Transfer Learning in Evolutionary Spaces

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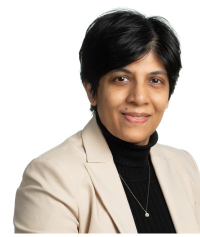
Instructor

Nelishia Pillay is a Professor at the University of Pretoria, South Africa. She holds the Multichoice Joint-Chair in Machine Learning and SARChI Chair in Artificial Intelligence for Sustainable Development. She is chair of the IEEE Technical Committee on Intelligent Systems Applications, Vice Chair of the IEEE Technical Committee on Evolutionary Computation, chair of the IEEE Task Force on Automated Algorithm Design, Configuration and Selection and chair of the IEEE CIS WCI subcommittee. Her research areas include hyper-heuristics, automated design of machine learning and search techniques, combinatorial optimization, genetic programming, genetic algorithms and deep learning for and machine learning and optimization for sustainable development and equity, diversity and inclusion. These are the focus areas of the NICOG (Nature-Inspired Computing Optimization) research group which she has established.



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Tutorial Website

https://www.cs.up.ac.za/cs/npillay/TLEA.htm

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Overview

- Transfer learning
- Transfer learning in search
- Benefits of TL in search
- Case study: solution space
- Case study: program space
- Case study: heuristic space
- Case study: design space
- Automated TL in EAs
- Discussion: future research directions

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Transfer Learning

- Transfer of knowledge
- What to transfer?
- How to transfer?
- When to transfer?
- Positive vs. negative transfer
- Focus on data and feature transfer
- TL in EC

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Transfer Learning in Search

- Knowledge learnt during search is transferred
- What is transferred?
  - Points in the search space
  - Elements of the population
  - Components of elements
  - Areas of the search space
- How is it transferred?
  - Forms part of the initial population of the target EA
- When is it transferred?
  - Last generations
  - Generation intervals

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Benefits of TL in Search

- Improvement in performance
- Reduction in computational cost
- Reduction in the amount of data needed
- Improved convergence

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Case Study: Solution Space

- Genetic algorithms for solving the travelling salesman problem (TSP)
- Symmetric TSP – Involves finding a route of minimum length that visits all cities exactly once and begins and ends at the same city. The distance between cities *m* and *n* is the same as the distance between *n* and *m*.
- Asymmetric TSP – Involves finding a route of minimum length that visits all cities exactly once and begins and ends at the same city. The distance between cities *m* and *n* is not necessarily the same as the distance between *n* and *m*.

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Case Study: Solution Space

- What is the aim of the transfer learning?
- Define the source and target domains
- What will be transferred?
- How will it be transferred?
- When will it be transferred?
- Transformation function needed?

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Solution Space TSP
TL Case Study Discussion

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Case Study: Program + Heuristic Space – Scheepers and Pillay, 2021 [2]

- Genetic programming generation construction hyper-heuristic
- Each point/element – a parse tree representing a heuristic
- Application one dimensional bin packing (1BPP)
- Aim – reduction in computational cost of solving more challenging problems
- Source domain – easy and medium 1 BPP problems
- Target domain – hard 1BPP problems

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Case Study: Program + Heuristic Space – Scheepers and Pillay, 2021 [2]

- What to transfer
  - Population of last generation (TL1)
  - Best individuals of each generation (TL2)
  - Areas of the search space
    - Frozen root (TL 2.1)
    - Frozen second level (TL2.2)
    - Frozen leaf nodes (TL2.3)
- How to transfer?
- When to transfer?

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Case Study: Program + Heuristic Space – Scheepers and Pillay, 2021 [2]

- Performance evaluation
  - Objective value – Number of bins
  - Computational effort – Koza computational effort formula

$$f(x, M, i) = R(x, M, i) * M * i \qquad R(x, M, i) = \lceil \frac{log(1-x)}{log(1-P(M,i))} \rceil$$

  - Generality – Standard deviation of differences (SDD)

$$SDD(H) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}}$$

where N is the number of problem instances, $x_i = 0$ if $o_i = 0$ and $b_i = 0$. Otherwise $x_i = (|o_i - b_i|)/average * 100$.

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Case Study: Program + Heuristic Space – Scheepers and Pillay, 2021 [2]

- Objective value performance
  - TL approaches performed better
  - TL2, TL2.2 and TL2.3 produced the best results
  - Best approach of the three is problem dependent
- Computational effort performance
  - TL2 best computational effort
  - TL2.1, TL2.2, TL2.3 better than TL1
- Generality performance
  - TL1 and TL2 best generality
  - TL2.1, TL2.2, TL2.3 worst generality

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Case Study: Heuristic Space

- Selection construction/perturbative genetic algorithm hyper-heuristic for educational timetabling
- Timetabling problems involve allocation of an entities, e.g. exams, classes to timetable slots to reduce had and soft constraints
- Educational timetabling
  - Examination timetabling
  - University course timetabling
  - School timetabling

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Case Study: Heuristic Space

- What is the aim of the transfer learning?
- Define the source and target domains
- What will be transferred?
- How will it be transferred?
- When will it be transferred?

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Heuristic Space Educational Timetabling
TL Case Study Discussion

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Case Study: Heuristic Space Singh and Pillay, 2022 [3]

- Ant colony optimization generation construction hyper-heuristic
- Aim: Reduction in computational cost
- Applications
  - Movie scene scheduling problem
  - Quadratic assignment problem
  - One dimensional bin packing
- Source domain: Simpler problem instance/s
- Target domain: Complicated problem instance/s

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Case Study: Heuristic Space - Singh and Pillay, 2022 [3]

- What is transferred?
  - Pheromone maps from of the last iteration of the ACO
- How is it transferred?
  - Best pheromone map of the last iteration of the source ACO hyper-heuristic is transferred
- When is it transferred?
  - Used at the beginning of the target ACO hyper-heuristic instead of creating the maps randomly
- Performance
  - Drastic reduction in computational cost
  - Improvement in objective value for MSSP and QAP, poorer objective values for 1BPP

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Case Study: Program Space

- Genetic programming for evolving prediction models for disease diagnosis
- Given relevant patient attributes the model predicts whether the patient has the disease or not
- Disease diagnosis
  - Heat disease
  - Diabetes
  - COVID-19

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Case Study: Program Space

- What is the aim of the transfer learning?
- Define the source and target domains
- What will be transferred?
- How will it be transferred?
- When will it be transferred?

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Program Space Prediction
TL Case Study Discussion

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Case Study: Design Space – Nyathi and Pillay, 2021 [1]

- Automated design of the genetic programming algorithm to produce classifiers
- Design decisions represented in chromosome
  - Representation
  - Parameter values
  - Genetic operators
  - Control flow
- Grammatical evolution used for automated design (AutoGE)
- Source domain: NSL-KDD
- Target domain: UCI benchmark set

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Case Study: Design Space – Nyathi and Pillay, 2021 [1]

- What is transferred?
  - Design of the GP classification algorithm
- How is it transferred?
  - Best performing designs from the source AutoGE to the target AutoGE
- When is it transferred?
  - Best performing designs form the initial population generation of the AutoGE
- Performance
  - Improved accuracy with using transfer learning
  - Reduction in computational cost

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Differences/Similarities for Different Spaces

- Benefit/aim of transfer learning
- What to transfer?
- How to transfer?
- When to transfer?
- Performance
- Challenges

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Automated Transfer Learning

- Automating TL design decisions
- Design decision
- Approaches
  - Selection perturbative hyper-heuristic – single point hyper-heuristic applied to randomly created design
  - Genetic algorithm – Each chromosome is a design
- Automated transfer learning for evolutionary algorithms (ATLEA)

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ATLEA Library Demonstration in Python

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Discussion: Future Research Directions

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