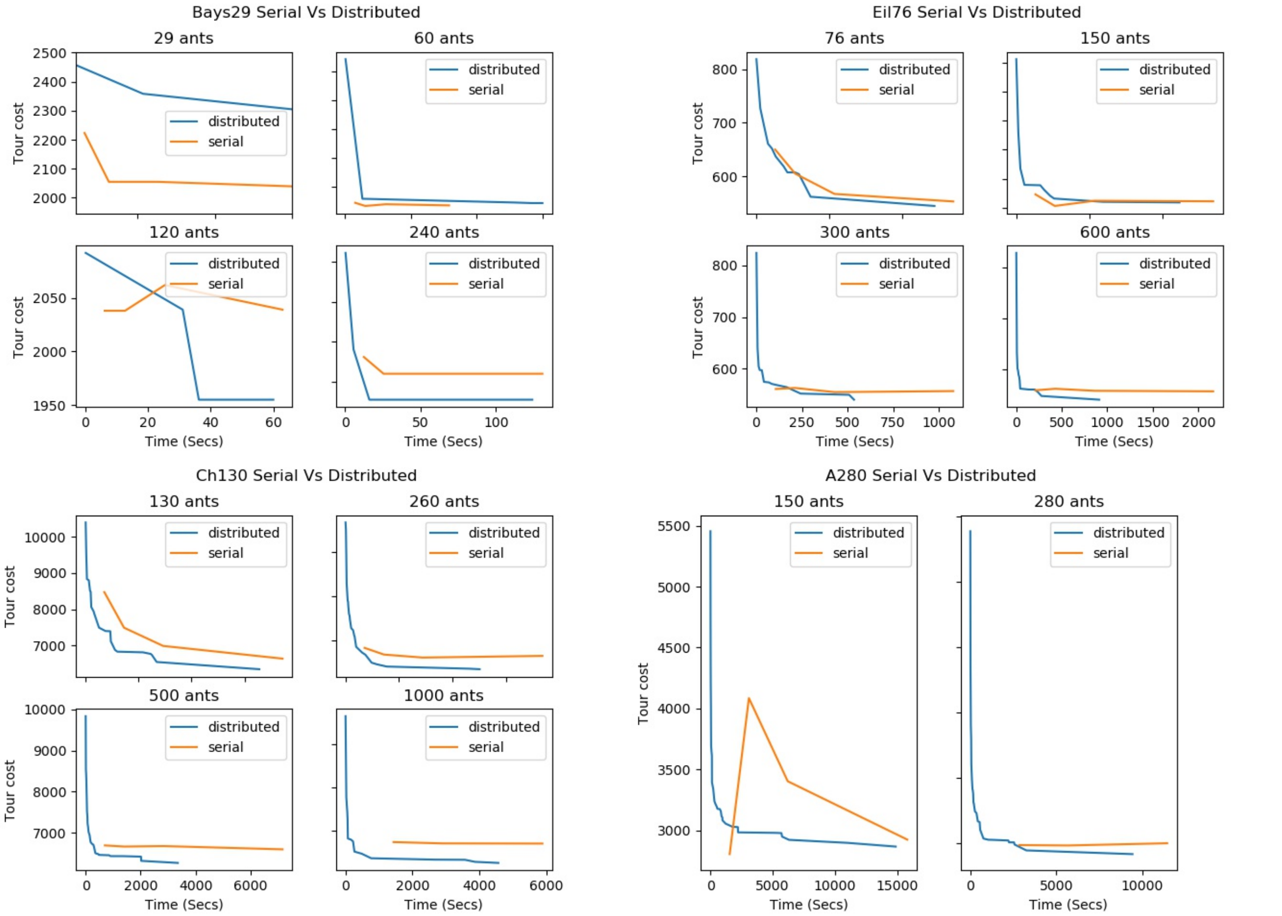
5 Experiments

The aim of the first set of experiments was to show correctness of the implementation and investigate how the convergence performance scales with the number of ant processes spawned. Since this is a probabilistic search and a naive version of this optimization algorithm, we were satisfied with convergence that approached the global minimum within some reasonable amount of time. Instances of the problem for testing were taken from TSPLIB95 [4], an open source repository for TSP benchmark problems. Four instances were chosen: bays29, eil76, ch130, and a280, each containing as many nodes as the number in their name. All experiments were run on a single 12 core desktop. As a general heuristic we began by spawning as many ant process as nodes in the graph, and doubling from there in successive rounds.

In Figure 1 we can see firstly that on a problem of very small size (29 node graph) this implementation finds the global minimum in just over 25 seconds using 120 ants, and just over 15 seconds using 240 ants. Once the problem size increases to 130 nodes, we see that the optimizer plateaus at approximately the same local minimum for every number of ants tested. We also see that the difference in performance as the number of ants is scaled up becomes less prominent as the size of the graph increases. In fact the speed advantage using 130 ants over 280 ants on a graph of size 130 is very modest, and the difference between 150 ants and 280 ants on a graph of size 280 is basically nonexistent.

Next we turned to compare this implementation against a single threaded one. For our experiments we ran the open sourced implementation ACOpy [5], which provides an easy to use

Figure 2: Comparing the performance of the Actor based Model against the serialized version



API for running the classical ACO on problem instances from the TSPLIB95. Figure 2 shows the progression over the four problem instances. We can see that barring the smallest problem size and fewest number of ants, the distributed implementation outperforms the serialized in all other cases in terms of cost of the optimal solution found, and usually in terms of time. Note that sometimes the serialized graph goes up instead of down- this is a result of the API only allowing the user to specify the amount of time for the solver to run and only providing the tour cost at the end of that run. Whereas data from our implementation reports from a single continuous run, the tour costs from the API are fragmented across several different runs.

6 Future Work

Likely apparent from the experiment set up is that the only process type with multiple instances spawned is the Ant process. The clear bottleneck in the current state of the implementation are the single Graph and Pheromone Managers. In fact, multiple instances of the Graph Manager could be spawned without any change in the code besides the process id given to each ant for communicating with the Graph Manager. For larger graphs, it may be worth the effort and space savings to allocate certain portions of the graph to the different Graph Managers and route Edge Requests from Ants to Graph Managers accordingly. On the other hand, further work is required to increase the number of Pheromone Managers beyond one. Each Pheromone Manager would need to be responsible for only some subset of edges, and incoming Pheromone Requests would be redirected as required. A new Pheromone Manager protocol would have to be installed for the different Pheromone Managers to conclude that a given round has been completed and transition to the next round together, before servicing new pheromone requests.

Finally, another source of limitation in these experiments is hardware, and an increase in the number of compute nodes would allow for the problem size and performace benefits to increase.

7 Conclusion

In this paper we have presented a method [1] for constructing the Distributed Ant Colony Optimizer under the message passing paradigm. As an alternative to the shared memory model of concurrency, message passing provides a very natural and straightforward mechanism for sharing state in this problem domain. Just the simplest of clocks that increment with the round count capture all of the ordering that is required and reflect the allowed concurrency of all of the ants on their own journeys within a given round. Using an ActorModel language like Elixir facilitated the organization of the algorithm into a set of state machines (agents) and the message traffic between them. With this method of construction, scaling processes with size of the problem becomes practically trivial. Best of all we found that performace under this architecture provides benefits in both speed and accuracy over classical serialized constructions.

[1] Code here: https://github.com/Akmalleo3/ACO

References

[1] Wikipedia Contributors. The travelling salesman problem, 2021. "[Online; accessed Dec 2021]".

[2] Marco Dorigo and Gianni A. Di Caro. Ant colony optimization: a new meta-heuristic. *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406)*, 2:1470–1477 Vol. 2, 1999.

[3] Marco Dorigo and Luca Maria Gambardella. Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Trans. Evol. Comput.*, 1:53–66, 1997.

[4] Universität Heidelberg Institut für Informatik Gerhard Reinelt. Tsplib95. Software Library http://comopt.ifi.uni-heidelberg.de/software/TSPLIB95/index.html, 1990.

[5] Robert Grant. Acopy. github, 2018.

[6] Carl Hewit and Henry Baker. *Massachusetts Institute of Technology AI Lab*, 1977.

[7] Sorin Ilie and Costin Bădică. Multi-agent approach to distributed ant colony optimization. *Science of Computer Programming*, 78(6):762–774, 2013. Special section: The Programming Languages track at the 26th ACM Symposium on Applied Computing (SAC 2011) Special section on Agent-oriented Design Methods and Programming Techniques for Distributed Computing in Dynamic and Complex Environments.

[8] Héctor Cancela Martín Pedemonte, Sergio Nesmachnow. A survey on parallel ant colony optimization. *Applied Soft Computing*, (11), 2011.

[9] Rafal Skinderowicz. the gpu-based parallel ant colony system.

[10] Mateusz Starzec, Grazyna Starzec, Aleksander Byrski, and Wojciech Turek. Distributed ant colony optimization based on actor model. *Parallel Computing*, 90:102573, 2019.

[11] Thomas Stützle and Holger Hoos. Max-min ant system. *Elsevier Science*, 16, 11 1999.