

Distance estimation in vehicle routing problems

An empirical approach using neural networks and ensemble learning

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Agenda

① Vehicle Routing Problems (VRPs)

② Route Distance Estimation

Relevance

Literature review

③ Methodology

Research design

Dataset

Models

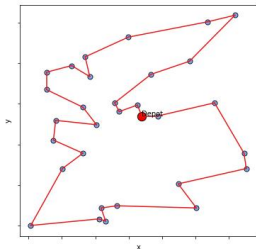
④ Results

⑤ Discussion

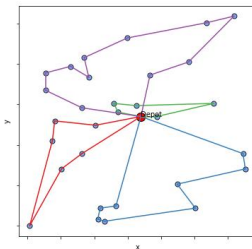
Vehicle Routing Problems (VRPs)

- Group of combinatorial optimization problems
- Problem description:
 - **Given:** 1. Set of customers, 2. Fleet of vehicles, 3. Various constraints
 - **Determine:** Feasible routes at minimum cost (typically total distance)
- Computationally expensive (NP-hard)

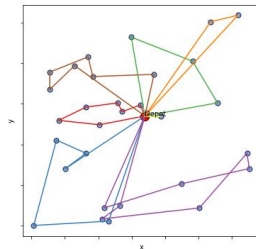
Traveling Salesman Problem (**TSP**)



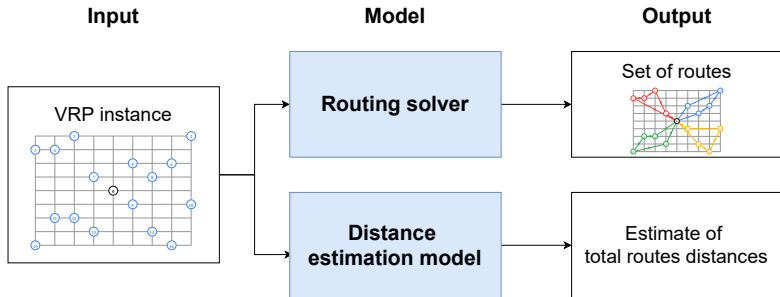
Capacitated Vehicle Routing Problem (**CVRP**)



Capacitated VRP with Time Windows (**CVRPTW**)



Route Distance Estimation



Why is distance estimation relevant?

- Integrated routing problems (e.g. location routing)
- Combinatorial auctions
- Managerial decisions

Literature Review

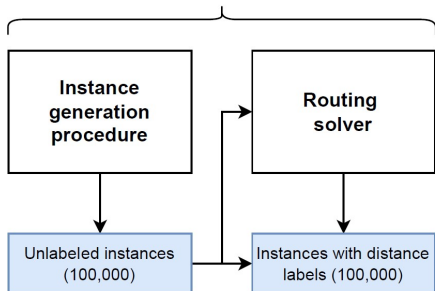
- Mostly linear regression with few predictors and strong assumptions about instance characteristics
- Many papers about the TSP, very few about the CVRPTW
- Current CVRPTW datasets are not well suited for distance estimation.
 - Only four public CVRPTW datasets in VRP-REP
 - Few instances, little variety in instance characteristics, old

Research objectives

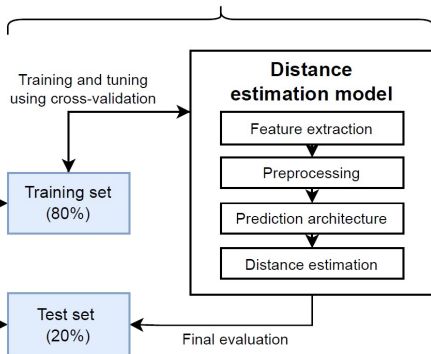
- ① A large CVRPTW **dataset** with instance characteristics from a wide variety of distributions
- ② New estimation **models** to predict distances more accurately than the linear approaches

Research Design

Objective 1:
Creating the dataset

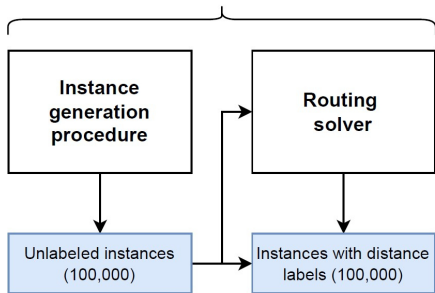


Objective 2:
Developing the model

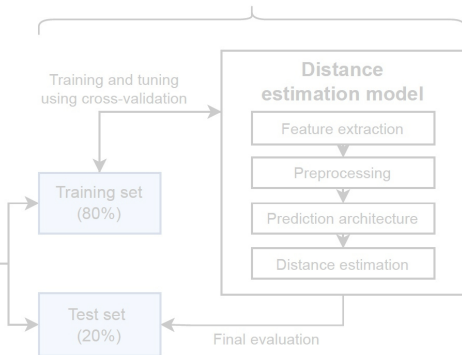


Research Design

Objective 1: Creating the dataset

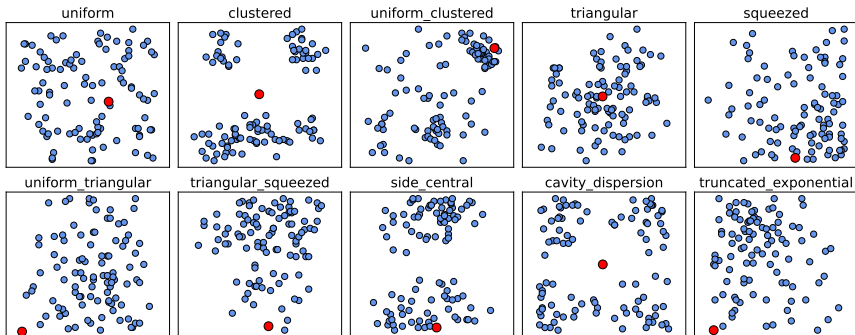


Objective 2: Developing the model



Instance Generation Procedure

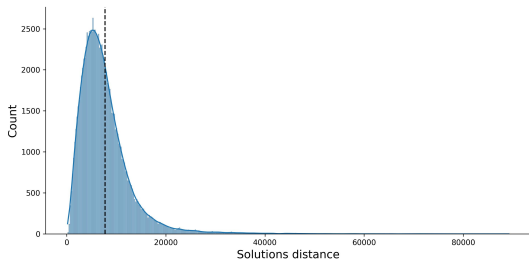
- A CVRP instance has 12 characteristics.
- Characteristics are sampled from 28 distributions.
- Examples:
 - The number of customers is uniform between 20 and 100.
 - Customer locations follow one of 10 distributions:



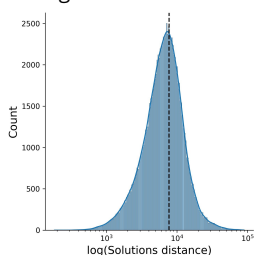
Routing Solver

- Meta-heuristics are most common in practice
- Implementation of 16 strategies using OR-Tools
 - Final solver: Path cheapest arc + Guided local search
 - 0.74% to optimal on benchmark by Solomon (1987)
- Full dataset solved on AWS c6g over 5000 hours (3min per instance)

Distribution of solver distances

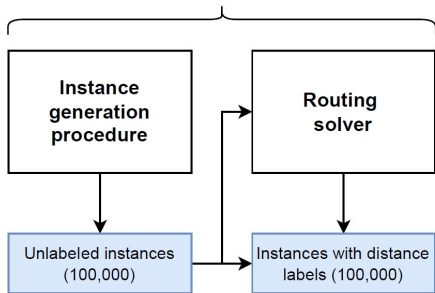


Log-transformation



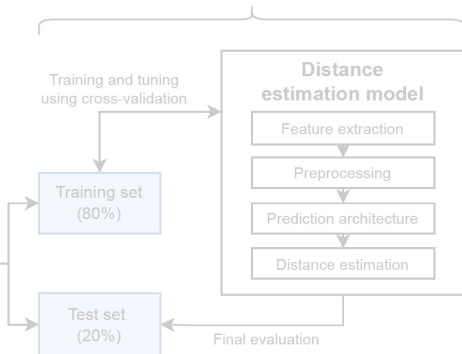
Research Design

Objective 1: Creating the dataset



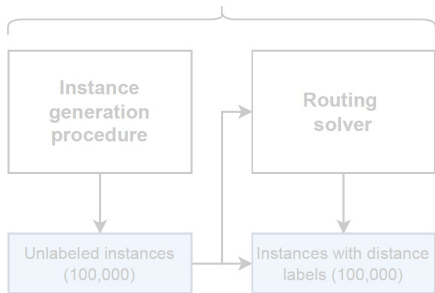
 Data

Objective 2: Developing the model



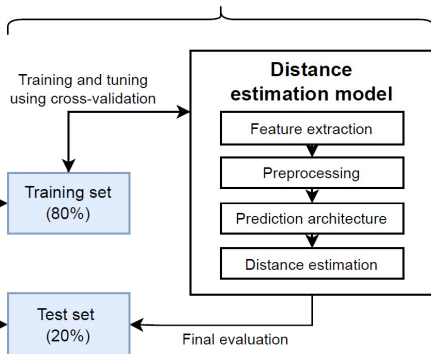
Research Design

Objective 1:
Creating the dataset



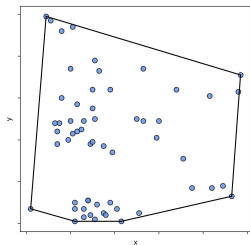
 Data

Objective 2:
Developing the model



Feature Extraction

- Goal: Capture informative signal from routing instances
- Definition of 45 different features
- Examples:
 - Number of customers
 - Size of the service area
 - Distance from depot to customers
 - Demand coverage
 - Average length of time windows



Convex hull

Model Architectures

Baseline models

- Constant model
- Other variants
- Greedy heuristic

Linear regression

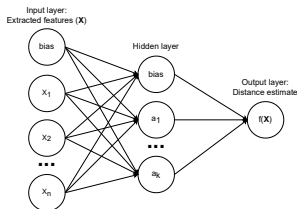
- Target transformation
- Feature selection
- Polynomial terms

Multilayer perceptron (MLP)

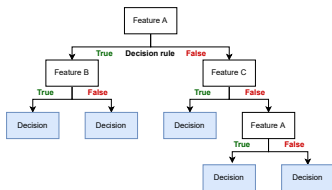
- Standardization $x' = \frac{x - \mu}{\sigma}$

Ensemble methods

- Random forest
- Gradient boosting



Multilayer perceptron



Decision tree

Model Training

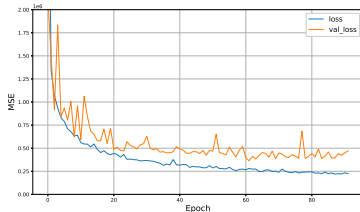
Optimization objective is the Root Mean Squared Error:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}$$

Hyperparameter tuning:

- Random grid search
- Large parameter space
- Iterative refinement
- Over 100 models fitted

Multilayer perceptron training



Results

| Model | RMSE | MAPE | Prediction time / 1,000 instances |
|-----------------------|--------|--------|--------------------------------------|
| Multilayer-perceptron | 636.7 | 4.48% | 8.57s |
| Gradient boosting | 695.9 | 4.80% | 8.54s |
| Polynomial regression | 859.2 | 5.56% | 8.55s |
| Random forest | 1045.0 | 6.83% | 8.55s |
| Greedy heuristic | 1115.6 | 10.11% | 734.14s |
| Linear regression | 1982.1 | 13.54% | 8.53s |
| Daganzo (1984) - CVRP | 2055.6 | 16.93% | 2.85s |
| Beardwood(1959) - TSP | 4498.6 | 28.49% | 2.80s |
| Constant model | 5627.0 | 78.42% | 0.00s |

- The new models can predict distances more accurately.
- No significant increase in computation time.
- Routing solver are too slow for distance estimation.

Opportunities

- More informed decision-making
- Economic value even for small improvements
- Estimating heuristics is realistic
- Easily adaptable to other routing variants

Limitations & Future Research

- Bad generalization to larger problems → active research field
- Fixed feature vectors → graph neural networks
- Slow feature extraction → improve code performance
- Real-world data

Conclusion

Topic relevance

- Distance estimation is important in situations that require cost estimates for a large number of instances in short computation time.

Research problems

- Current CVRPTW datasets are not suitable distance estimation.
- Most studies rely on linear models, few predictors, and strong assumptions.

Methodology

- A large CVRPTW dataset with high variance is created and solved.
- Three new distance estimation models are developed.

Results

- The new models achieve better estimates at similar computation time.
- Particularly the MLP and gradient boosting show promising results.
- Further exploration of this approach in richer routing variants is suggested.