

Metropolis-Hastings sampling of alternatives for route choice models

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Motivation

- a route choice model describes what way from an origin to a destination is chosen in a network
- universal set of alternatives is unknown and intractably large
- estimation of route choice models requires selection of a subset

Approaches to route choice set generation

- modeling of consideration sets
 - deterministic (e.g., K-SP) or stochastic (randomized SP)
 - unrealistic: fail to capture the chosen alternative
- assume that decision maker considers all alternatives
 - also unrealistic
 - sampling protocol generates operational subset
 - correct for sampling in the estimation

Sampling of alternatives

- sample \mathcal{C}_n with replacement from \mathcal{C} according to $\{q(i)\}_{i \in \mathcal{C}}$
- add the chosen alternative
- k_{in} is the number of times alternative i is contained in \mathcal{C}_n
- correct for sampling when estimating logit model

$$P(i|\mathcal{C}_n) = \frac{e^{\mu V_{in} + \ln\left(\frac{k_{in}}{b(i)}\right)}}{\sum_{j \in \mathcal{C}_n} e^{\mu V_{jn} + \ln\left(\frac{k_{jn}}{b(j)}\right)}}$$

where $\{b(i)\}_{i \in \mathcal{C}}$ is such that $q(i) = b(i) / \sum_{j \in \mathcal{C}} b(j)$

objective: sample paths according to pre-specified $\{b(i)\}_{i \in \mathcal{C}}$

Using Markov chains (MCs)

- finite state space
- discrete time $k = 0, 1, \dots$
- at time k , process is in state i^k
- $q(i, j)$ is one-step probability to reach state j from state i
- process has a unique stationary distribution if
 - every state eventually reaches every other state
 - there is at least one state i with $q(i, i) > 0$

objective: build MC of routes with stationary distribution $\{q(i)\}_{i \in \mathcal{C}}$

Metropolis-Hastings (MH) algorithm

- given a finite state space, positive weights $\{b(i)\}_i$ and “well-mixing” proposal transition distribution $q(i, j)$, MH generates MC that converges to $q(i) = b(i) / \sum_j b(j)$
1. set iteration counter $k = 0$
 2. select arbitrary initial state i^k
 3. repeat beyond stationarity
 - 3.1 draw candidate state j from $\{q(i^k, j)\}_j$
 - 3.2 compute acceptance probability $\alpha(i^k, j) = \min\left(\frac{b(j)q(j, i^k)}{b(i^k)q(i^k, j)}, 1\right)$
 - 3.3 with probability $\alpha(i^k, j)$, let $i^{k+1} = j$; else, let $i^{k+1} = i^k$
 - 3.4 increase k by one

Application of MH for route choice set generation

- state space comprises \mathcal{C}
- weights $b(i)$ favor plausible paths (importance sampling)
- transition distribution $q(i, j)$ creates local path modifications
 - too little variability: slow convergence
 - too much variability: random search

State space

- notation
 - Γ = a path (node sequence)
 - $\Gamma(u)$ = u th node of path Γ
 - $\Gamma(u, v)$ = sub-path from the u th to the v th node of Γ
 - $|\Gamma|$ = number of nodes in path Γ
- state = (a path Γ , two SPLICE locations, one SPLICE node)
 - SPLICE locations $u, d \in \mathbb{N}$ with $1 \leq u < d \leq |\Gamma|$
 - SPLICE node v
 - (state expansion helps to compute $q(i, j)$)

Proposal transition distribution

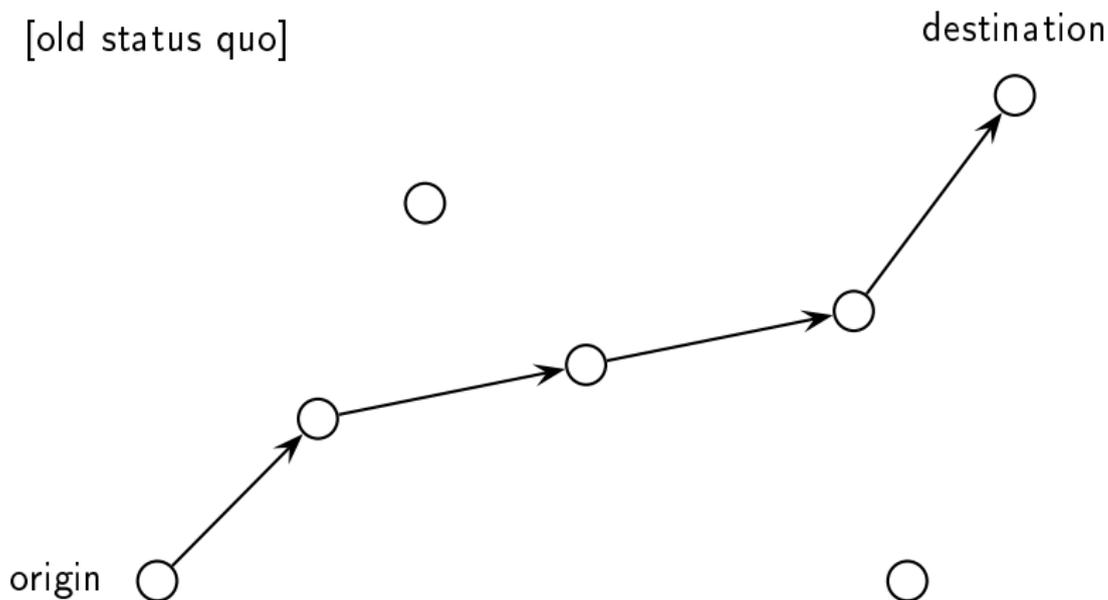
- SPLICE operation
 - compute (random) path from $\Gamma(u)$ to v
 - compute (random) path from v to $\Gamma(d)$
 - replace $\Gamma(u, d)$ by that sequence
- SHUFFLE operation
 - re-sample (uniformly) splice locations u and d
 - re-sample splice node v near to $\Gamma(u, d)$
- randomly select one procedure

$$q(i, j) = \gamma q_{SPLICE}(i, j) + (1 - \gamma) q_{SHUFFLE}(i, j)$$

with $0 < \gamma < 1$

Illustrative example

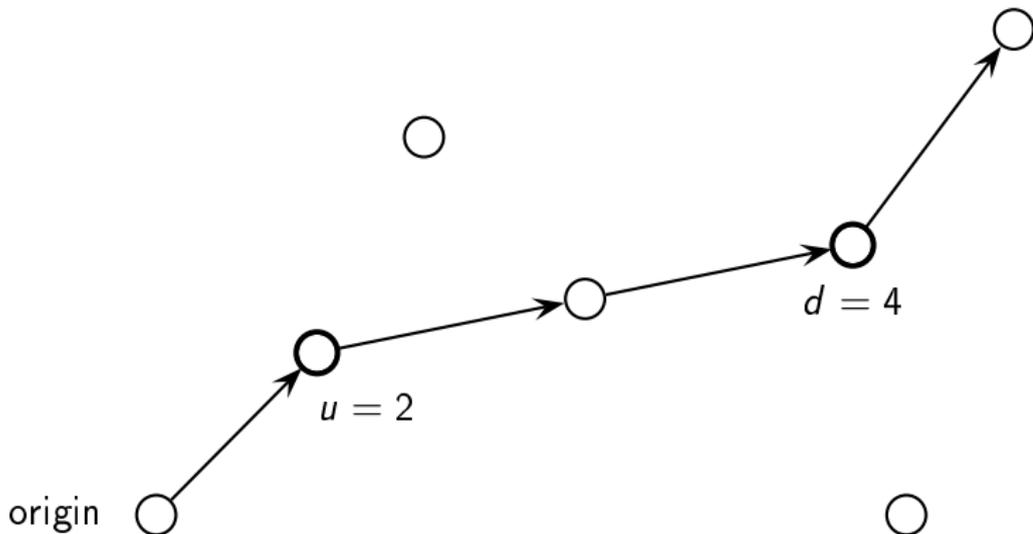
[old status quo]



Illustrative example

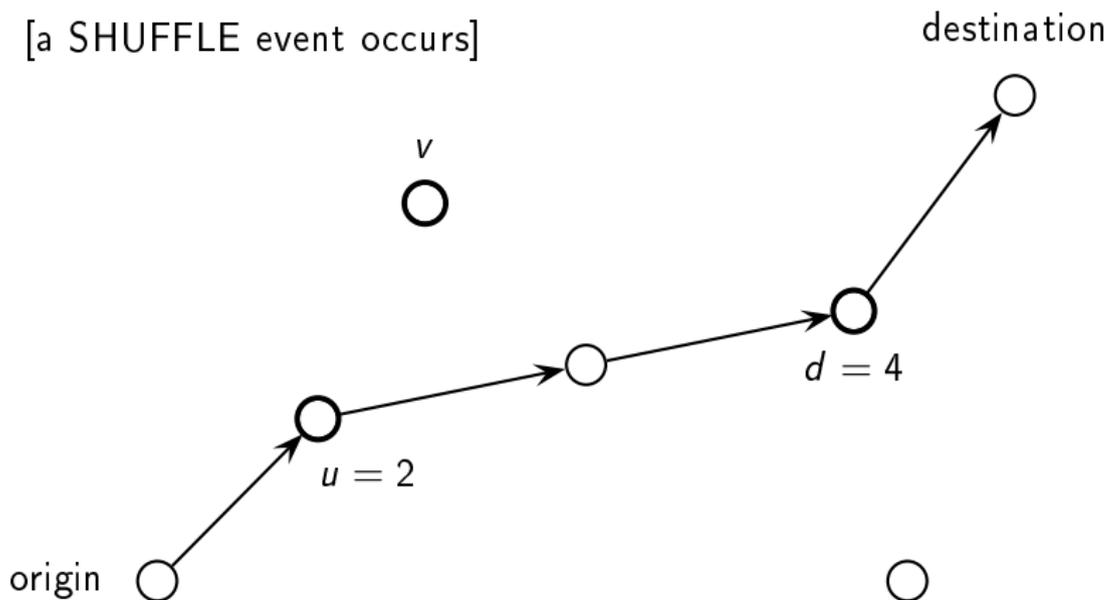
[a SHUFFLE event occurs]

destination



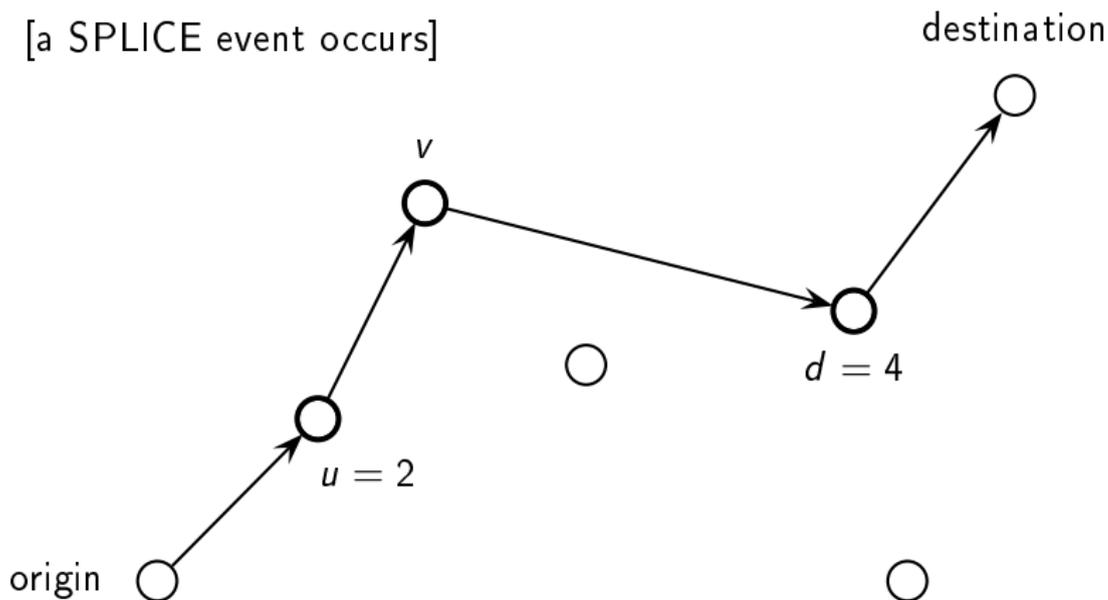
Illustrative example

[a SHUFFLE event occurs]

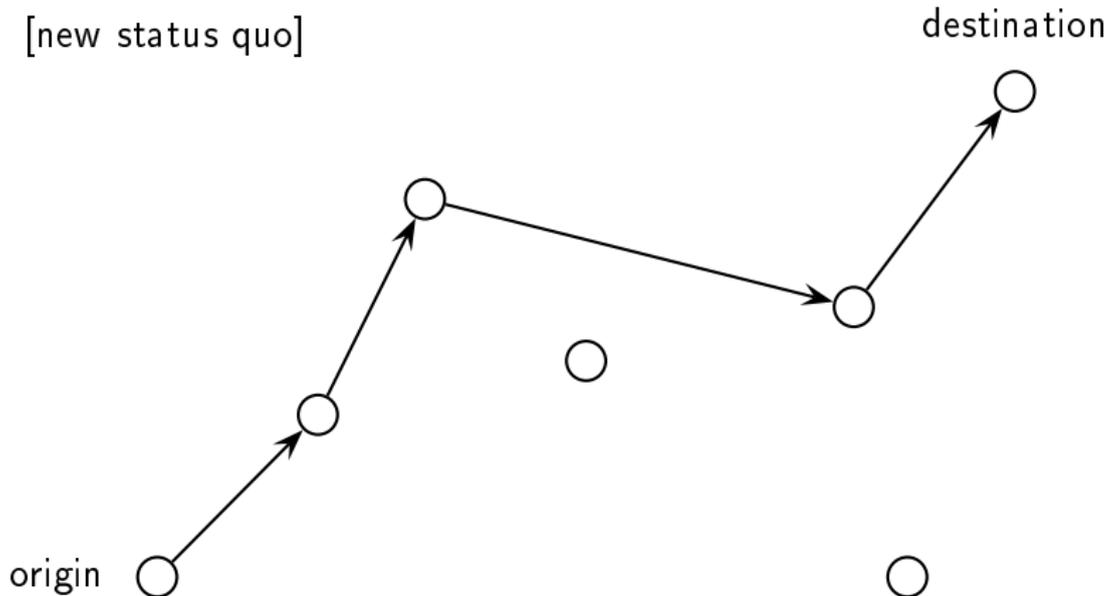


Illustrative example

[a SPLICE event occurs]



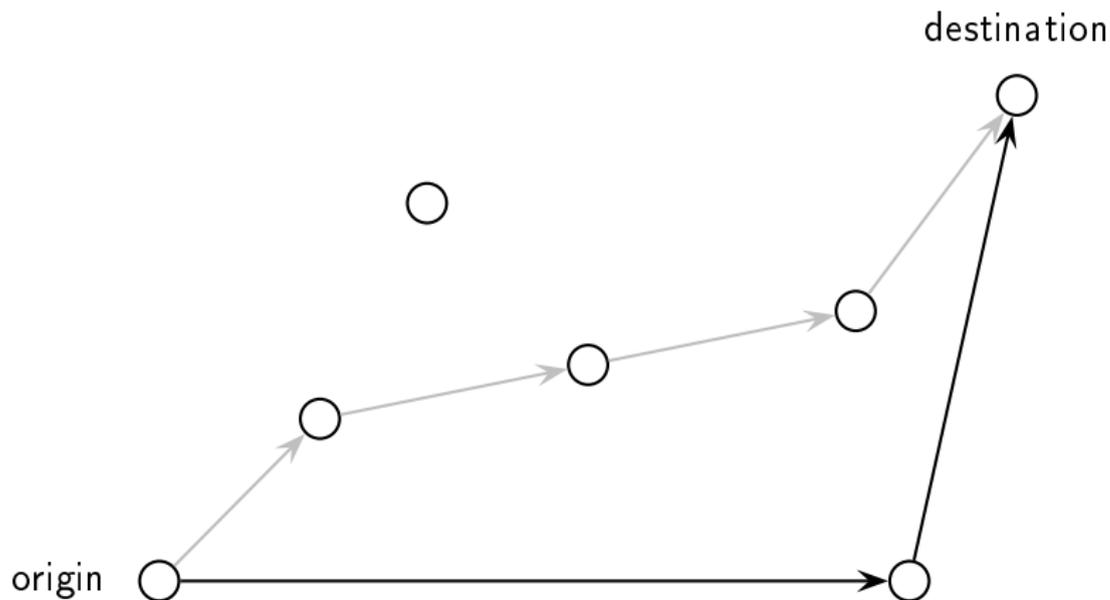
Illustrative example



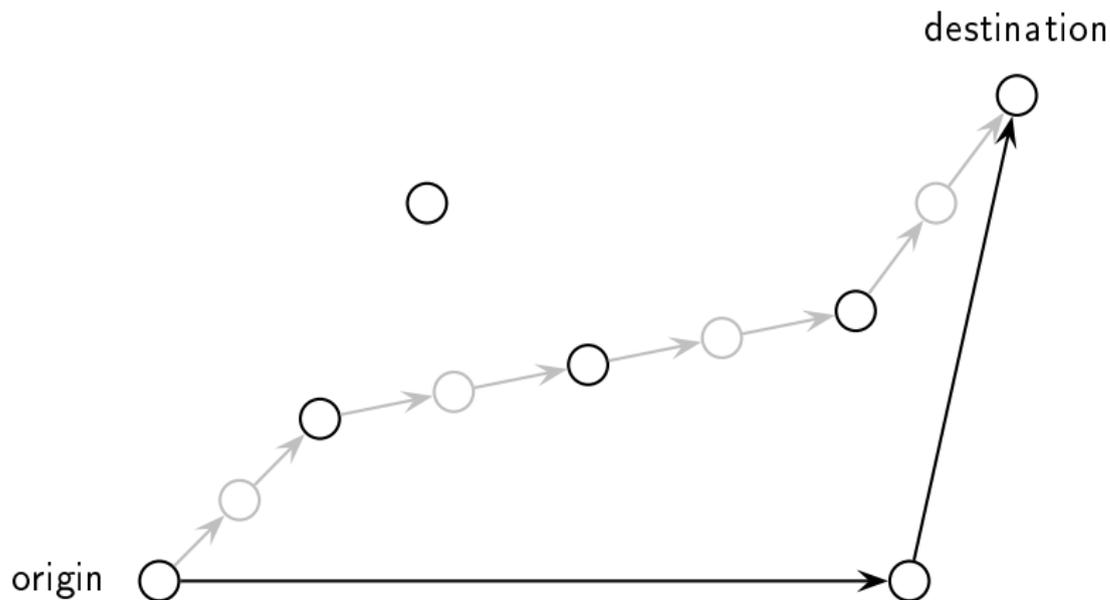
Discussion

- this *eventually* draws paths from *any* distribution
- computationally
 - feasible path in every iteration
 - need to reach and identify stationarity
 - strong auto-correlation of subsequent paths
- behaviorally
 - explorative travel behavior?
 - occasional intermediate destinations?
- iterated DTA simulations (such as MATSim)
 - an all-day plan is a generalized path
 - small plan choice set for computational reasons
 - challenge: capture distribution in simulated conditions

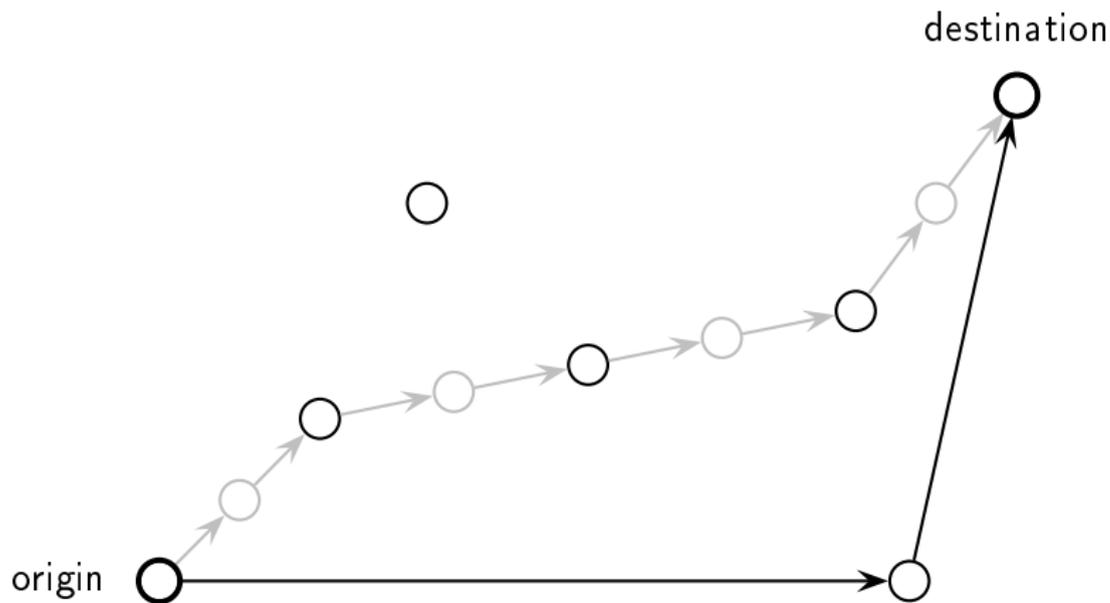
Shortest path SPLICE reaches every path



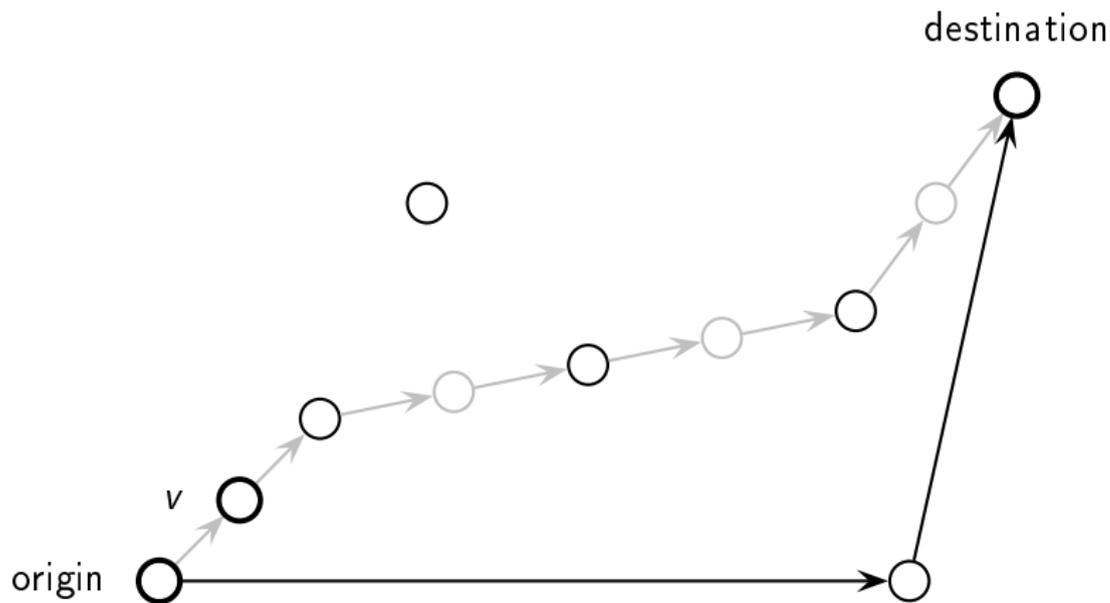
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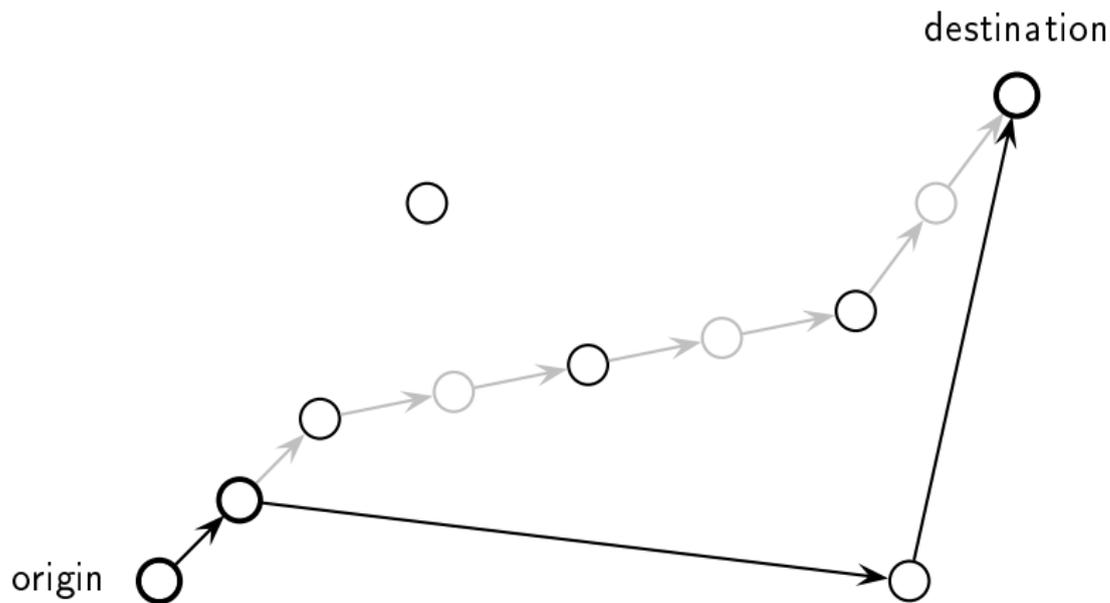
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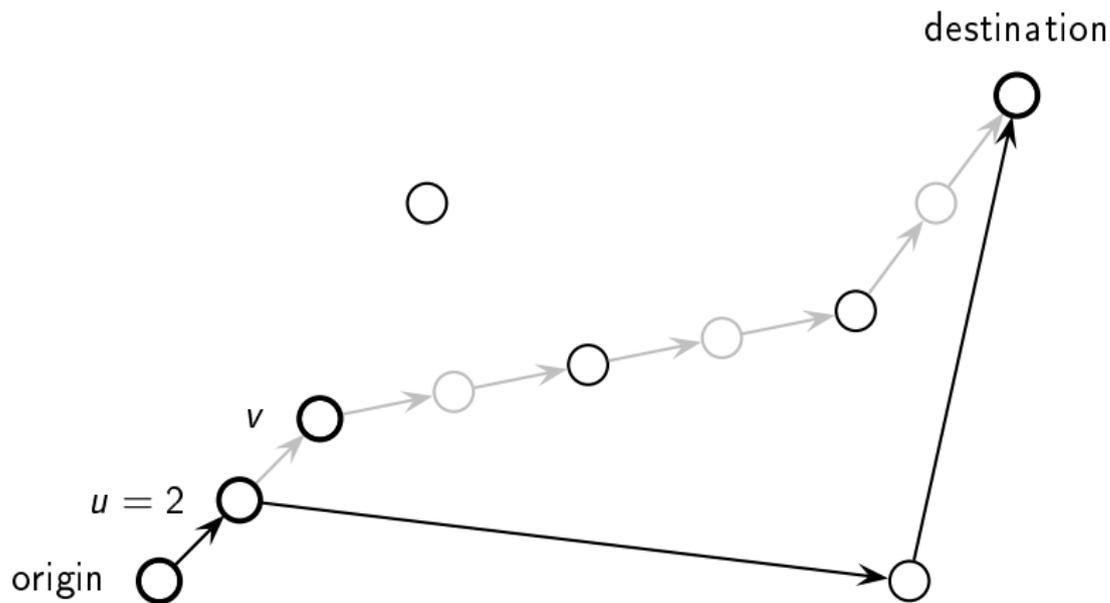
Shortest path SPLICE reaches every path



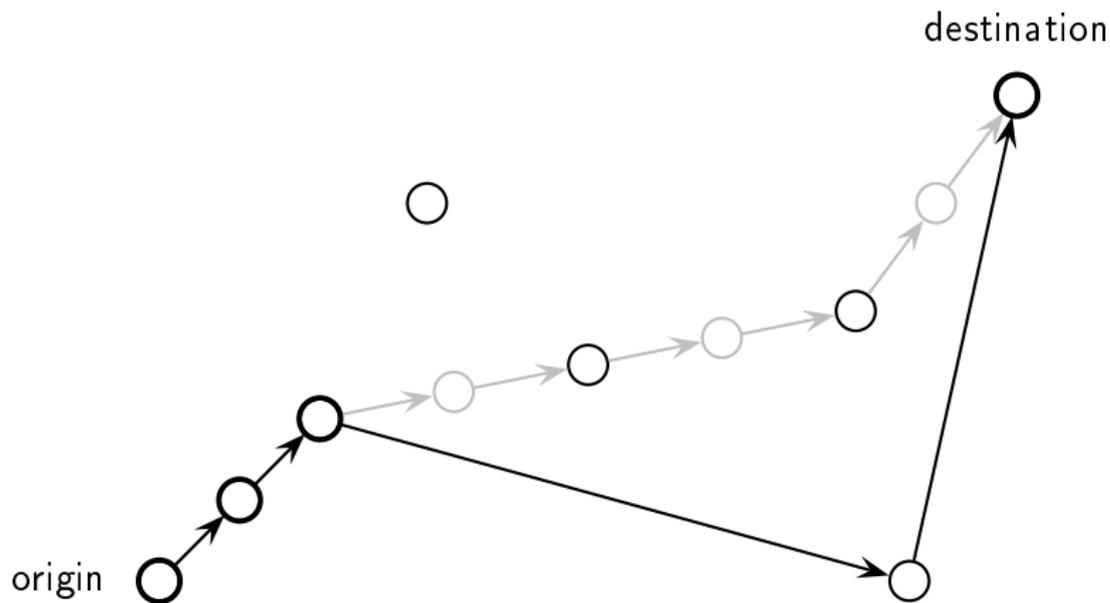
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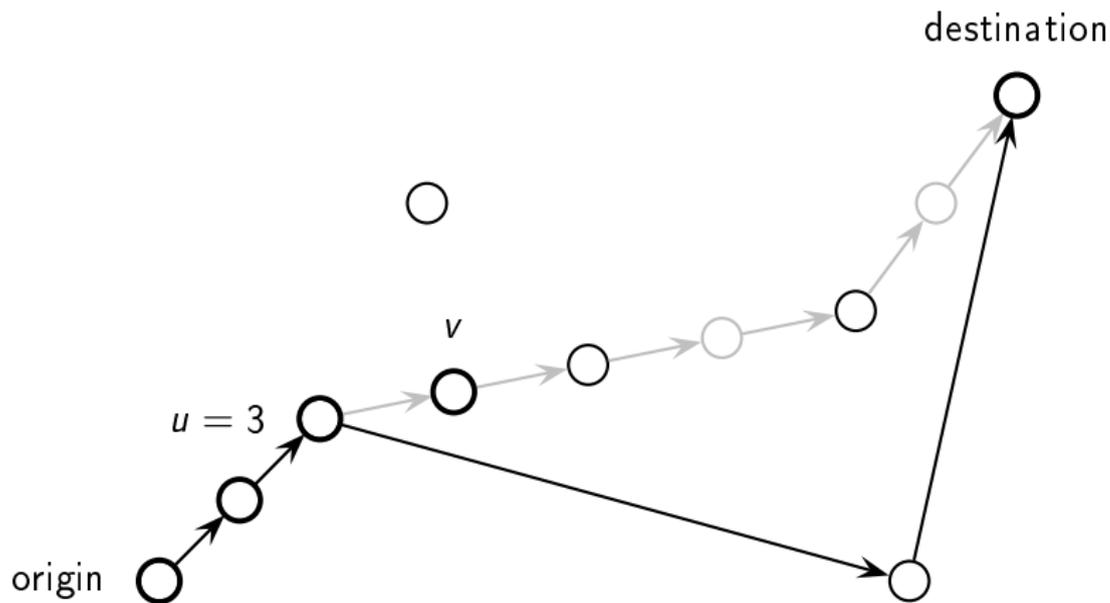
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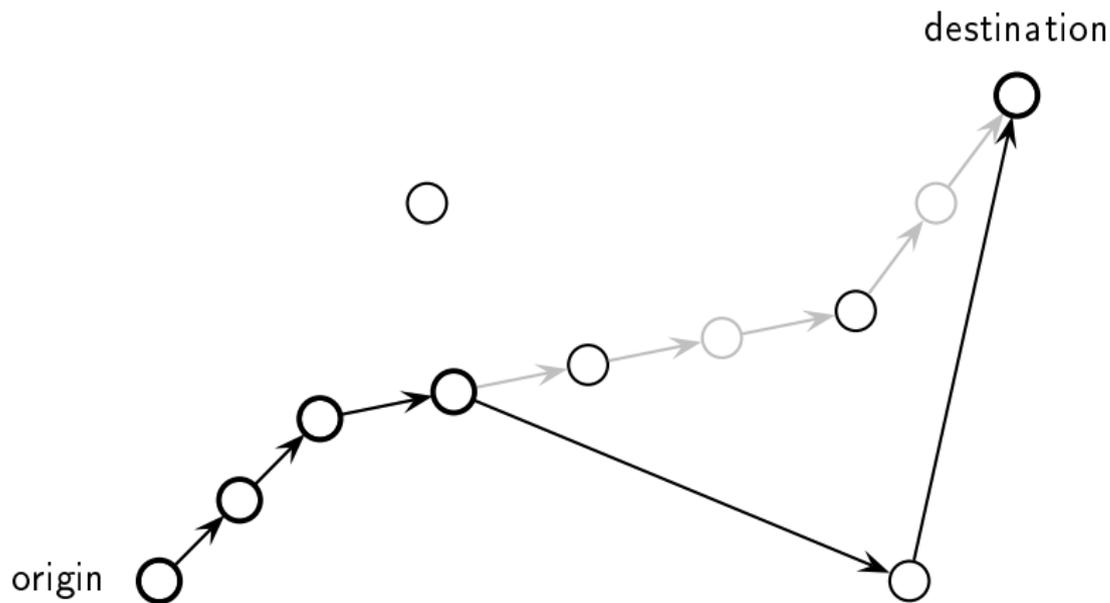
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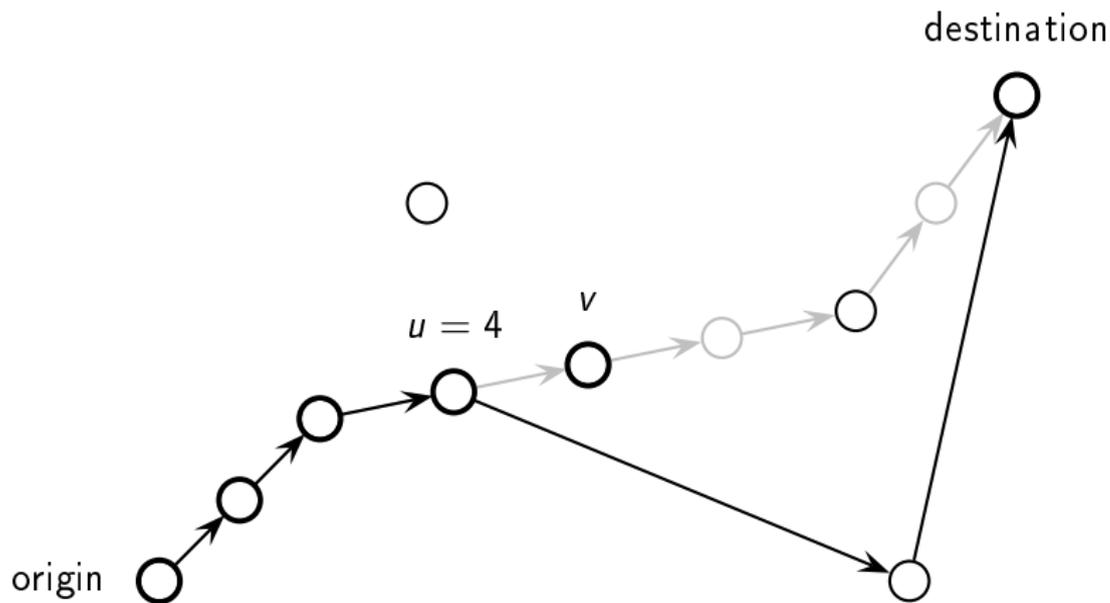
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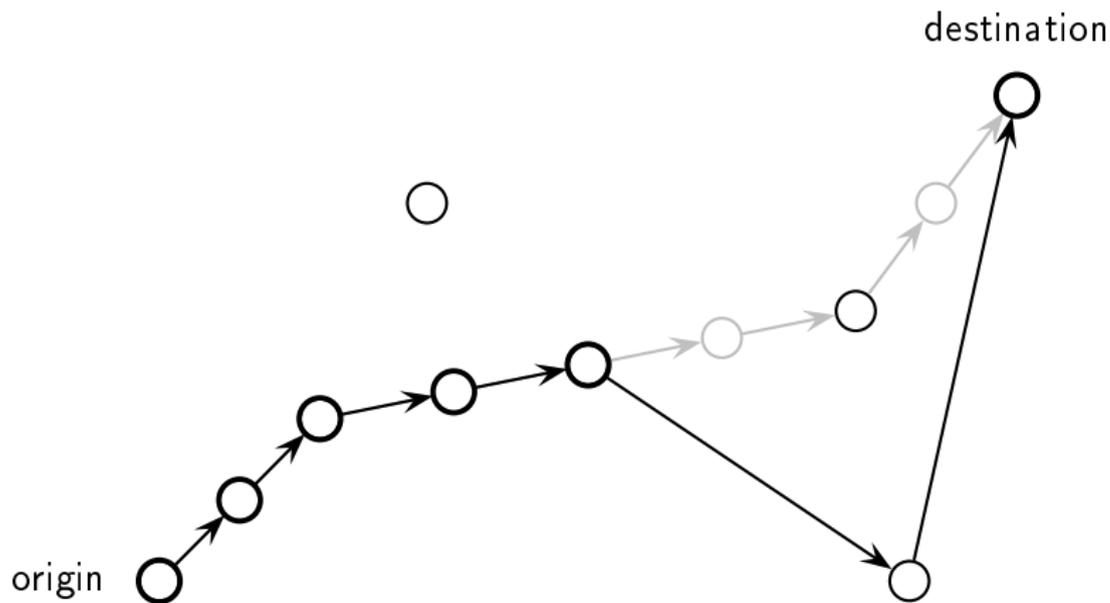
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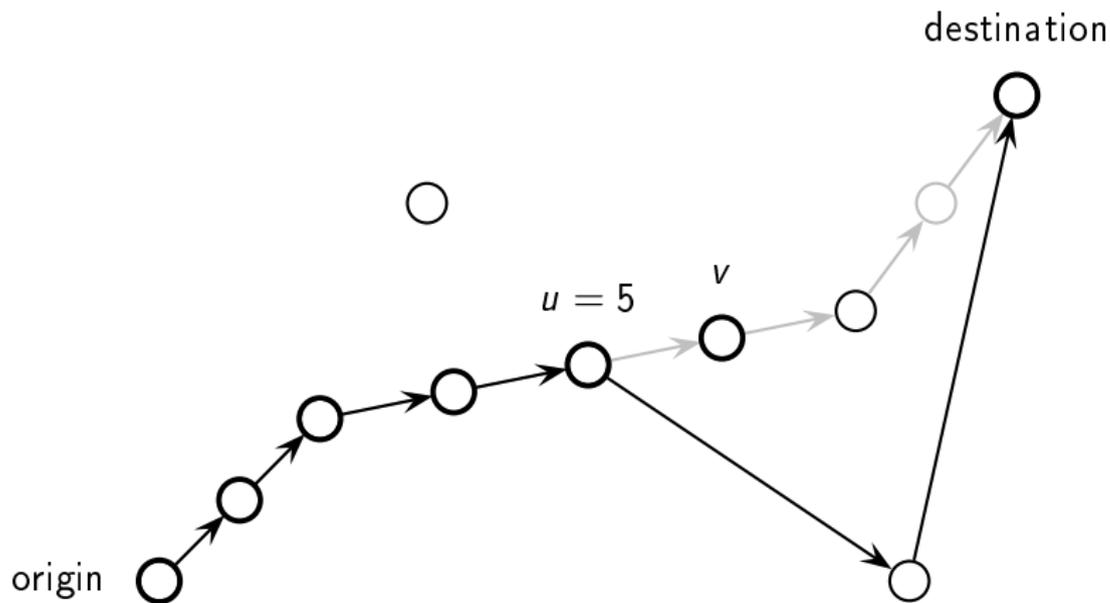
Shortest path SPLICE reaches every path



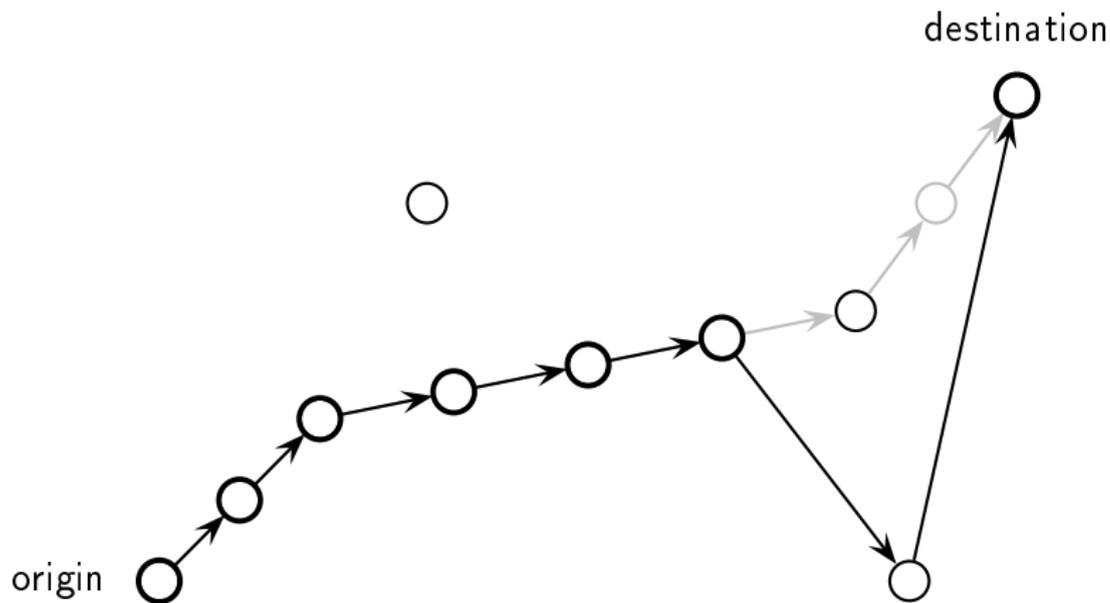
Shortest path SPLICE reaches every path



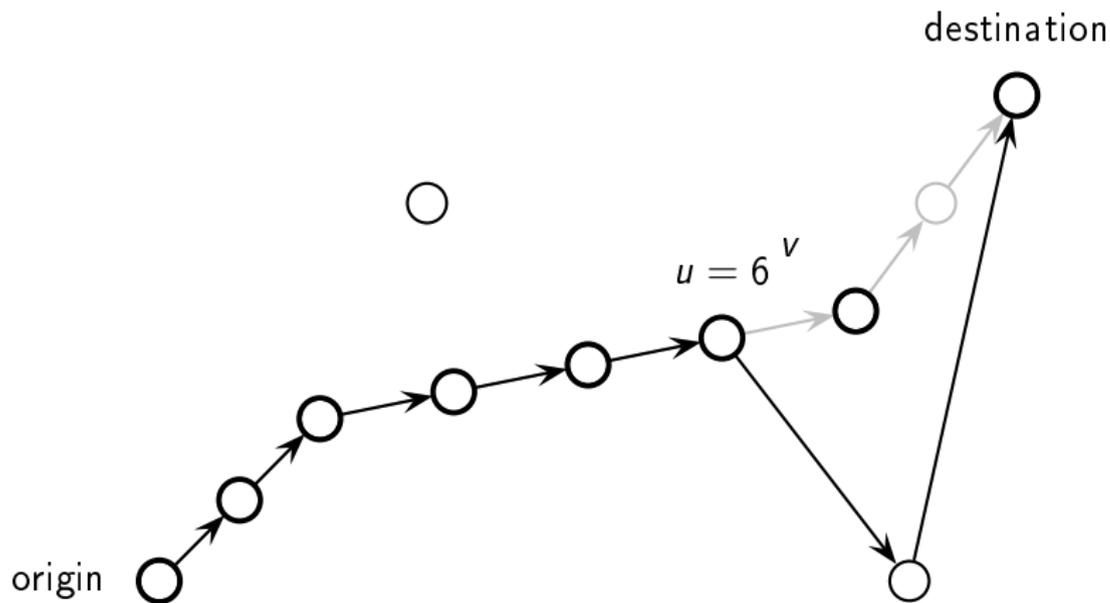
Shortest path SPLICE reaches every path



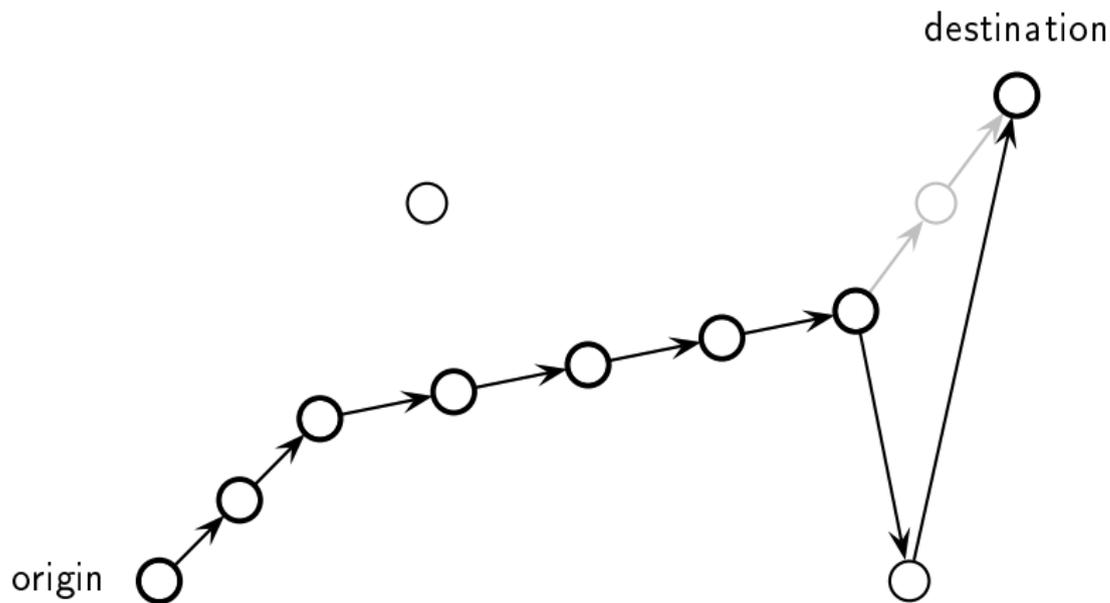
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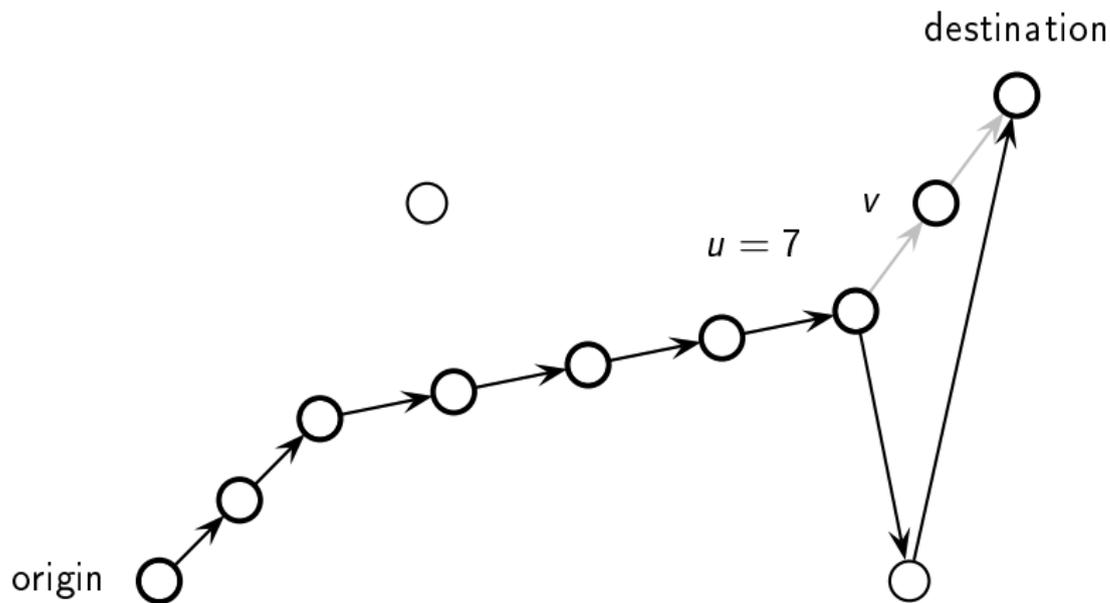
Shortest path SPLICE reaches every path



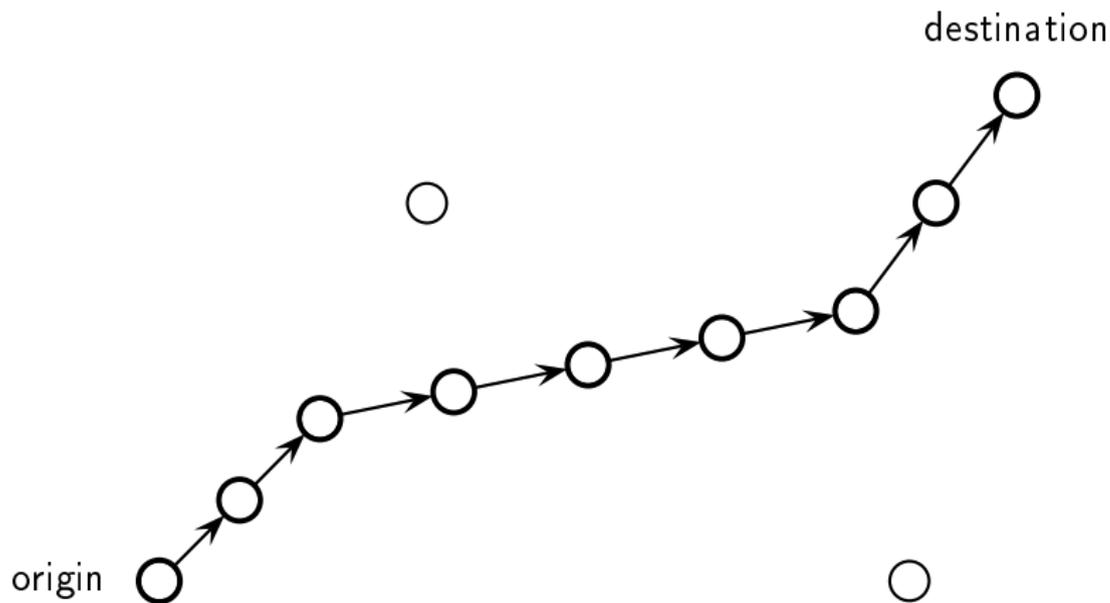
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