ML in OR

Machine and Deep Learning

- Problems are solved by helping machines "discover" their "own" algorithms, without needing to be explicitly told what to do by any human-developed algorithms
- Machine-learning approaches have been applied to large language models, computer vision, speech recognition, etc.
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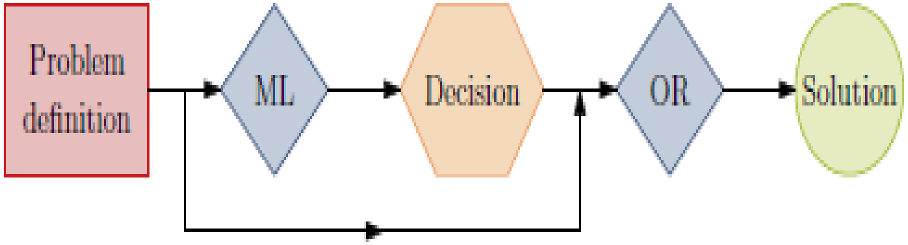
Machine learning for combinatorial optimization

- Parameter prediction (prediction of any parameter of the algorithm) – estimating time window of the problem, time of solver execution
- Fast generation of many local solutions which can be further processed by solver



Y. Bengio, A. Lodi, Provoust: Machine learning for combinatorial optimization: A methodological tour d'horizon

Q. Cappart, D. Chetelat, E. Khahil, A. Lodi, C. Morris, P. Velickovic: Combinatorial Optimization and Reasoning with Graph Neural Networks

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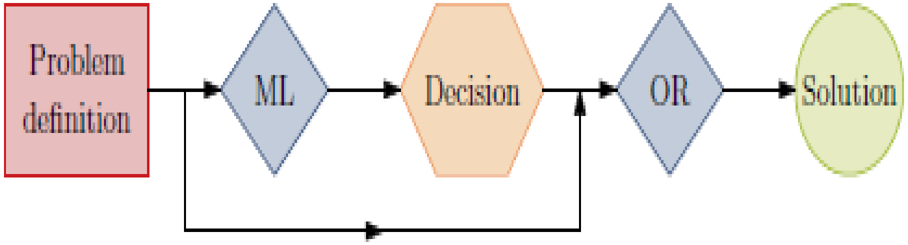

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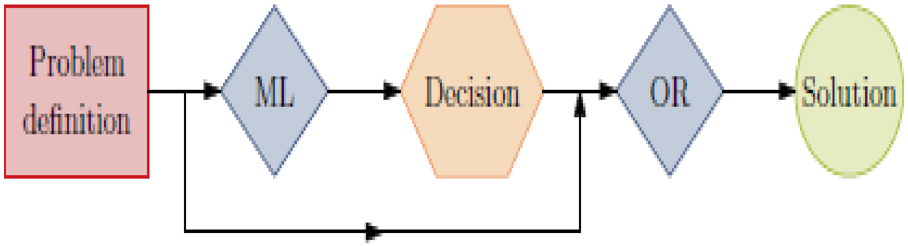

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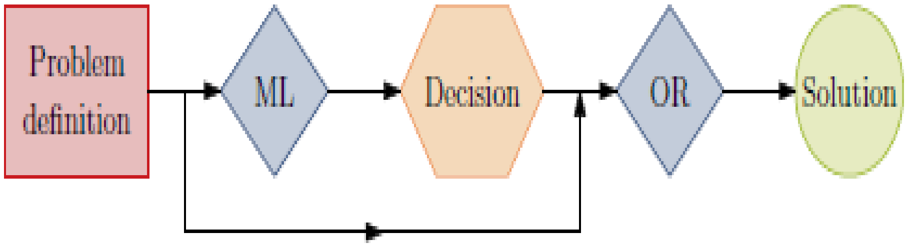

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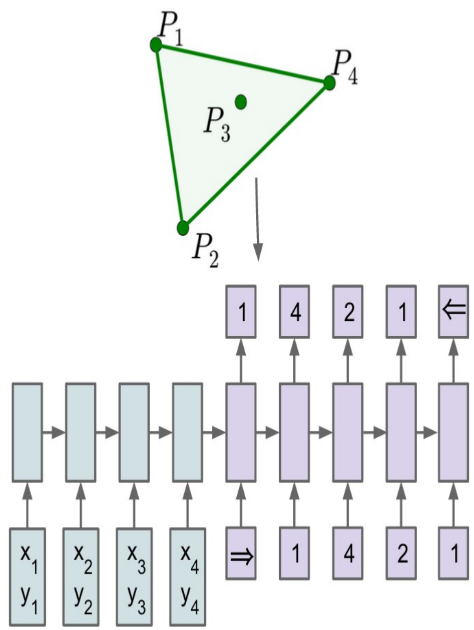
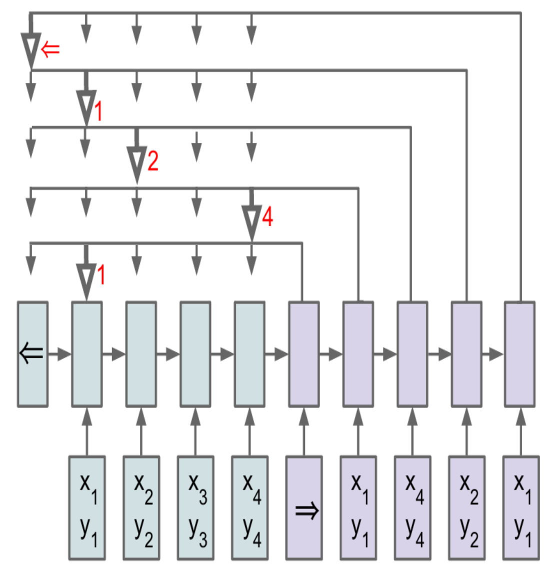
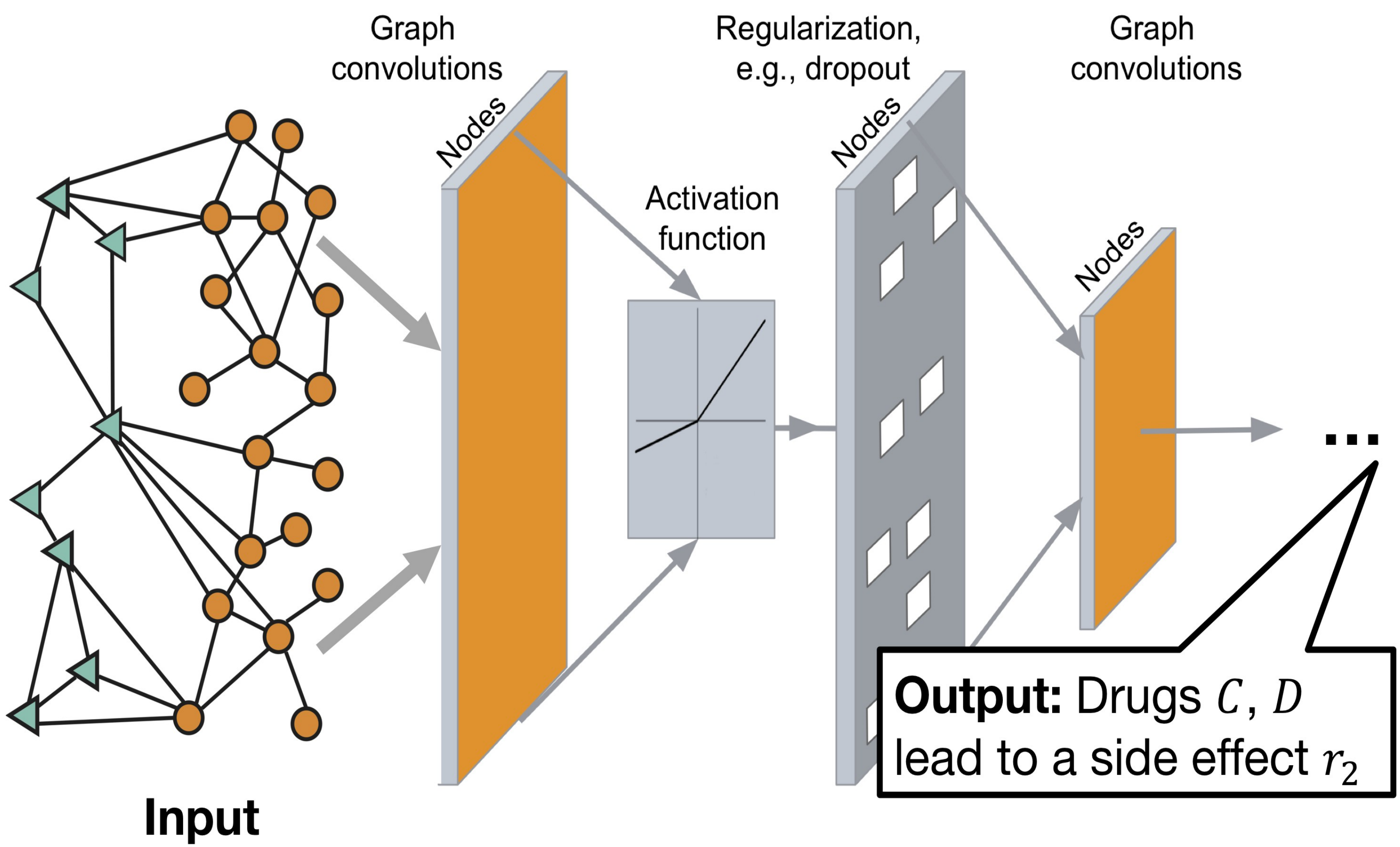
Pointer Network

- Sequence-to-sequence model
- Architecture inherited from language translation model



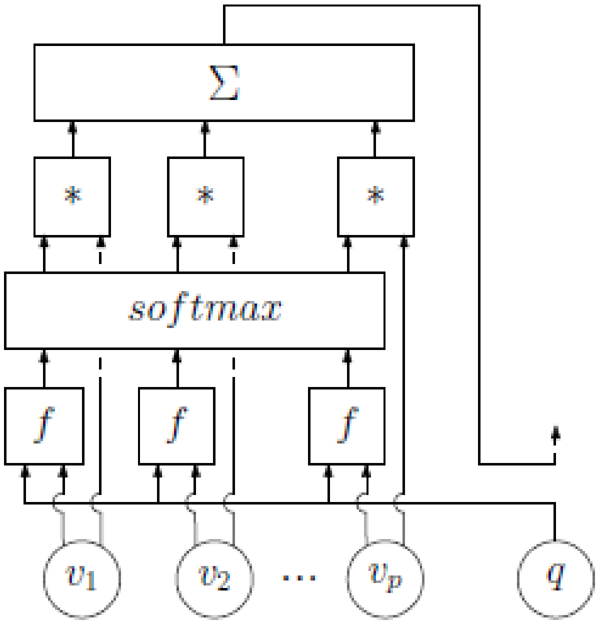


Graph Neural Networks



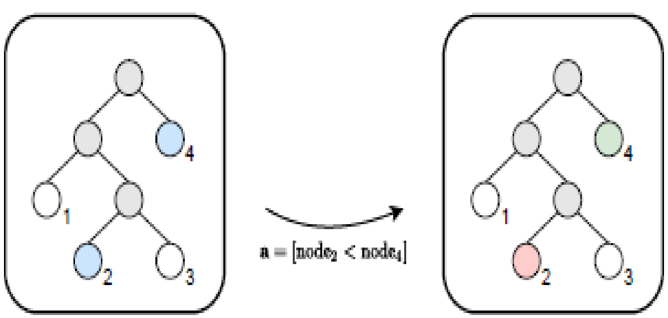
GAT - Graph Attention Networks

- End-to-end solver or can support local search
- GNN incorporated with attention mechanism



Node comparing

- Constraint embeddings represented by graph neural network
- Nodes are represented by the state (set of equations)
- State is GNN model
- Nodes are compared by Siamese network



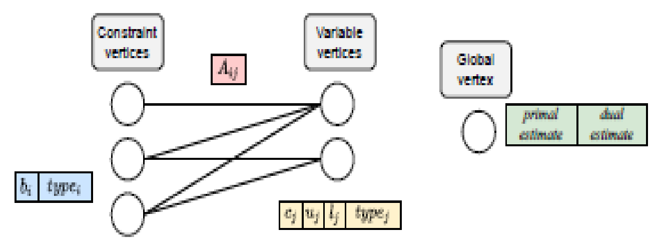
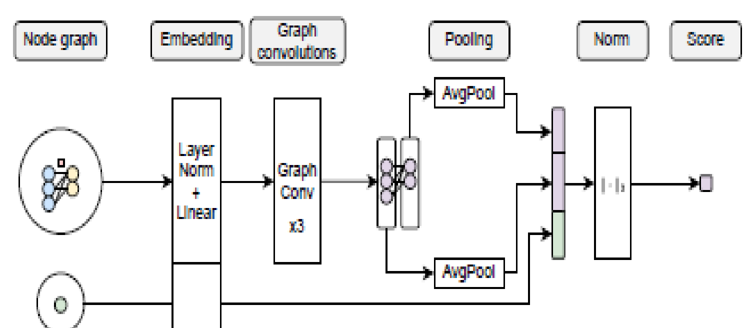


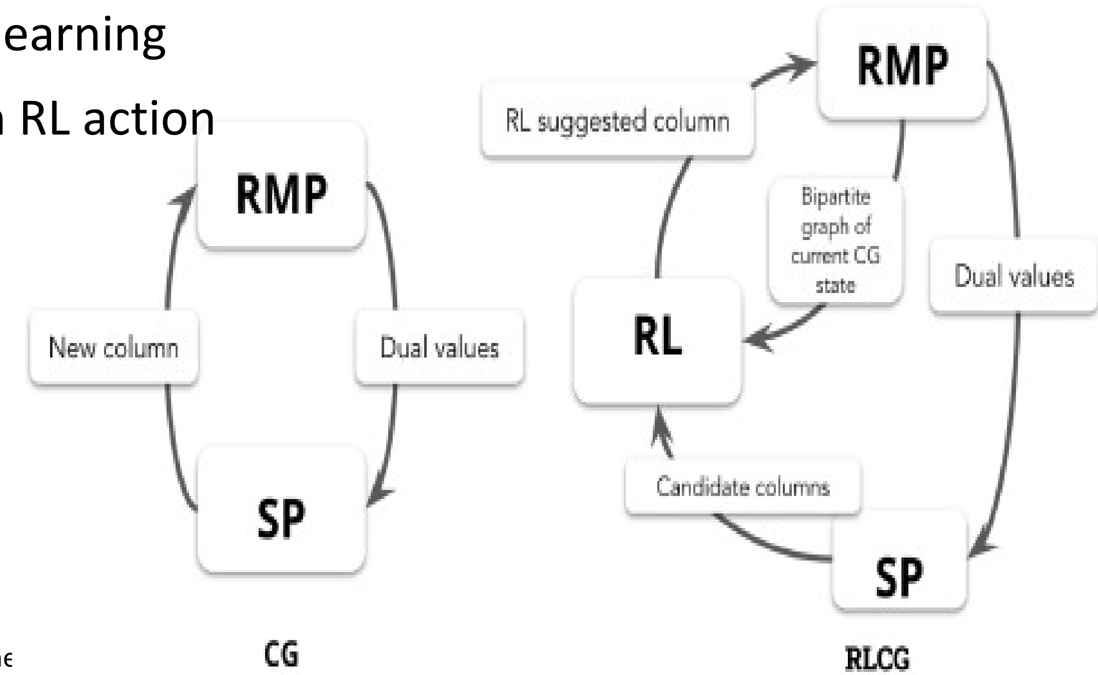
Figure 2: Bipartite graph representation of a node.



Column generation

Branch and price:

- Column selection
- State represented by GNN
- Model is trained by reinforcement learning
- The column is selected based on an RL action



A. Lodi: A Deep Reinforcement Learning Framework for Column Gene

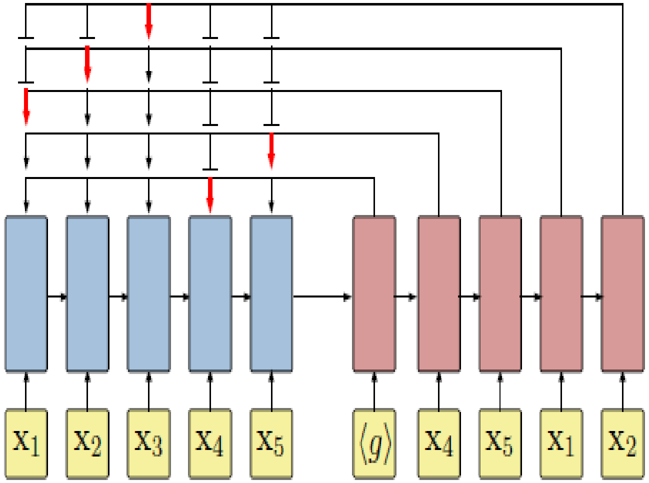
ML for column generation support

Using machine learning to improve a column generation framework for a tail assignment optimizer (Lukas Enarsson and Karthikeyan Jeganathan):

- Standard ML models (Naive Bayes, SVM, Random Forest, ANN)
- Models trained to choose the strategy: *1. Current heuristic. 2. Only use warm start. 3. Only use cold start. 4. Start with warm start and switch starts every 10th iteration. 5 Cold start every 20th iteration, else warm start. 6. Cold start first 10 iterations, then switch every 10th iteration. 7. Cold start first 15 iterations, then use the current heuristic. 8. Warm start first 15 iterations, then use the current heuristic. 9. Dynamic strategy based on the lower bound.*
- Feature engineering: 1. Number of flight legs. 2. Number of aircraft. 3. Number of global constraints. 4. Number of soft cumulative rules. … *12. Number of connections of duration - 0–10 minutes. 13. Number of connections of duration - 10–20 minutes. 14. Number of connections of duration - 20–30 minutes. 15. Number of connections of duration - 30–45 minutes. 16. Number of connections of duration - 45–60 minutes. … 28. Average length of flights.*
- Use case and benchmark : Jeppesen data

Reinforcement learning

- Neural Combinatorial Optimization (NCO)
- Pointer Network is used for policy gradient optimization
- One of the first deep learning approach for optimization problem (~1500 citations)



Method overview

Method	Paper	Datasets
Node/Variable selection in MILP	https://arxiv.org/pdf/2210.16934.pdf https://arxiv.org/pdf/2205.14210.pdf https://github.com/ds4dm/learn2comparenodes	Fixed Charge Multicommodity Network Flow, Maximum Satisfiability, Generalized Independent Set
Pointer Networks	https://arxiv.org/pdf/1506.03134.pdf	TSP (good results up to 40 points), Covex Hull, Delaunay Triangulation
RL with Pointer Network (NCO)	https://arxiv.org/abs/1611.09940	TSP (up to 100 points)
Parameter prediction strategies config in column generation/selection	https://odr.chalmers.se/server/api/core/bitstreams/62ae292b-e078-4c41-8a14-4fcf41408872/content	Jeppesen data
Column generation/selection in MILP	https://arxiv.org/pdf/2206.02568.pdf	Vehicle Routing Problem with Time Window, Cutting Stock Problem
Exact GNN	https://arxiv.org/pdf/1906.01629.pdf	Maximum Independent Set, Set Covering

Machine learning approaches for air transport management

Trajectory optimizer:

Khan, W.A., Ma, H.-L., Ouyang, X., Mo, D.Y., 2021. Prediction of aircraft trajectory and the associated fuel consumption using covariance bidirectional extreme learning machines.
Khan, Chung. Optimized covariance bidirectional extreme learning machine for prediction and feature analysis of IATA coded flight delays subcategories
Filom, S., Amiri, A.M., Razavi, S., 2022. Applications of machine learning methods in port operations–A systematic literature review. Transp. Res. E Logist.Transp. Rev. 161, 102722
Alcaraz, J.J., Losilla, F., Caballero-Arnaldos, L., 2022. Online model-based reinforcement learning for decision-making in long distance routes. Transp. Res. E Logist. Transp. Rev. 164, 102790.

Reinforcement and machine learning for air transport management

Aircraft maintenance:

Ruan, J., Wang, Z., Chan, F.T., Patnaik, S., Tiwari, M.K., 2021. A reinforcement learning-based algorithm for the aircraft maintenance routing problem. Expert Syst. Appl. 169, 114399. - RL-based Q-learning algorithm to solve the operational aircraft maintenance routing problem, Upon benchmarking with several meta-heuristics, they concluded that the proposed RL-based algorithm outperforms these metaheuristics (operational aircraft maintenance routing problem – OAMRP, four types of maintenance)

Hu, Y., Miao, X., Zhang, J., Liu, J., Pan, E., 2021. Reinforcement learning-driven maintenance strategy: A novel solution for long-term aircraft maintenance decision optimization

Handle capacity imbalances:

Kravaris, T., Lentzos, K., Santipantakis, G., Vouros, G.A., Andrienko, G., Andrienko, N., Crook, I., Garcia, J.M.C., Martinez, E.I., 2022. Explaining deep reinforcement learning decisions in complex multiagent settings: towards enabling automation in air traffic flow management. Appl. Intell. 1–36. Deep multi-agent RL method to handle demand and capacity imbalances in actual air traffic management settings with many agents, which addressed the challenges of scalability and complexity in the proposed problem.

ChatGPT

- Language model can be treated as an additional model which can help in building final solution
- It can give answer for a simple questions (for simple question it gives correct answers with high accuracy and certainty)
- From received answers the main module can give final answer for more complex problem

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Method	Paper	Datasets
OPRO (prompt optimization)	https://arxiv.org/abs/2309.03409	TSP, Big-Bench Hard tasks
Tree of Thoughts	https://arxiv.org/abs/2305.10601	Game of 24, Creative Writing

Conclusions

- Many DL models give promising results in OR problems (most of them are routing, transportation problems)
- Some deep learning-based approaches achieve results similar to hand-crafted algorithms
- In case of the large instance problems the ML based approach is very often worse than hand-crafted approaches
- Generalization is till open issue: how to transfer model to instances with different size
- Feature engineering
- Data generation

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Other papers with ML in OR

Pham, D.-T., Tran, P.N., Alam, S., Duong, V., Delahaye, D., 2022. Deep reinforcement learning based path stretch vector resolution in dense traffic with uncertainties. Transp. Res. C Emerg. Technol. 135, 103463. utilized the RL approach to solve the conflict resolution problem with surrounding traffic and uncertainty in air traffic management

Šemrov, D., Marsetič, R., Žura, M., Todorovski, L., Srdic, A., 2016. Reinforcement learning approach for train rescheduling on a single-track railway. Transp. Res. B 86, 250–267.

Yan, Y., Chow, A.H., Ho, C.P., Kuo, Y.-H., Wu, Q., Ying, C., 2022. Reinforcement learning for logistics and supply chain management: Methodologies, state of the art, and future opportunities. Transp. Res. E Logist. Transp. Rev. 162, 102712.

Basso, R., Kulcsár, B., Sanchez-Diaz, I., Qu, X., 2022. Dynamic stochastic electric vehicle routing with safe reinforcement learning. Transp. Res. E Logist. Transp. Rev. 157, 102496.

Claudia Bongiovanni*, Mor Kaspi, Jean François Cordeau, Nikolas Geroliminis. A machine learning-driven two-phase metaheuristic for autonomous ridesharing operations.