Robust Traffic Matrix Estimation with Imperfect Information: Making Use of Multiple Data Sources

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SIGMETRICS/PERFORMANCE 2006

Traffic Matrix (TM) and its usefulness

- The aggregate traffic volume for every origin/destination (OD) pair T_{ij}, $i, j = ...$, useful for
  - Capacity planning and forecasting
  - Routing configuration
  - Network fault/reliability diagnoses
  - Provisioning for service level agreements (SLA)

Existing Approaches

- Indirect inference from SNMP link counts and the routing matrix by making statistical assumptions about the traffic matrix elements to be estimated, such as [Vardi:2006, ZRDG:2002, ZRLD:2003, SNCLT:2004]

- Direct measurement through
  - Sampled NetFlow, such as [Feldmann et. al. 2000]
  - Data streaming algorithms, such as [ZKWX:2005]

What inspires this work?

- TM can be (and had been) estimated from each of the following two data sources:
  - Traffic volume at each link reported by SNMP and routing matrix (which router path does an OD flow take?)
  - Sampled NetFlow records at (possibly a subset of) network ingress points

- Our question: how to combine the information at both data sources to obtain more accurate TM estimations?

Additional challenges addressed by this work

- Partial NetFlow deployment problem: Netflow is available at only a subset of of ingress points. Our solution is an Equivalent Ghost Observation (EGO) method that helps blend the gravity model with our statistical model.

- Dirty data problem: both the traffic volume and sampled NetFlow data can be dirty or missing. Our idea is to use both data sources as "error correction codes" to each other.

- Routing change problem: routing tables change in the middle of a measurement interval.

TM estimation with clean and complete data I

$$\left.\begin{array}{l}\widehat{\mathbf{X}} = \mathbf{X} + \varepsilon^{\mathbf{X}} \\ \widehat{\mathbf{B}} = \mathbf{A}\mathbf{X} + \varepsilon^{\mathbf{B}}\end{array}\right\} \quad \mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{N}$$

$\mathbf{A}$ is the routing matrix.

$\mathbf{B}$ is the link counts; $\widehat{\mathbf{B}}$ is the corresponding SNMP link count measurement.

$\mathbf{X}$ is the traffic matrix organized as a vector; $\widehat{\mathbf{X}}$ is its estimation obtained from sampled NetFlow records.

$\varepsilon^{\mathbf{X}}$ is the measurement noise of sampled NetFlow data.

$\varepsilon^{\mathbf{B}}$ is the measurement noise of SNMP link counts.

TM estimation with clean and complete data II

- The measurement noises $\varepsilon^{\mathbf{X}}$ and $\varepsilon^{\mathbf{B}}$ can faithfully modeled as $N(0, \sigma_i^2)$ and $N(0, \mu_i^2)$, respectively.

- The least-squares (LS) estimator is to minimize
$$||\frac{\mathbf{X} - \widehat{\mathbf{X}}}{\mathbf{\Sigma}}||^2 + ||\frac{\mathbf{AX} - \widehat{\mathbf{B}}}{\mathbf{\Gamma}}||^2$$
where $\mathbf{\Sigma^2} = (\sigma_1^2, \sigma_2^2, \cdots, \sigma_n^2)^T$ and $\mathbf{\Gamma^2} = (\mu_1^2, \mu_2^2, \cdots, \mu_m^2)^T$

- The LS estimator is equal to $\mathbf{X} = (\mathbf{H}^T\mathbf{K}^{-1}\mathbf{H})^{-1}\mathbf{H}^T\mathbf{K}^{-1}\mathbf{Y}$ where $\mathbf{K}$ is the covariance matrix of $\mathbf{N}$. It is also the best linear unbiased estimator (BLUE) by Gauss-Markov Theorem.

Technique to Reduce Computational Complexity

- Singular-Value Decomposition (SVD) is used to compute the pseudo-inverse.

- The number of OD flows could be very large (e.g., several tens of thousands). We want to reduce the dimension of the problem.

  - only focus on the subvector $\mathbf{X_L}$ of $\mathbf{X}$ where the corresponding OD flows estimation is larger than a predefined threshold T (e.g., 0.01% of the total traffic)

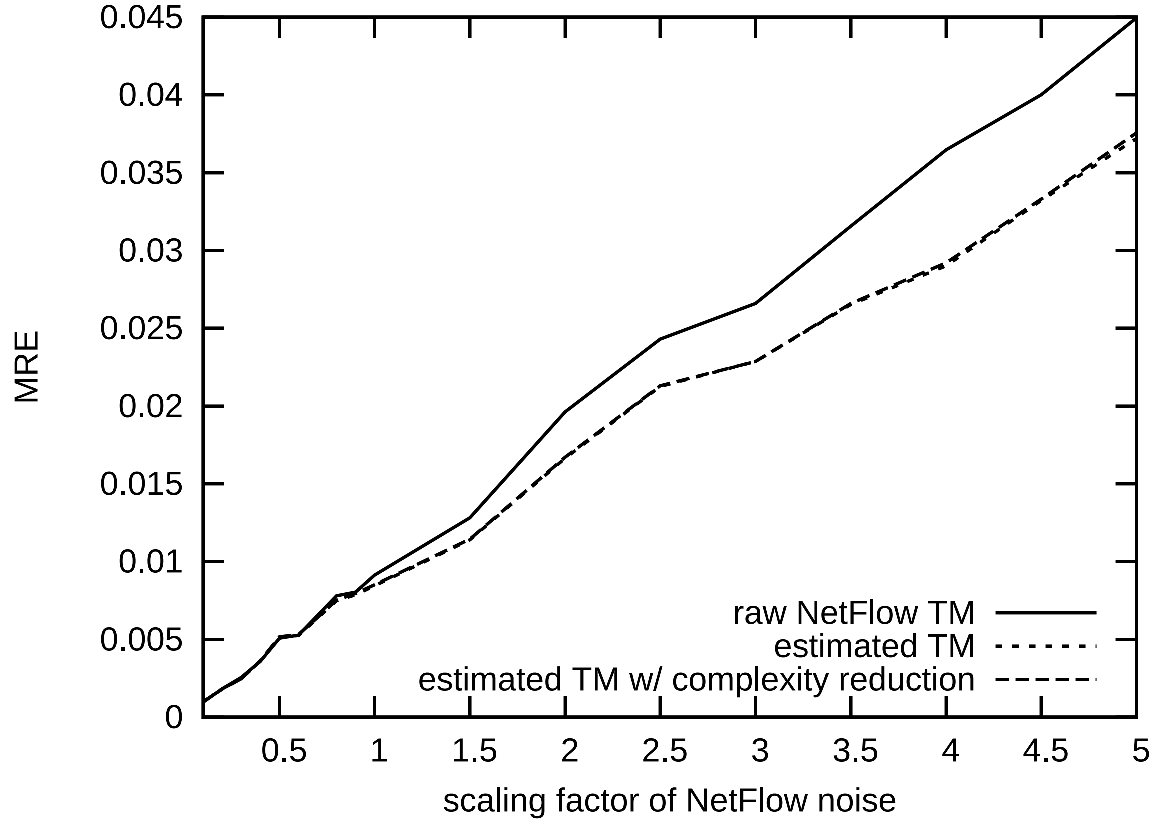
  - treating the remaining subvector $\mathbf{X_S}$ as known

Evaluation

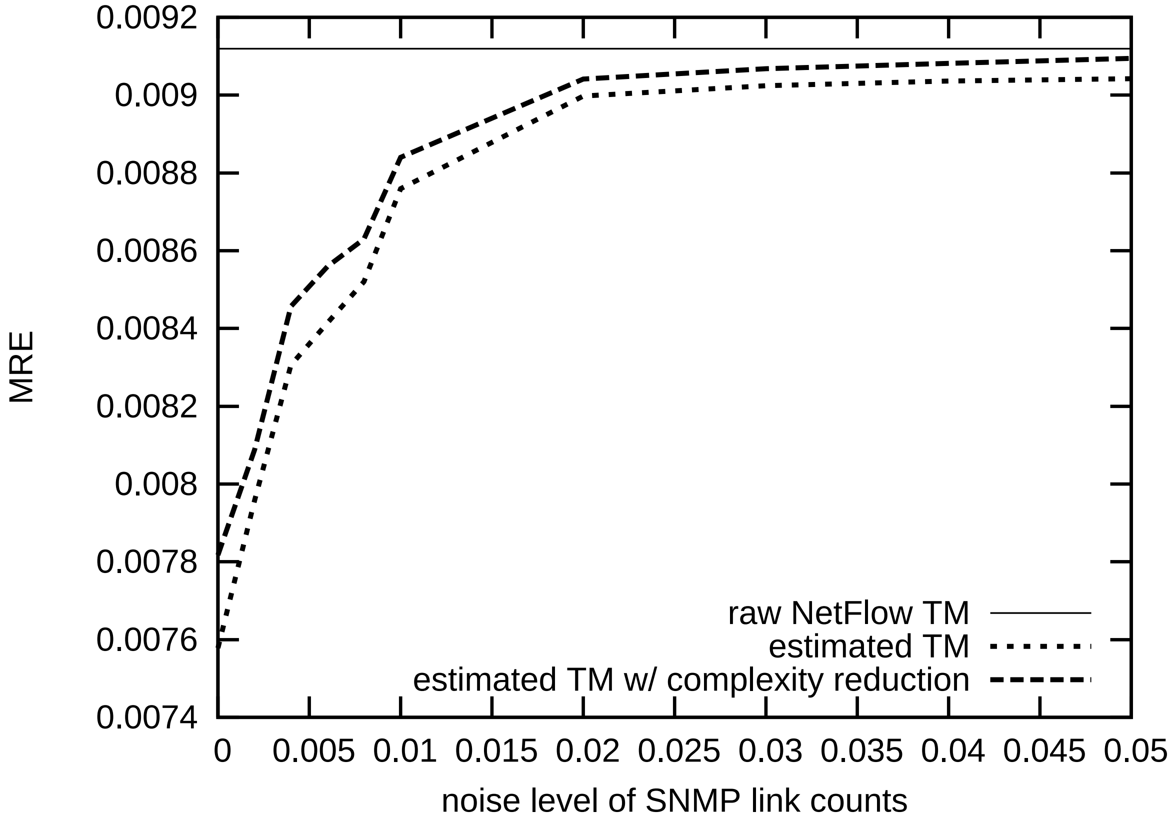
- Data gathering method
  - Traffic matrices : Sampled NetFlow data
  - Routing matrices : Simulate OSPF routing
  - Link counts: Project the above traffic matrices on a routing matrix

- Performance metric: mean relative error (MRE) equal to $\frac{1}{N_T}\sum_{i:x_i>T}\left|\frac{\widehat{x_i}-x_i}{x_i}\right|$ where N_T is the number of matrix elements that are greater than a threshold value T, i.e., $N_T = |\{x_i|x_i > T, i = 1, 2, \cdots, N\}|$.

Noise in NetFlow measurement



Noise in SNMP measurement



TM estimation with partial NetFlow coverage

- With partial NetFlow coverage, while the same LS and BLUE estimator can still be estimated, it is not a good estimator due to the fact that the probability model is severely under-populated (already observed in [ZRDG:2002])

- Our idea: populate our probability model with the gravity model in [ZRDG:2002], i.e., using estimations from the gravity model as a starting point for TM elements that are not covered by NetFlow observations

- Challenge: the gravity model is not a probability model

Overview of the Generalized Gravity Model [ZRDG:2002]

- Simple gravity model: $T_{i,j} \propto T_{i,*} \cdot T_{*,j}$, resulting in a default estimation $\mathbf{T}^{(g)}$ to be corrected by SNMP link count observations. Generalized Gravity model = Simple Gravity Model + Side Information (e.g., link classification and routing policy).

- The probability model of the gravity model can be implicitly characterized as "the probability model under which the following Tomogravity constrained optimization problem produces a good estimator":

$$\begin{array}{rl} \text{minimize} & ||(\mathbf{T} - \mathbf{T}^{(g)})/\sqrt{\mathbf{T}^{(g)}}||_2 \\ \text{subject to} & ||\mathbf{AT} - \mathbf{B}|| \text{ being minimized} \end{array}$$

  We discovered the explicit probability model underlying the gravity model.

Equivalent Ghost Observation (EGO)

- Let $\widehat{\mathbf{X}} = \mathbf{T}^{(g)}$ and $\widehat{x_i} - x_i \sim N(0, v_i^2)$ where $v_i \propto \sqrt{\mathbf{T}^{(g)}}$. The least-squares (LS) estimator of X, which minimizes

$$||\frac{\mathbf{X} - \widehat{\mathbf{X}}}{\mathbf{V}}||^2 + ||\frac{\mathbf{AX} - \widehat{\mathbf{B}}}{\mathbf{\Gamma}}||^2$$

is exactly the Tomogravity constrained optimization result.

- In other words, EGO's $\widehat{\mathbf{X}}$ are statistically equivalent to the implicit beliefs of the gravity model.

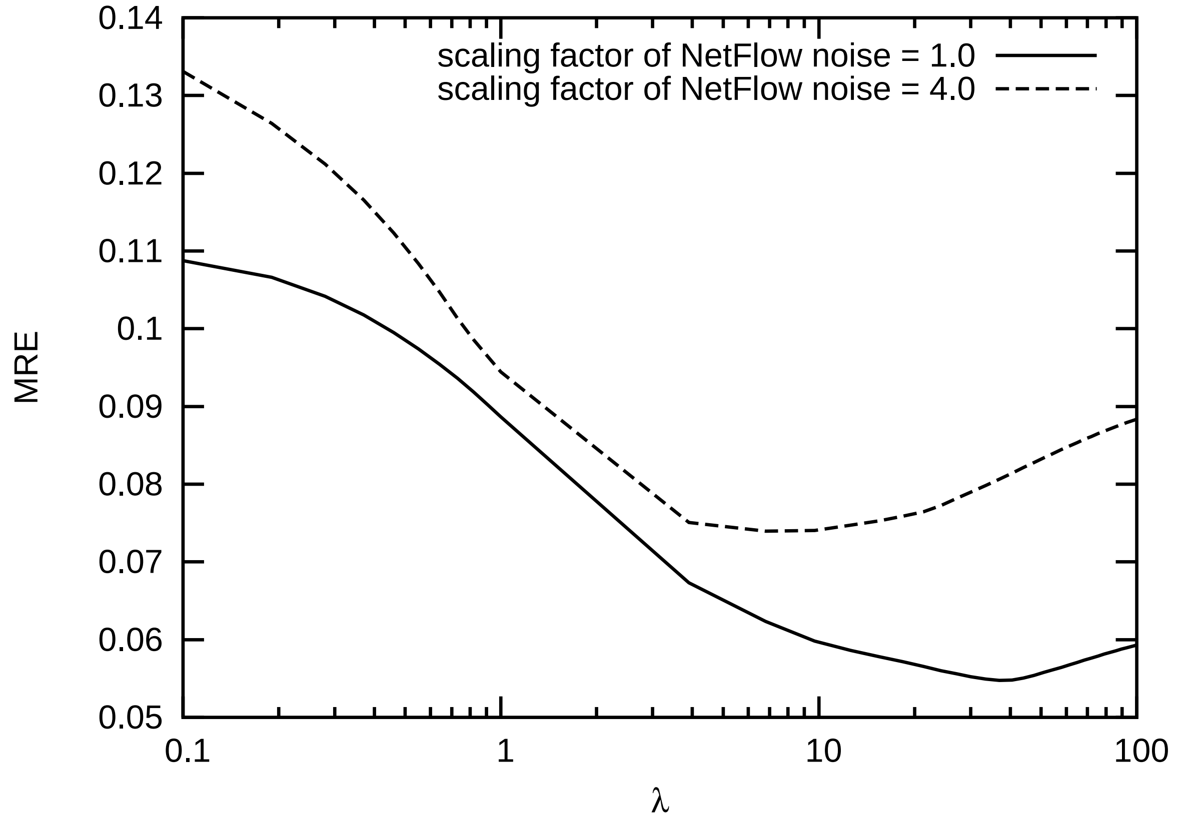
Blending EGO's with NetFlow observations

- If a TM element X_i is covered by NetFlow, $\varepsilon_i^{\mathbf{X}} \sim N(0, \sigma_i^2)$;

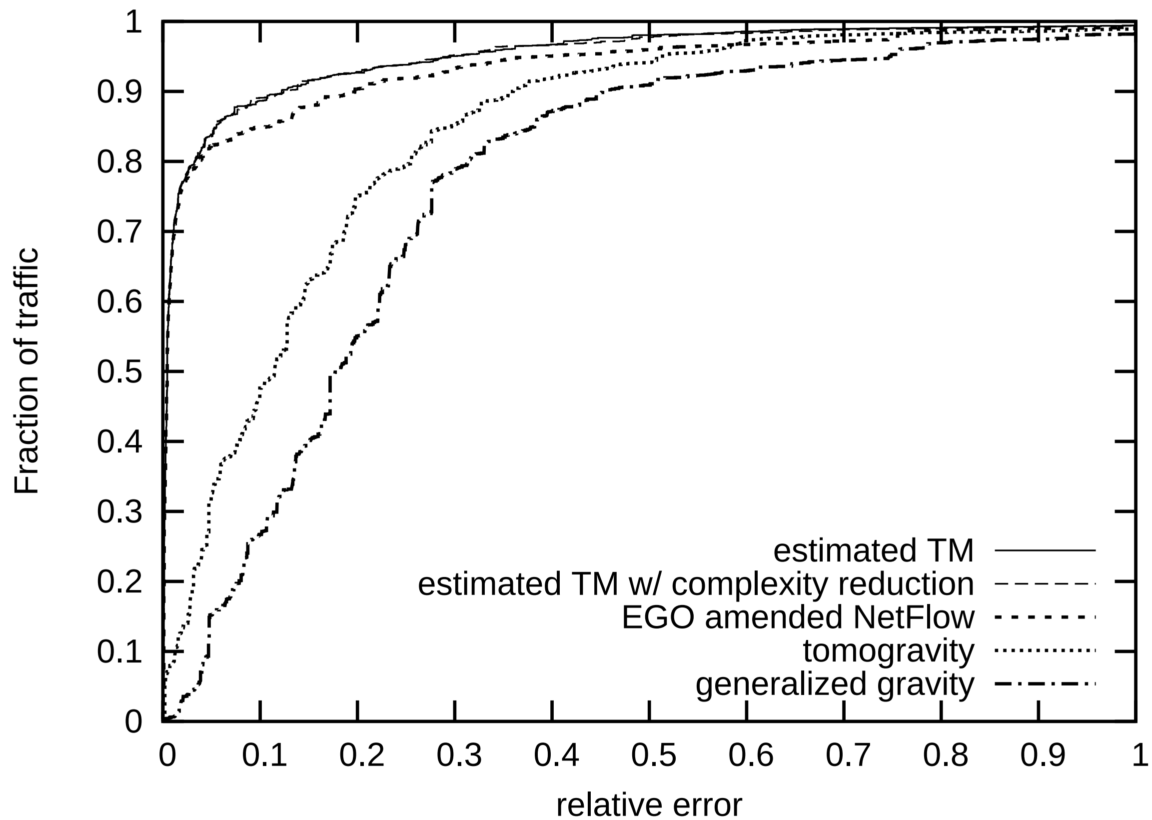
- Otherwise, $\varepsilon_i^{\mathbf{X}} \sim N(0, \lambda\sigma_i^2)$ where σ_i^2 is the corresponding element in $T^(g)$

- The parameter λ is a normalization factor that captures the relative credibility of an EGO to a NetFlow observation.

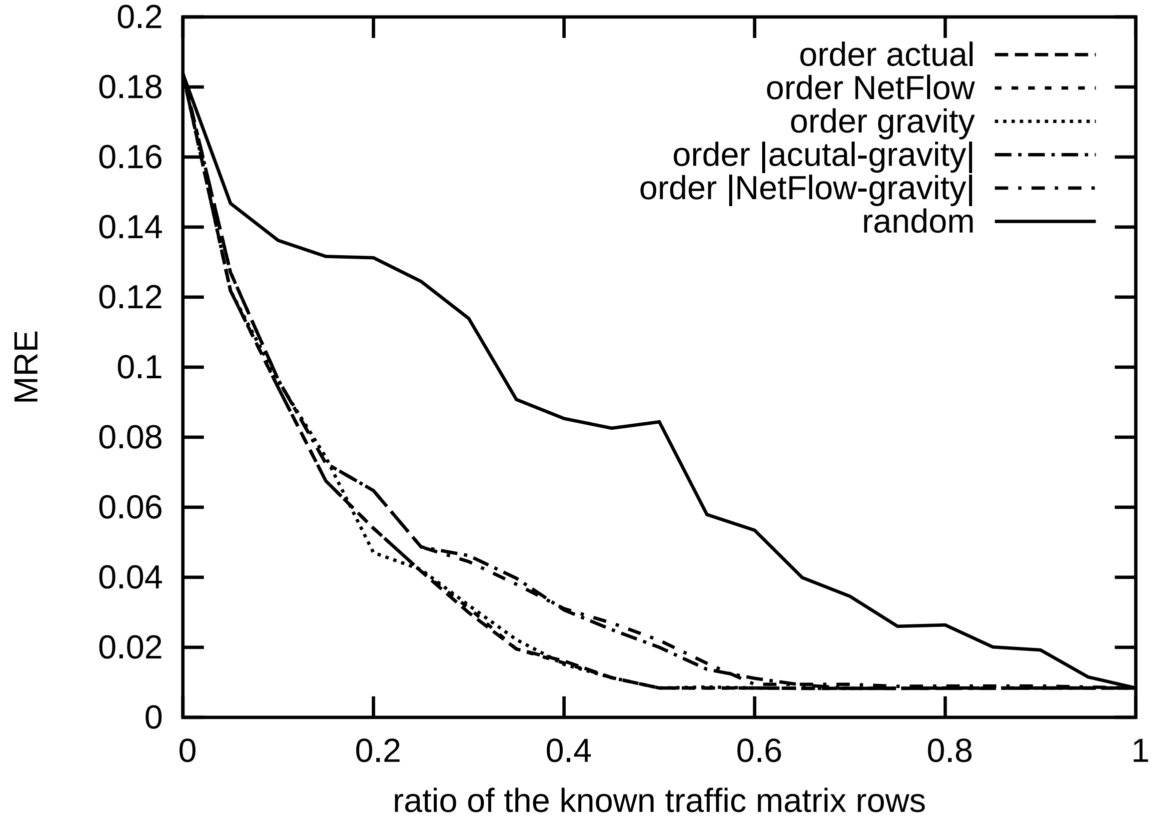
MRE under different values of λ (20% NetFlow coverage)



The Weighted CDF of the relative error (20% NetFlow coverage).



Impact of partial deployment of NetFlow on traffic matrix estimation (20% NetFlow coverage).



Removal of Dirty Data

- Dirty Data: Measurement error in SNMP or NetFlow or both due to hardware, software or transmission faults

- We can rewrite the previous equations about the observations of NetFlow and link counts

$$\mathbf{X} = \widehat{\mathbf{X}} + \varepsilon^{\mathbf{X}} + \xi^{\mathbf{X}}$$

$$\mathbf{B} = \widehat{\mathbf{B}} + \varepsilon^{\mathbf{B}} + \xi^{\mathbf{B}}$$

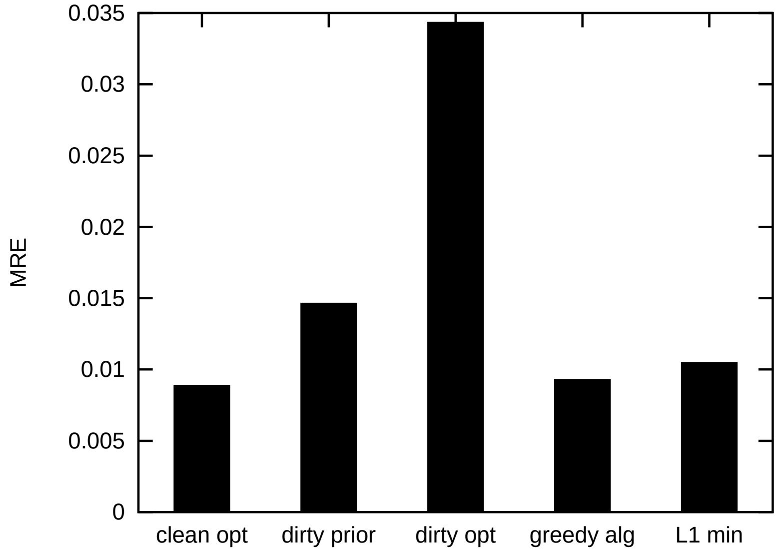
- We expect

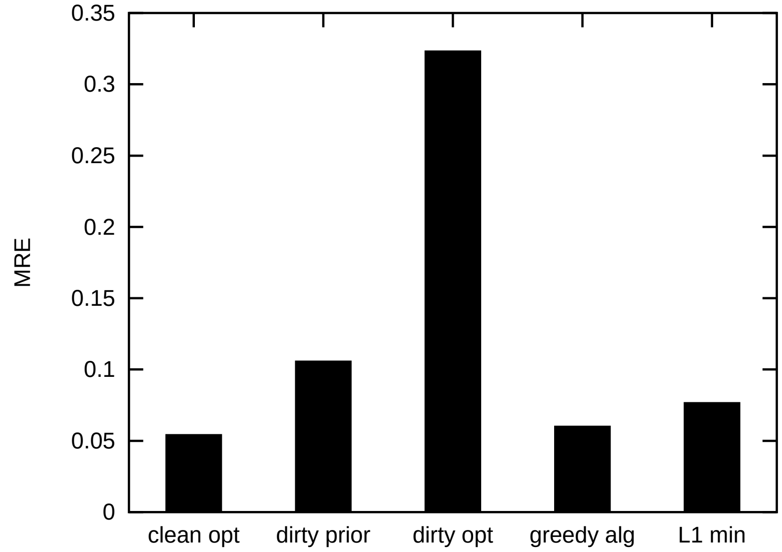
$$|\xi_i^{\mathbf{X}}| \gg |\varepsilon_i^{\mathbf{X}}|, \quad |\xi_j^{\mathbf{B}}| \gg |\varepsilon_j^{\mathbf{B}}| \Longrightarrow \xi \equiv \begin{pmatrix} \varepsilon^{\mathbf{X}} + \xi^{\mathbf{X}} \\ \varepsilon^{\mathbf{B}} + \xi^{\mathbf{B}} \end{pmatrix}$$

Sparsity Maximization

- We expect there are only a small number of dirty data.
- Minimize $||\delta||_0$ subject to the observation
- L_0 norm is *not* convex and hence hard to minimize
  - Greedy heuristic algorithm
  - L_1 norm minimization
- Comparing the computed results with 3.09 times of the standard deviation of the Gaussian measurement noise to identify and remove the dirty data.

Traffic Matrix Estimation with and without Dirty Data



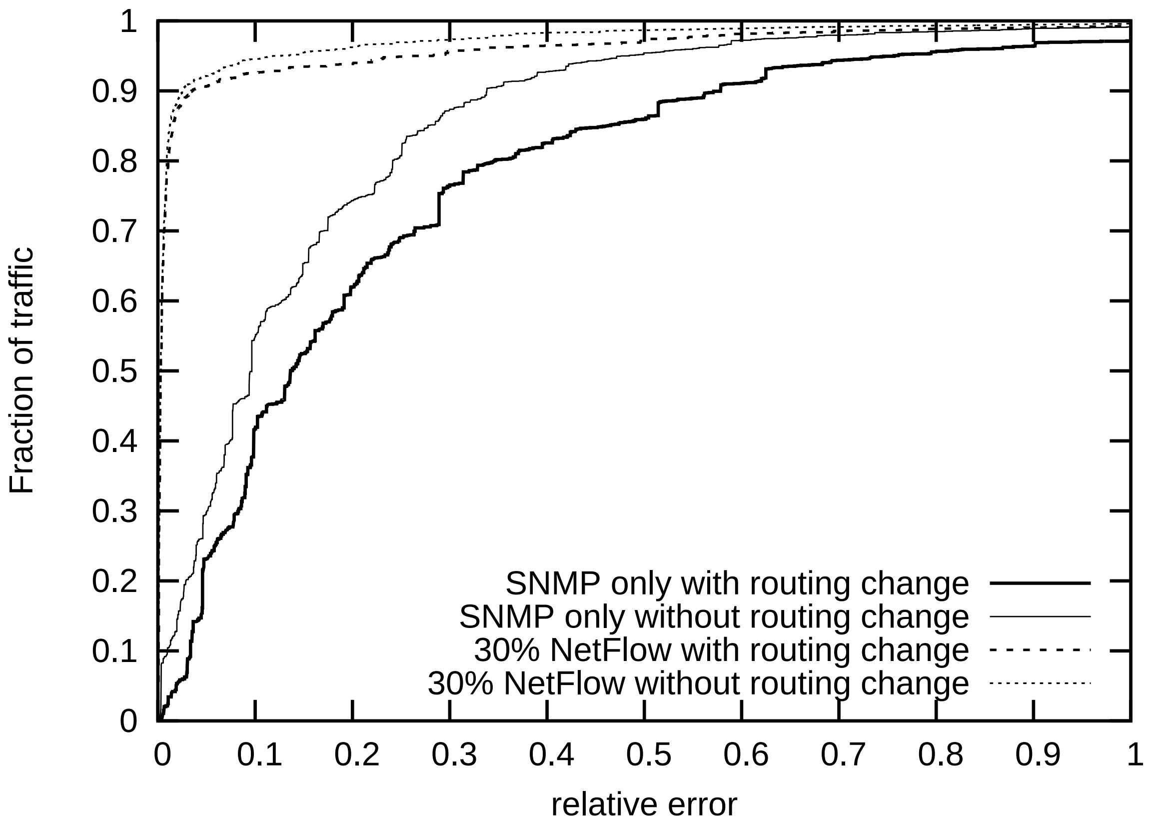


Handling of Routing Changes

- Assume the routing only changes once.
- $$\mathbf{A_1 X_1 + A_2 X_2 = B}$$
- $$\left.\begin{aligned} \widehat{\mathbf{X_1}} &= \mathbf{X_1} + \varepsilon^{\mathbf{X_1}} \\ \widehat{\mathbf{X_2}} &= \mathbf{X_2} + \varepsilon^{\mathbf{X_2}} \\ \widehat{\mathbf{B}} &= \mathbf{A_1 X_1 + A_2 X_2} + \varepsilon^{\mathbf{B}} \end{aligned}\right\} \quad \mathbf{Y = HX + N}$$

  where $\mathbf{X} = \begin{pmatrix} \mathbf{X_1} \\ \mathbf{X_2} \end{pmatrix}$.

Weighted CDFs of the relative errors



Conclusion: Strength of Combining Multiple Information Sources

- Provide a comprehensive formulation and design an algorithm for estimating traffic matrices

- Extend the formulation and algorithm to the case where sampled NetFlow only covers partial ingress points

- Design two algorithms to identify and remove dirty data in measurements

- Develop algorithm to estimate traffic matrices upon routing changes