Demand Routing for Intermodal Transportation Networks using a Design-as-Inference Approach

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Outline

• **Problem**
  – Intermodal freight routing
  – Terminal planning

• **Methods**
  – Design-as-inference
  – Markov-chain Monte Carlo (MCMC)

• **Current status & future work**
Intermodal Freight Network

\[ N = 9 \times 8 \quad d = \{d_1, d_2, ..., d_N\} \]
Intermodal Freight Network

\[ k = \{k_1, k_2, \ldots, k_K\} \]
\[ T = \{T_1, T_2, \ldots, T_K\} \]

\[ K = 3 \quad M = 3 \times 2 \]
Intermodal Freight Network

\[ \mathbf{x} = \{ x_1^0, x_1^1, \ldots, x_1^M, \ldots, x_N^0, x_N^1, \ldots, x_N^M \} \]

\[ \mathbf{c} = \{ c_1^0, c_1^1, \ldots, c_1^M, \ldots, c_N^0, c_N^1, \ldots, c_N^M \} \]
Freight Demand Routing

• Routing demand through fixed network
• Must meet demand estimates and terminal capacity constraints
Terminal Planning

• Terminals may be added to ease congestion, add capacity, and ultimately reduce the cost of using the network

• Costs of building and running terminal must be weighed against the reduction in transportation cost by routing a greater portion of demand over rail

• Fixed cost of terminal becomes important
Cost and Terminal Capacity

\[ C(x) = \sum_{n=1}^{N} \sum_{m=0}^{M} c_n^m x_n^m + \sum_{k=1}^{K} F_K \]

\[ t_k(x) = \sum_{n=1}^{N} \sum_{m \in M^k} x_n^m \]

\[ t_k(x) \leq T_k \text{ for } 1 \leq k \leq K \]
Design-as-Inference

\[ d_n = \sum_{m=0}^{M} x_n^m \quad \text{for } 1 \leq n \leq N \]

- Demand estimates can be distributions
- Enables incorporation of uncertainty in demand estimates
Design-as-Inference

\[
p(x|d, c, T, k) \propto p(x|T, k, d) p(c|x, k)
\]

Posterior \( P(x) \) \hspace{2cm} Prior \( \pi(x) \) \hspace{2cm} Likelihood \( L(x) \)

\[
\log L(x) = -\frac{1}{2\sigma^2}C(x)
\]

\[
p(k|d, c, T) \propto Z
\]
Design-as-Inference

\[ Z = \int \pi(x)L(x) \, dx \]

- Evidence is used to compare different proposed terminal locations.
- Terminals that would be a net benefit to the network have a higher evidence value.
MCMC

\[ \xi(\mathcal{L}) = \int_{\mathcal{L}(x) > \mathcal{L}} \pi(x) \, dx \]

\[ Z = \int_{0}^{1} \mathcal{L}(\xi) \, d\xi \]
Preliminary Results
Preliminary Results
Preliminary Results
Preliminary Results
Roadmap

• Address terminal addition
• Improve prior exploration in nested sampling
• Use mapping data to generate more realistic test cases
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