Predator-Prey Interaction for Max-Min Ant System

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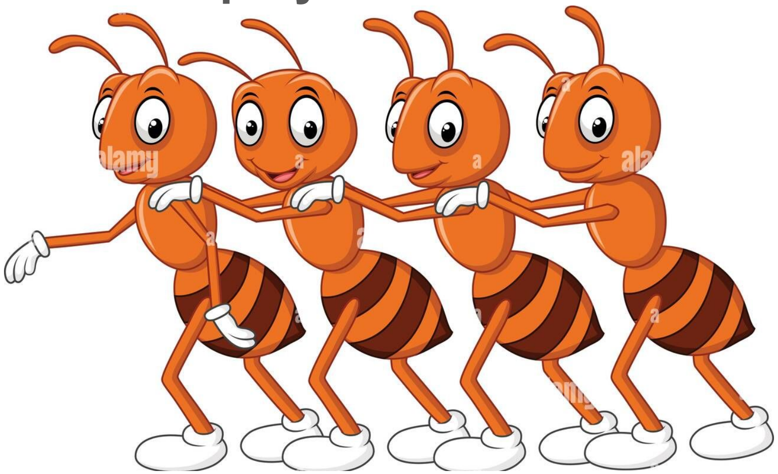
Introduction

- Max Min Ant Systems (MMAS)
- Ant Colony Optimization (ACO)
- Combinatorial and graph problems
  - TSP (traveling salesman problem)

Predator and prey



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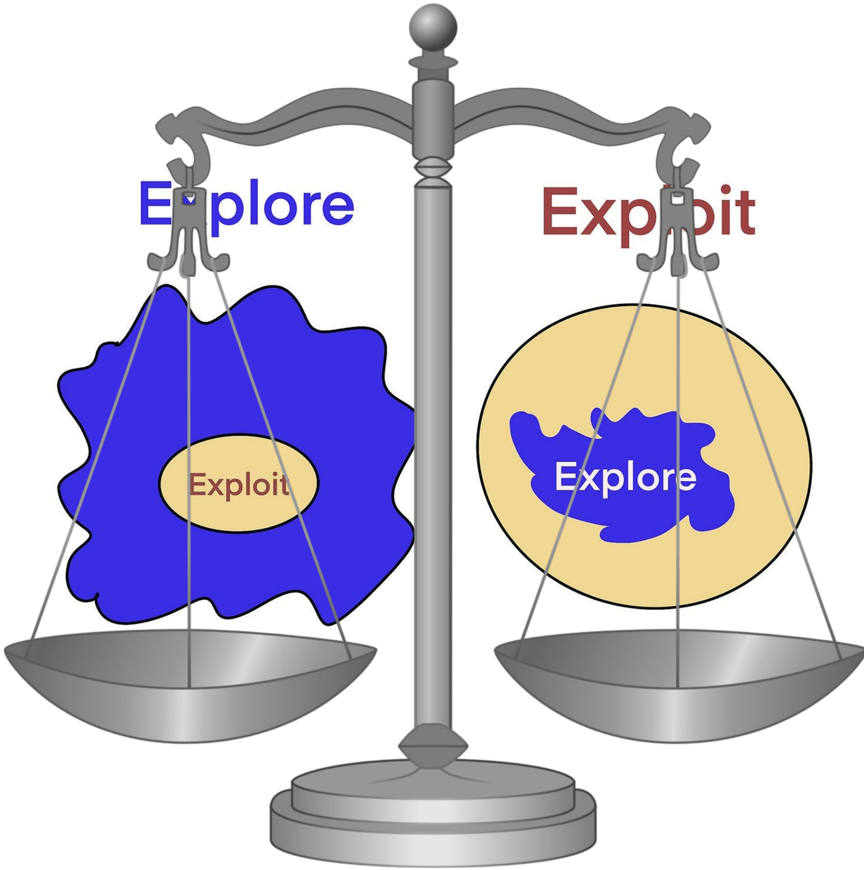
So what?

- Random forest good but…
  - Overdependence on hyperparameters
- Exploration vs exploitation
  - MMAS suffers from premature convergence
- PP-MMAS will balance



Has it been done before?

- Nature-inspired algorithms
  - Sparrow Search
  - Harris Hawk (Tuah) Optimization
- Ant colony optimizations?
  - CV edge detection
  - Efficacy of different ACOs
  - X-ray reconstruction

PP-MMAS is completely new!

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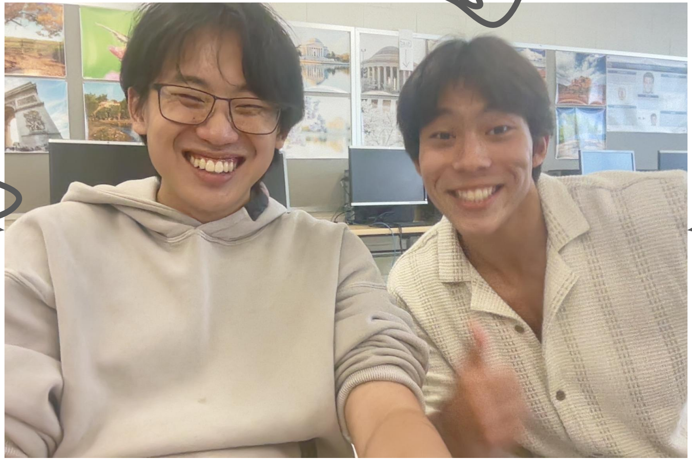
Data

- TSP samples from TSPLIB
- Autism Dataset from Kaggle
  - 800 labels - 639 neg, 161 pos
  - Removed: id, age, age_desc, contry_of_res, relation, result of AQ-10
  - Leaves: A1_Score, A2_Score, A3_Score, A4_Score, A5_Score, A6_Score, A7_Score A8_Score, A9_Score, A10_Score, gender, ethnicity, jaundice, autism, used_app_before



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Random Forest

- Ensemble learner
- Decision trees
- Hyperparameter space
    - num_attributes
    - num_sample
    - num_trees
    - max_depth
    - min_split
    - min_leaf
    - criterion

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Max-Min Ant System

$$\tau_{ij} = [\tau_{ij} \times (1 - \rho) + \Delta\tau_{ij}]_{\tau_{min}}^{\tau_{max}}$$

- Ant system to focus on exploitation of search space
  - ACO: initialize swarm of ants, walk random paths, deposit pheromone
- MMAS differs:
  - Bounds concentration of pheromone on trails
  - Updates pheromone along only iteration best path

PREMATURE CONVERGENCE

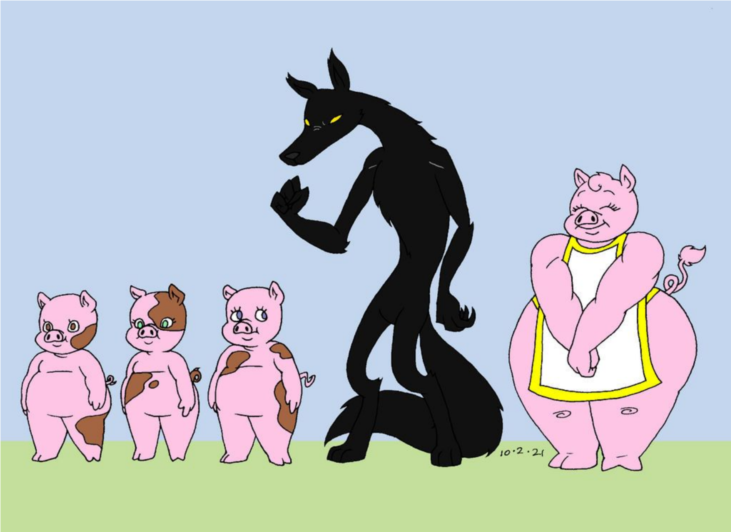
Predator Prey

- Label proportion of N ants as prey ants
- Predators choose paths based on amount of pheromone
- Proportional probability that prey ant chooses path:

$$p_{ij} \propto \frac{\tau_{ij}(t)(\eta_{ij})^{\beta}}{1+(P_{ij})^{\zeta}}$$

where η_{ij} is a measure of the heuristic function. In the case of the TSP, the heuristic is chosen as distance^{-1} to encourage shorter paths, and used to aid both predators and prey in their search. β is a hyperparameter for the strength assigned to the heuristic function, P_{ij} denotes the number of predators that traversed a single edge, and ζ (zeta) is the proportion of predator ants.

yap



Predator Prey (cont.)

$$\zeta = (1 - \xi^{1+\frac{i}{k}})$$

- Prey population starts high, then decays exponentially
- Best prey ant can deposit pheromone to induce predators to explore space

$$\Delta\tau_{ij}^{prey} = \Delta\tau_{ij} \times (1 - \zeta)$$

can be observed that even in the worst case, the system performs just as well as MMAS, since a proportion of the population (predator ants) act independently of the predator-prey interaction.

Hyperparameters

- ρ: experimentally-determined optimum at 0.5
- β: conservative value of 5
- ξ: 0.7 to encourage high exploration
- N: 100 for variability in search

PARAMETER + 

= HYPERPARAMETE
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Metrics of Evaluation

- PRC AUC, MCC
    - Imbalanced classes (80% to 20%)
- Accuracy
    - General overview

According to my metrical evaluation…

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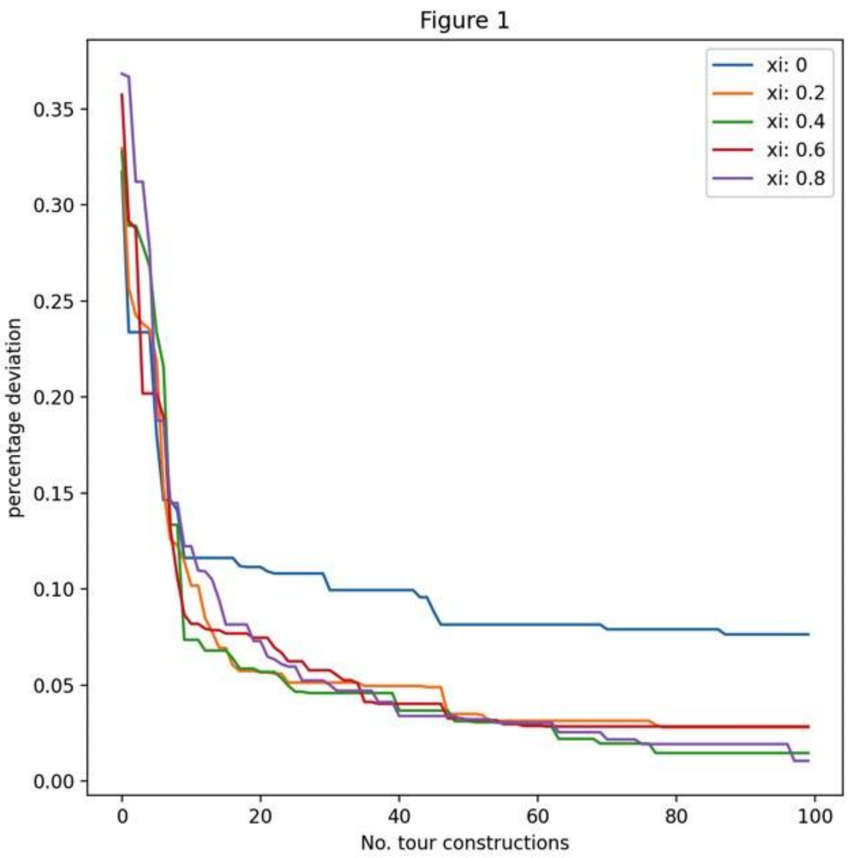
Results - Benchmark

PP-MMAS:

TSP_route	opt_length	dev_from_opt	iterations
dantzig42	699	0	82
fri26	937	0	7
gr17	2085	0	5
kroA100	21321.79953	0.001890345991	308
att48	33614	0.001877738368	352

MMAS:

TSP_route	opt_length	dev_from_opt	iterations
dantzig42	700	0.001430615165	53
fri26	937	0	40
gr17	2085	0	26
kroA100	21415.36532	0.006286910068	964
att48	33633	0.002444040416	111



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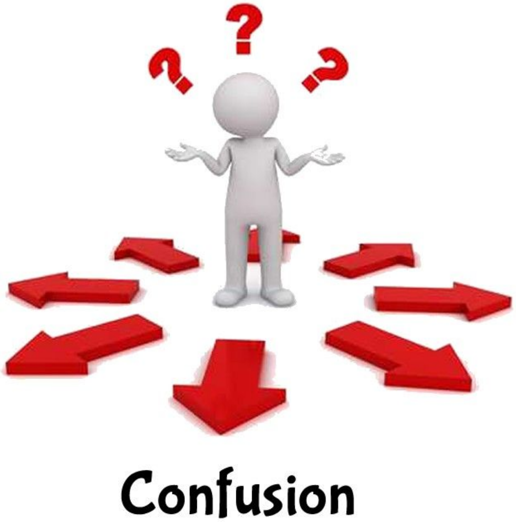
Results - Dataset

Model	accuracy	num_trees	max_depth	num_features	max_samples	criterion
1	0.92083	80	6	1	500	0
2	0.91667	115	5	1	260	2
3	0.91257	70	6	2	340	2
4	0.90833	135	2	5	130	2
5	0.90417	25	2	9	100	0

Choose model 1 for highest accuracy

Confusion matrix:

	Predicted Pos	Predicted Neg
Actual Pos	182	4
Actual Neg	15	39



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Overfitting???

Training results similar to test → not overfitting

Accuracy	MCC	ROC	AUPRC
0.89286	0.63547	0.79815	0.5568167813

	Predicted Pos	Predicted Neg
Actual Pos	431	22
Actual Neg	38	69

TRAIN SET

TEST SET

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Result - Dataset (cont.)

	Accuracy	AUPRC	MCC	ROC
RF	0.89167	0.62377	0.67851	0.82497
RF_Selection	0.92083	0.71754	0.76301	0.85
NaiveBayes	0.83333	0.529	0.599	0.837
DecisionTree	0.84167	0.5168	0.57103	0.79928

Figure 2

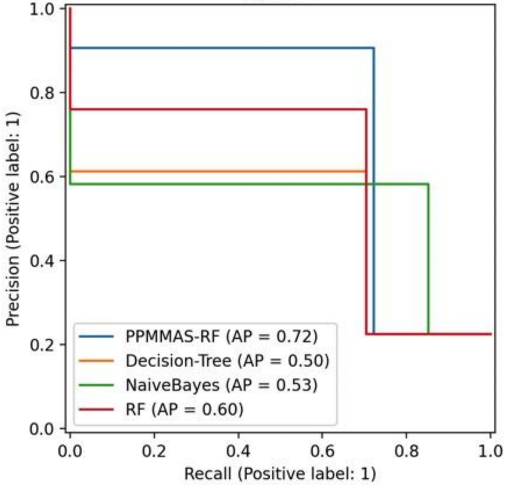
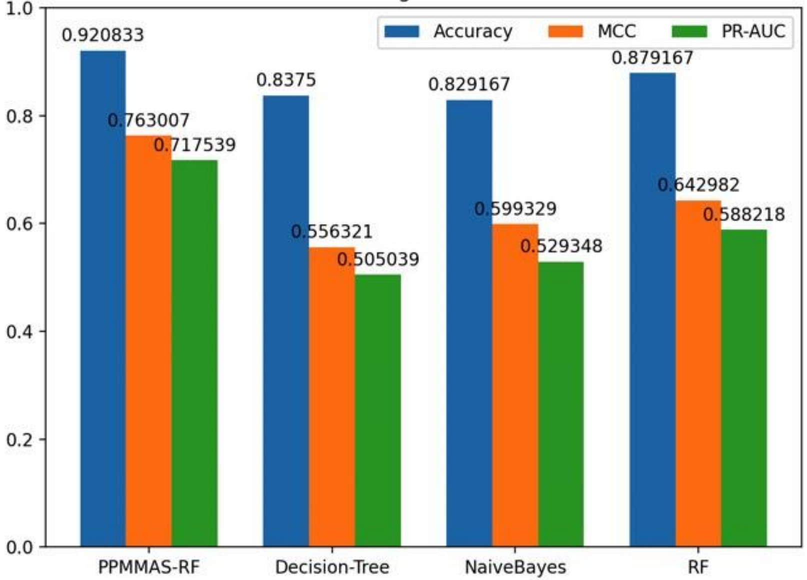


Figure 3



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Analysis - Benchmarks

- Both perform well on simple routes (gr17, fri26)
- PP-MMAS converges with lower deviation for more complex routes

- MMAS generally converges quicker on a less optimal solution
- gets stuck in a local optimum and cannot escape due to lack of exploration

PP-MMAS:

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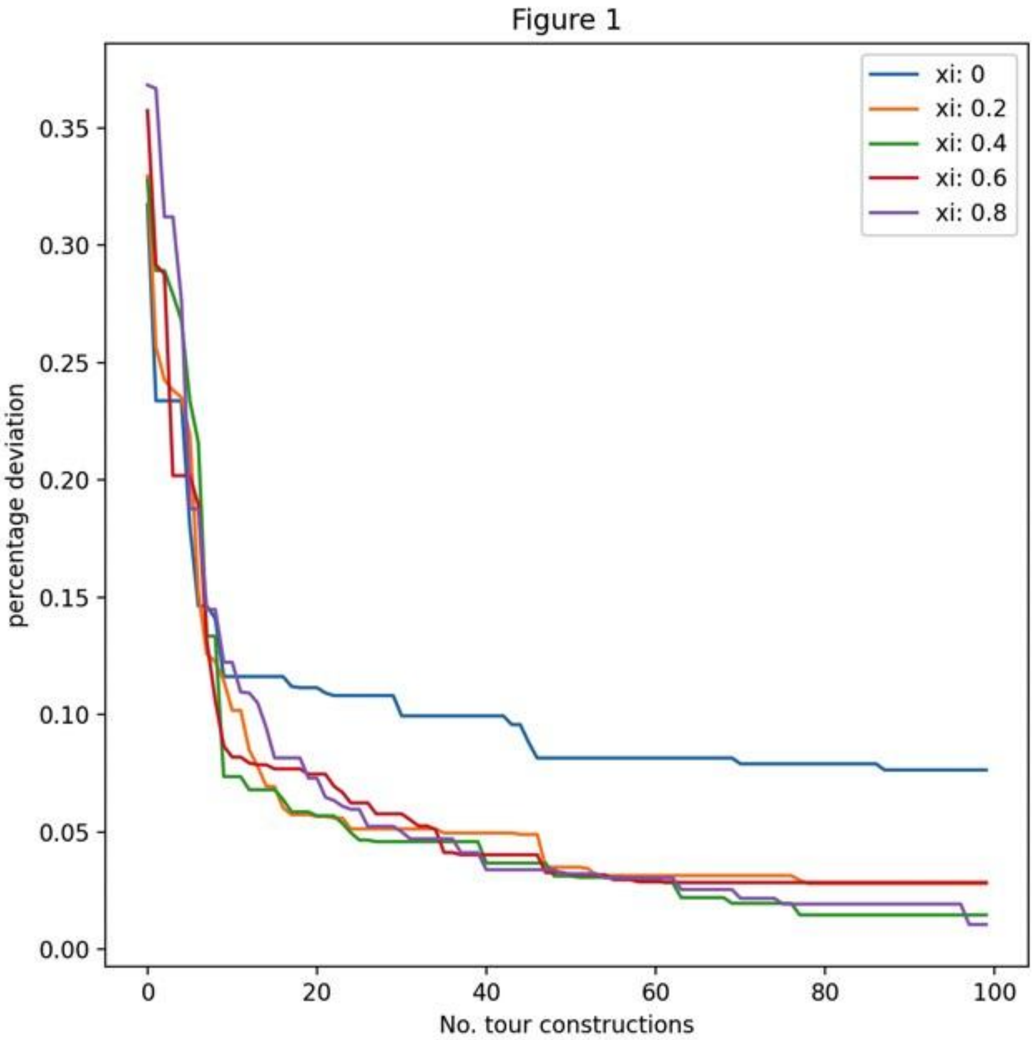
Analysis - xi

- Higher value of xi = faster convergence
- At xi = 0, PP-MMAS degenerates into pure MMAS
    - Convergence slowest



Analysis - Dataset

AUPRC

1. RF_Selection: 0.71754
2. RF: 0.62377
3. NaiveBayes: 0.529
4. DecisionTree: 0.5168

MCC

1. RF_Selection: 0.76301
2. RF: 0.67851
3. NaiveBayes: 0.599
4. DecisionTree: 0.57103

Accuracy

1. RF_Selection: 0.92083
2. RF: 0.89167
3. DecisionTree: 0.84167
4. NaiveBayes: 0.83333

PP-MMAS beats others

PP-MMAS

Others

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Conclusion

- PP-MMAS balances exploration/exploitation
- Only did it for hyperparameter selection on RF
- Use in other graph-type optimization problems
    - Image segmentation/thresholding
    - Control theory, optimize PID controller coefficients

Questions?