Structural Analysis of Network Traffic Flows

Eric Kolaczyk

Anukool Lakhina, Dina Papagiannaki, Mark Crovella, Christophe Diot, and Nina Taft

Traditional Network Traffic Analysis

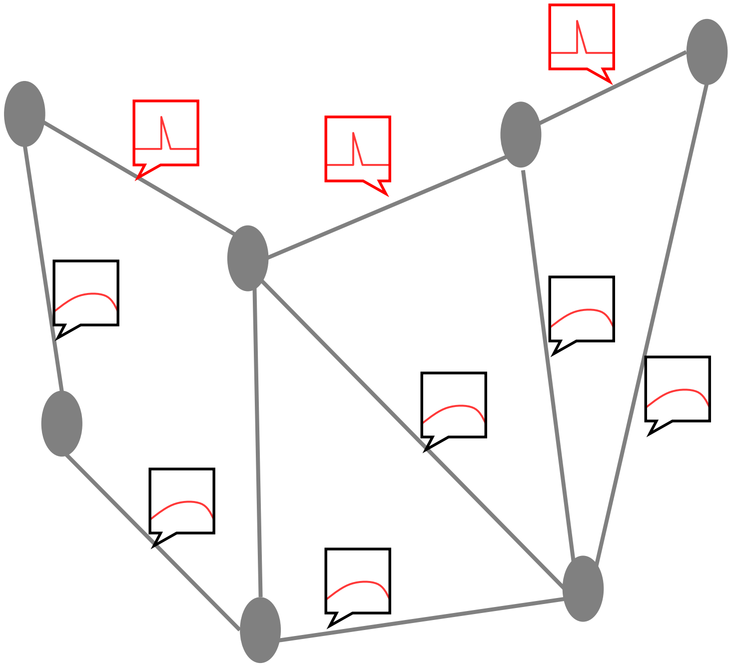
- Focus on
  - Short ‘stationary’ timescales
  - Traffic on a single link in isolation
- Principal results
  - Scaling properties
  - Packet delays and losses

What ISPs Care About

- Focus on
  - Long, nonstationary timescales
  - Traffic on all links simultaneously
- Principal goals
  - Capacity planning
  - Traffic engineering
  - Anomaly detection

Need for *Whole-Network* Traffic Analysis

- Traffic Engineering: How does traffic move *throughout* the network?
- Anomaly Detection: *Which* links show unusual traffic?
- Capacity planning: How much and *where* in network to upgrade?

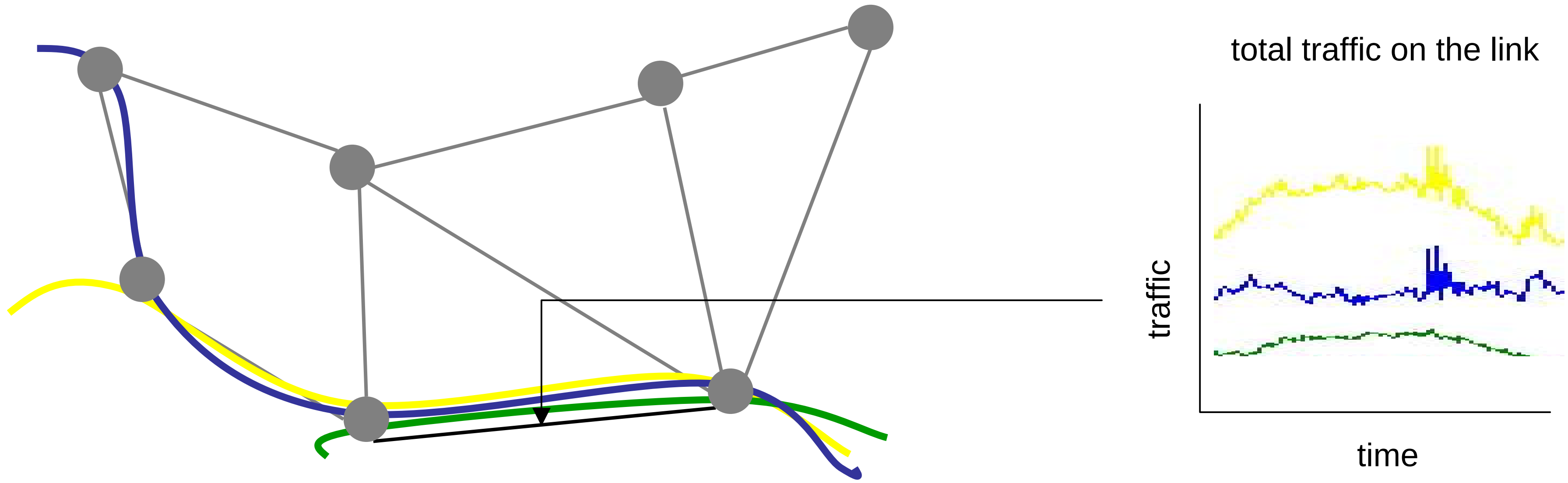


This is Complicated!

- Measuring and modeling traffic on *all* links *simultaneously* is challenging.
  - Even single link modeling is difficult
  - 100s of links in large IP networks
  - *High-Dimensional* timeseries
- Significant correlation in link traffic

- Is there a more fundamental representation?

Origin-Destination Flows



- Link traffic arises from the superposition of *Origin-Destination* (OD) flows
- Modeling OD flows instead of link traffic removes a significant source of correlation
- A fundamental primitive for whole-network analysis

But, This Is Still Complicated

- Even more OD flows than links
- Still a high dimensional, multivariate timeseries

- How do we extract meaning from this high dimensional structure in a systematic manner?

High Dimensionality: A General Strategy

- Look for good *low-dimensional* representations

- Often a high-dimensional structure can be explained by a small number of independent variables

- A commonly used technique: *Principal Component Analysis* (PCA) (aka KL-Transform, SVD, …)

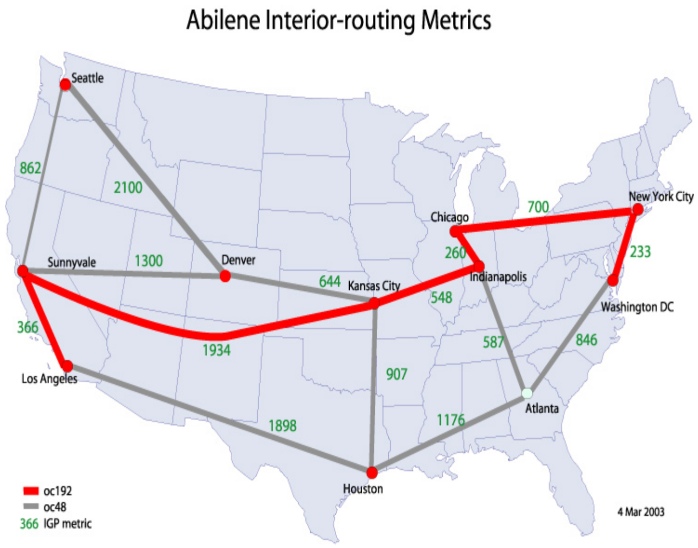
Our work

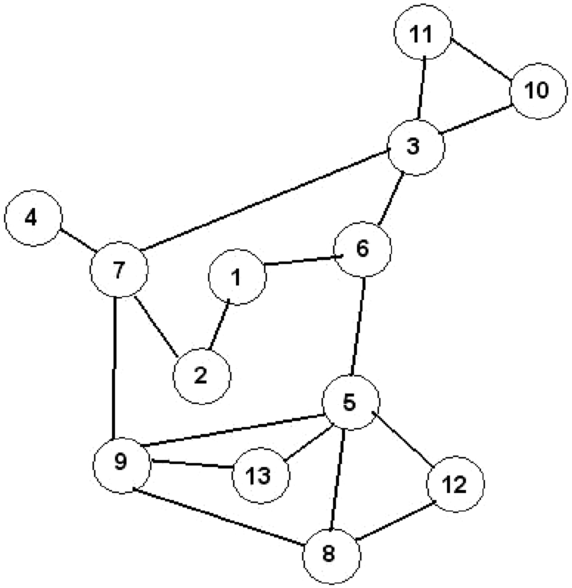
- Measure complete sets of OD flow timeseries from two backbone networks

- Use PCA to understand their structure
  - Decompose OD flows into simpler features
  - Characterize individual features
  - Reconstruct OD flows as sum of features

- Call this *structural analysis*

Datasets

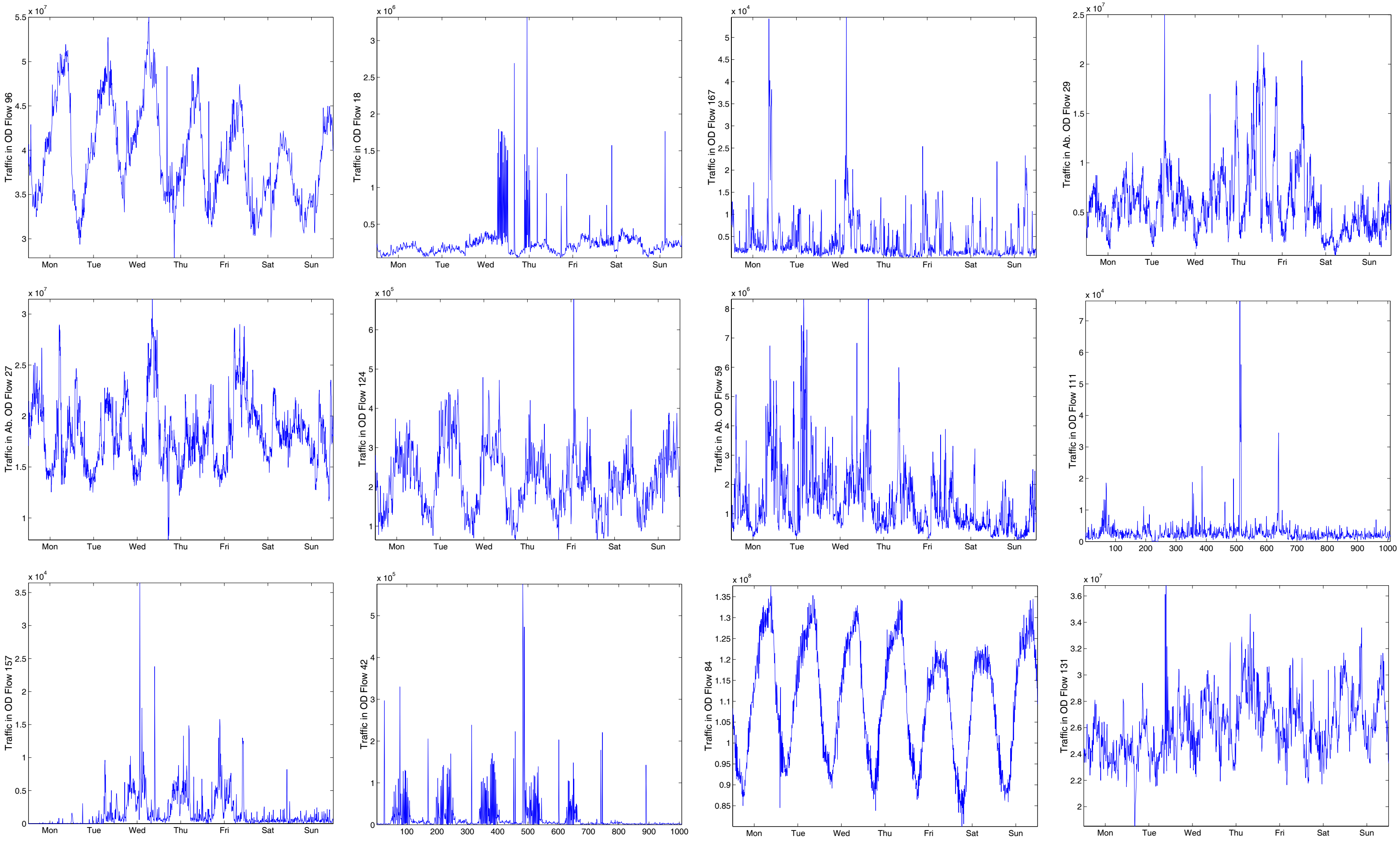




Sprint Europe Topology

- *Abilene*: 11 PoPs, 121 OD flows.
- *Sprint-Europe*: 13 PoPs, 169 OD flows.
- Collect sampled traffic from every ingress link using NetFlow
- Use BGP tables to resolve egress points
- Week-long datasets, 5- or 10-minute timesteps

Example OD Flows



Some have visible structure, some less so…

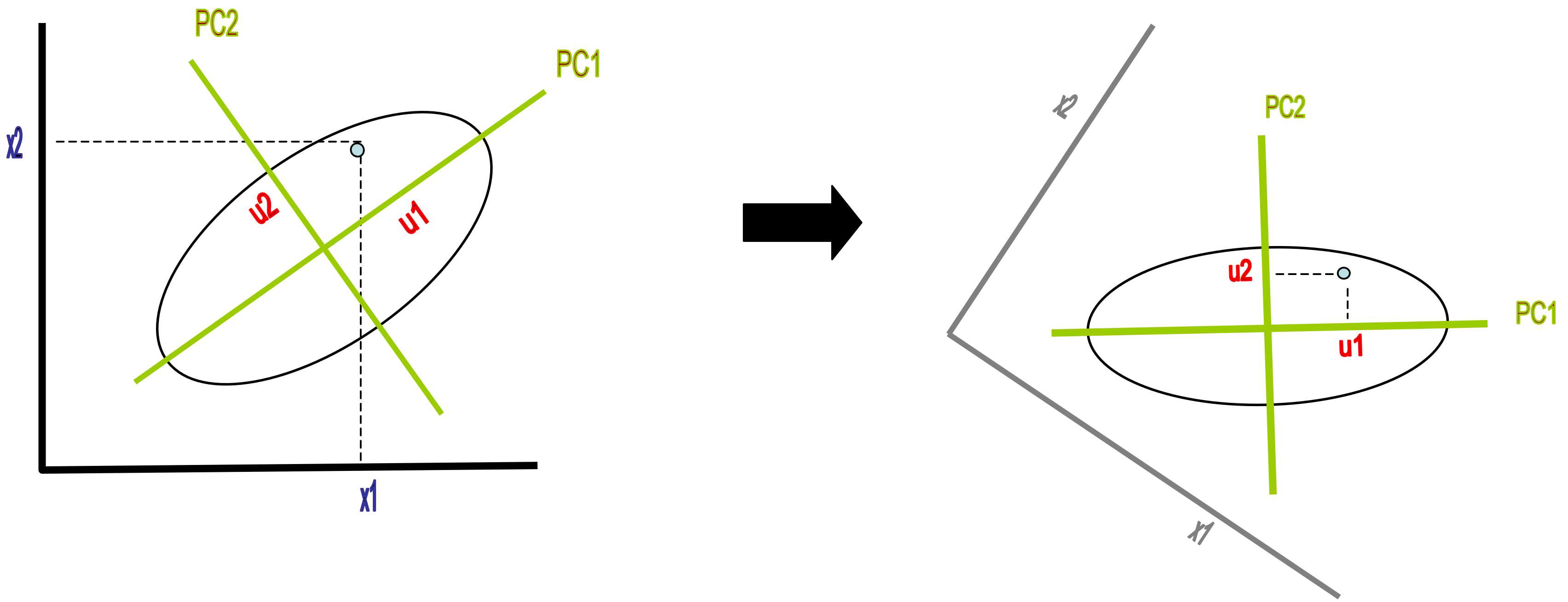
Specific Questions of Structural Analysis

- Are there low dimensional representations for a set of OD flows?
- Do OD flows share common features?
- What do the features look like?
- Can we get a high-level understanding of a set of OD flows in terms of these features?

Principal Component Analysis

Coordinate transformation method

Original Data | Transformed Data



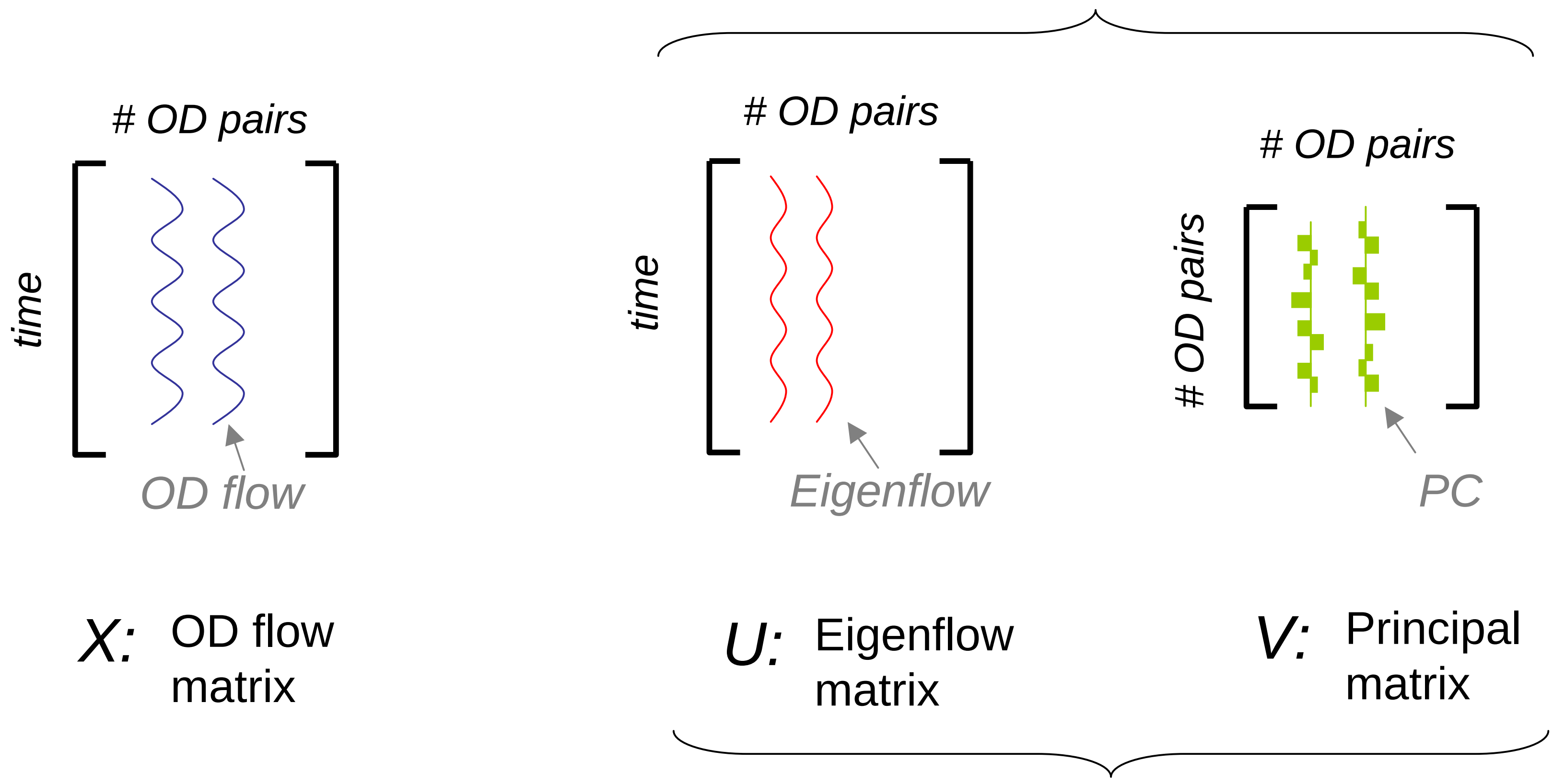
[x1 , x2] → [u1 , u2]

Properties of Principle Components

- Each PC in the direction of maximum (remaining) energy in the set of OD flows
  - Ordered by amount of energy they capture

- ***Eigenflow*:** set of OD flows mapped onto a PC; a common trend
  - Ordered by most common to least common trend

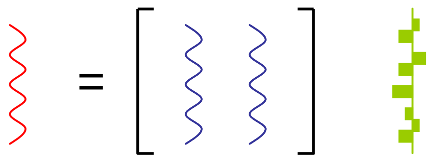
PCA on OD flows



$$X = U \Sigma V^T$$

PCA on OD flows (2)

$$u_i = \frac{Xv_i}{\sigma_i} \quad i = 1, \ldots, p$$



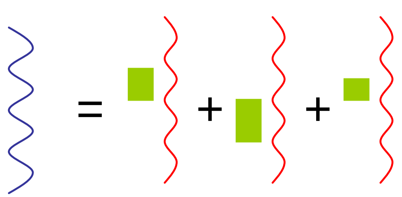
Each eigenflow is a weighted sum of all OD flows

Eigenflows are orthonormal

$$\|Xv_i\| = \lambda_i \quad ; \quad \sigma_i = \sqrt{\lambda_i}$$

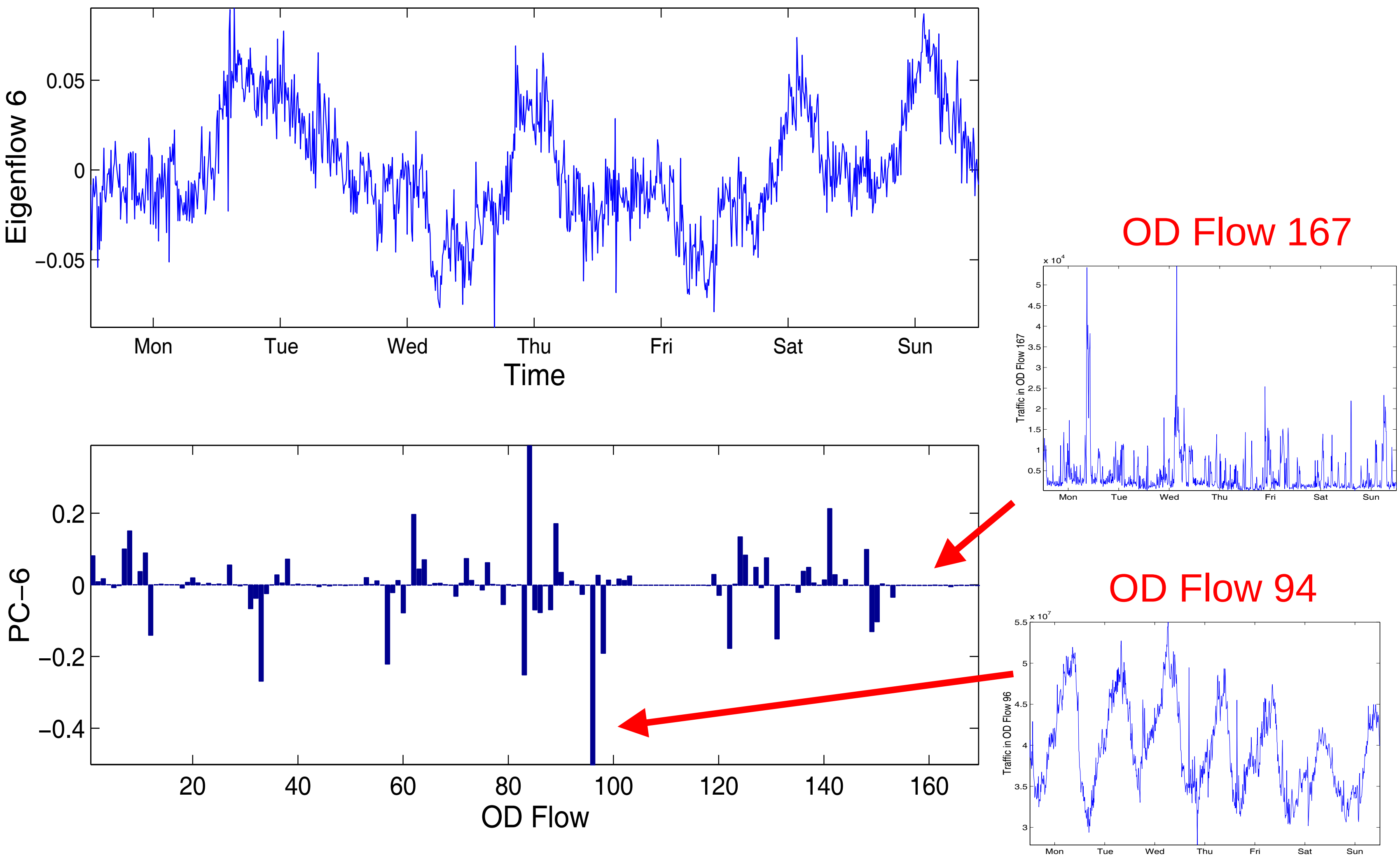
Singular values indicate the energy attributable to a principal component

$$\frac{X_i}{\sigma_i} = U(V^T)_i \quad i = 1, \ldots, p$$



Each OD flow is weighted sum of all eigenflows

An Example Eigenflow and PC



Outline For Rest of Talk

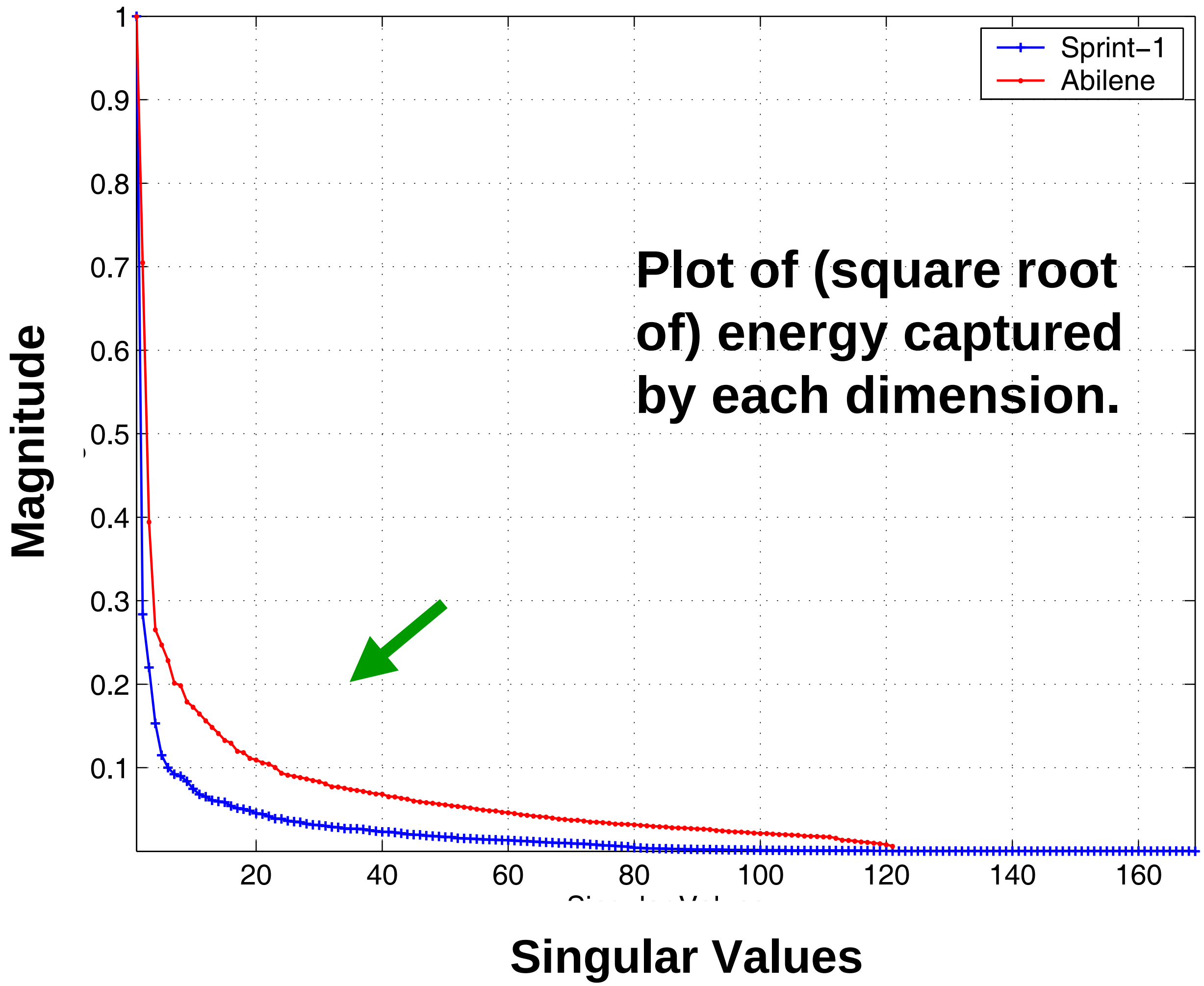
- Find intrinsic dimensionality of OD flows

- Decompose OD flows
- Characterize eigenflows
- Reconstruct OD flows

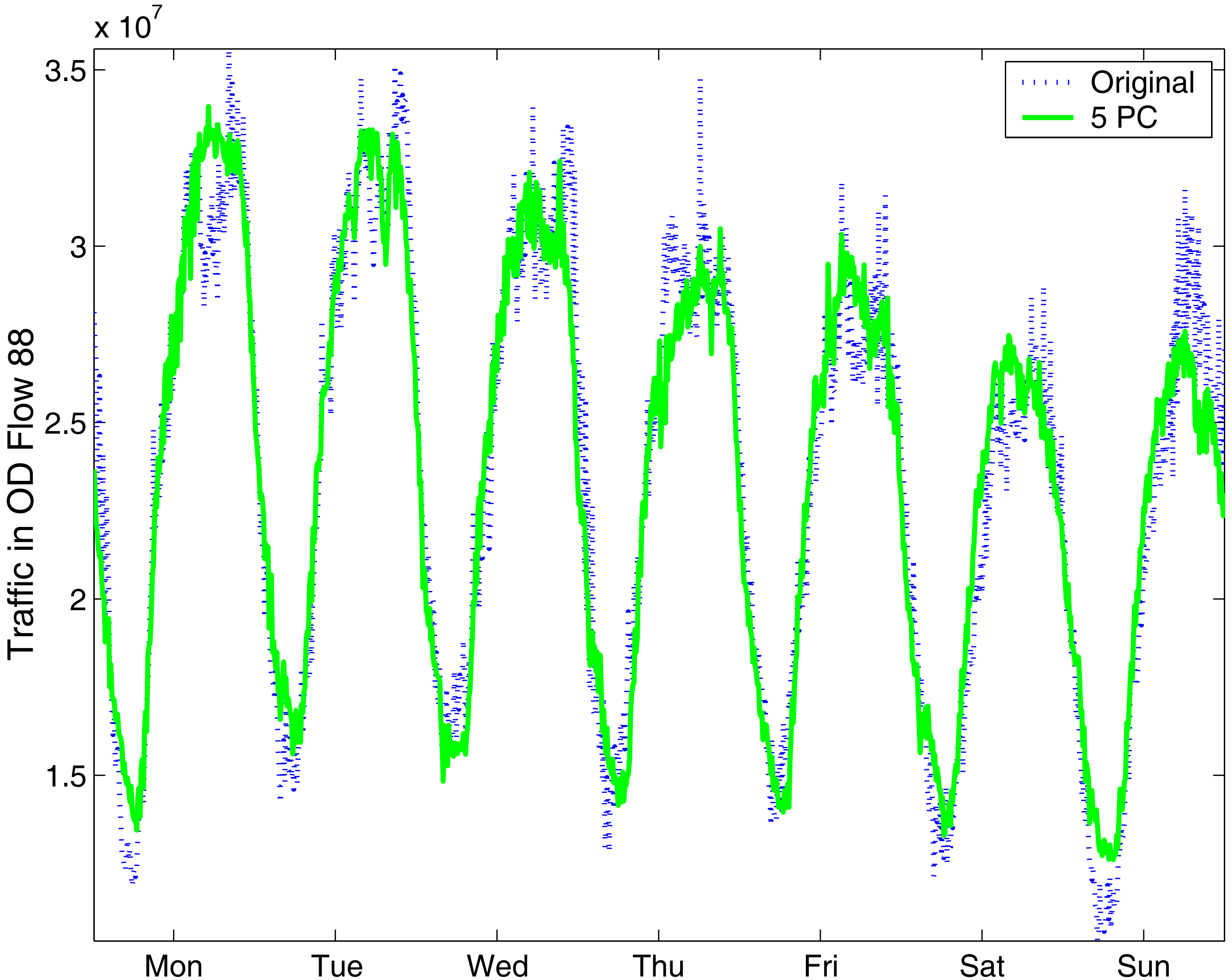
Structural Analysis

- Potential applications

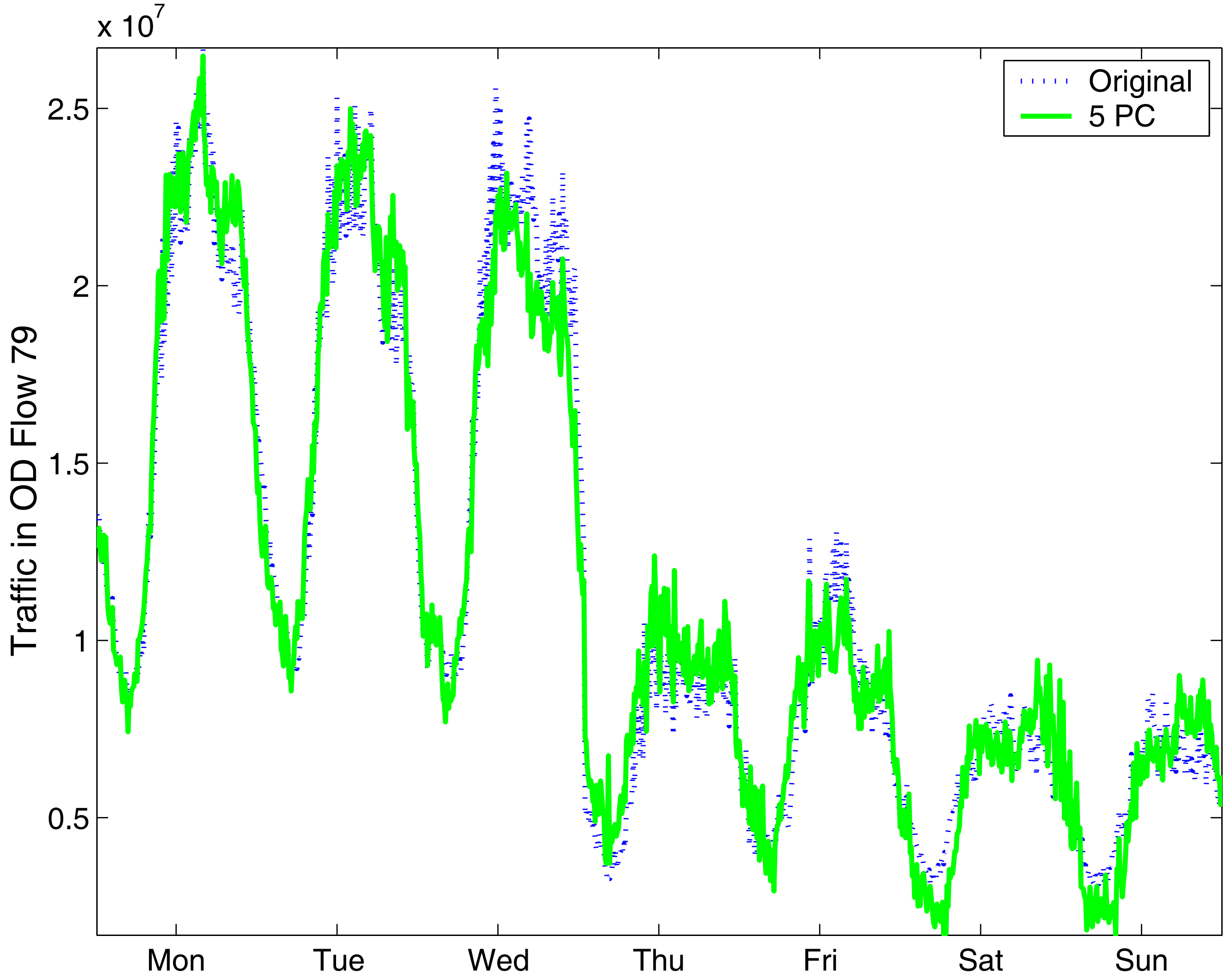
Low Intrinsic Dimensionality of OD Flows



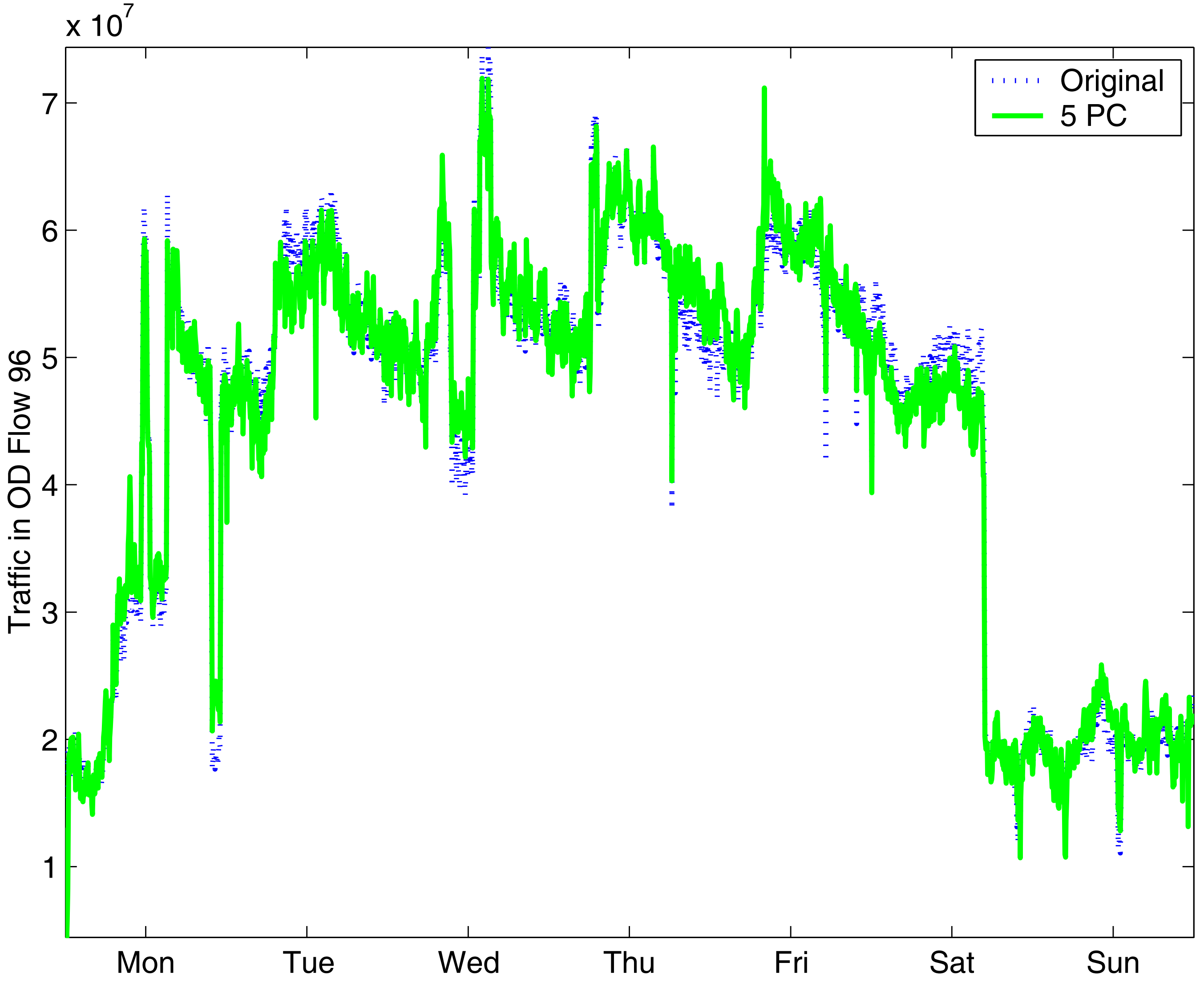
Approximating With Top 5 Eigenflows



Approximating With Top 5 Eigenflows



Approximating With Top 5 Eigenflows



Outline

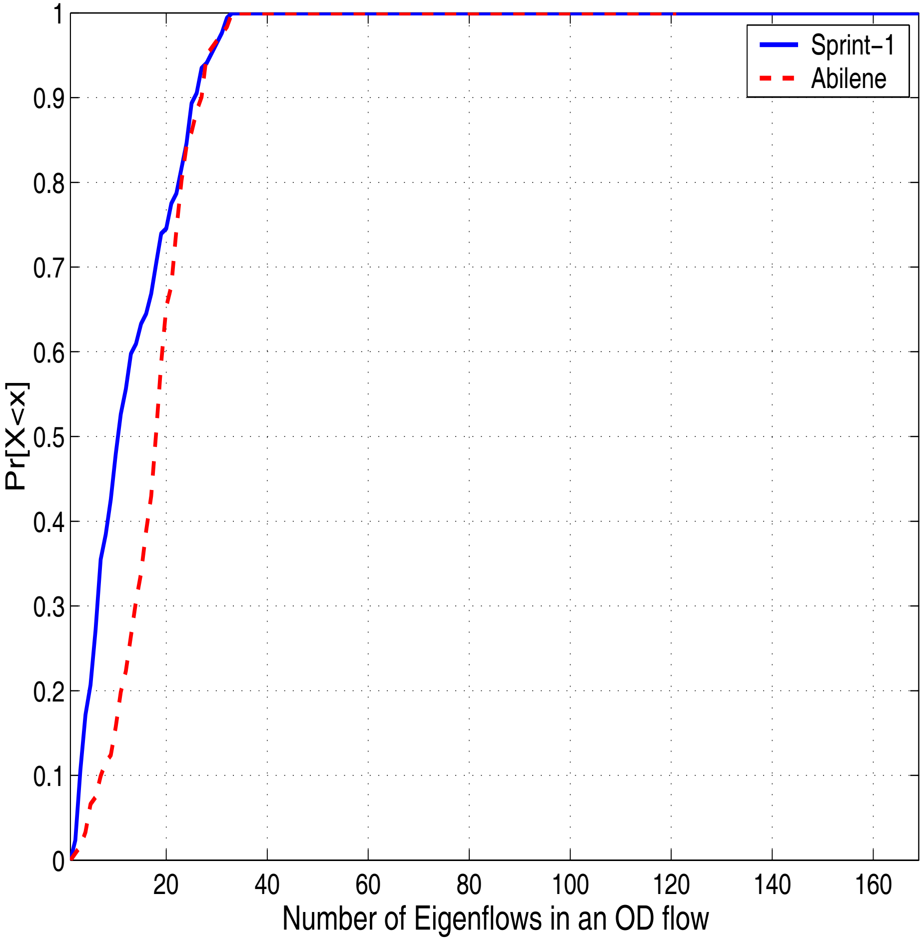
- Find intrinsic dimensionality of OD flows

- Decompose OD flows
- Characterize eigenflows
- Reconstruct OD flows

Structural Analysis

- Potential applications

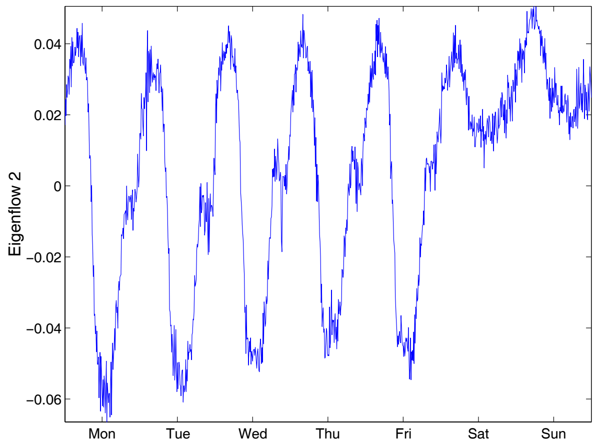
Structure of OD Flows

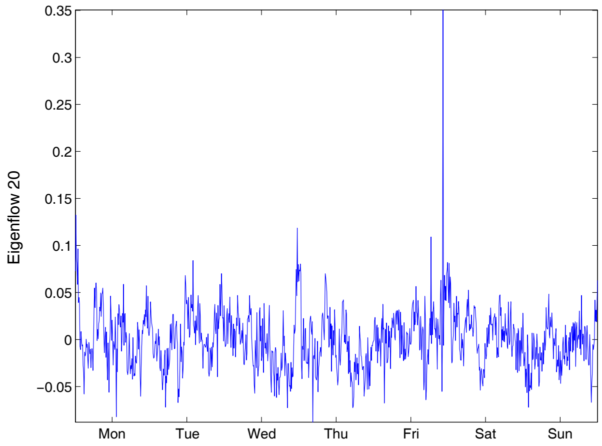


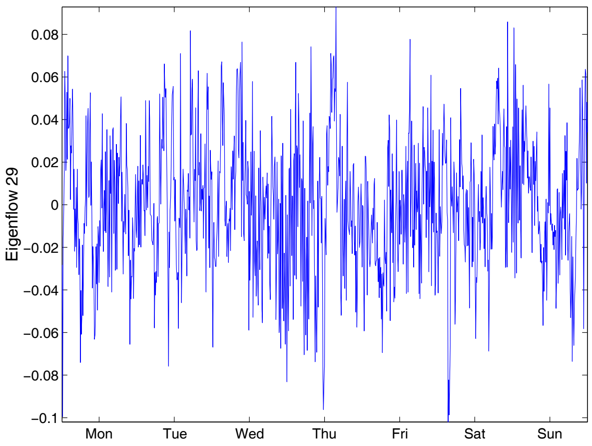
Most OD flows have less than 20 significant eigenflows

Can think of each OD flow as having only a small set of “features”

Kinds of Eigenflows







Deterministic
d-eigenflows

Predictable (periodic) trends

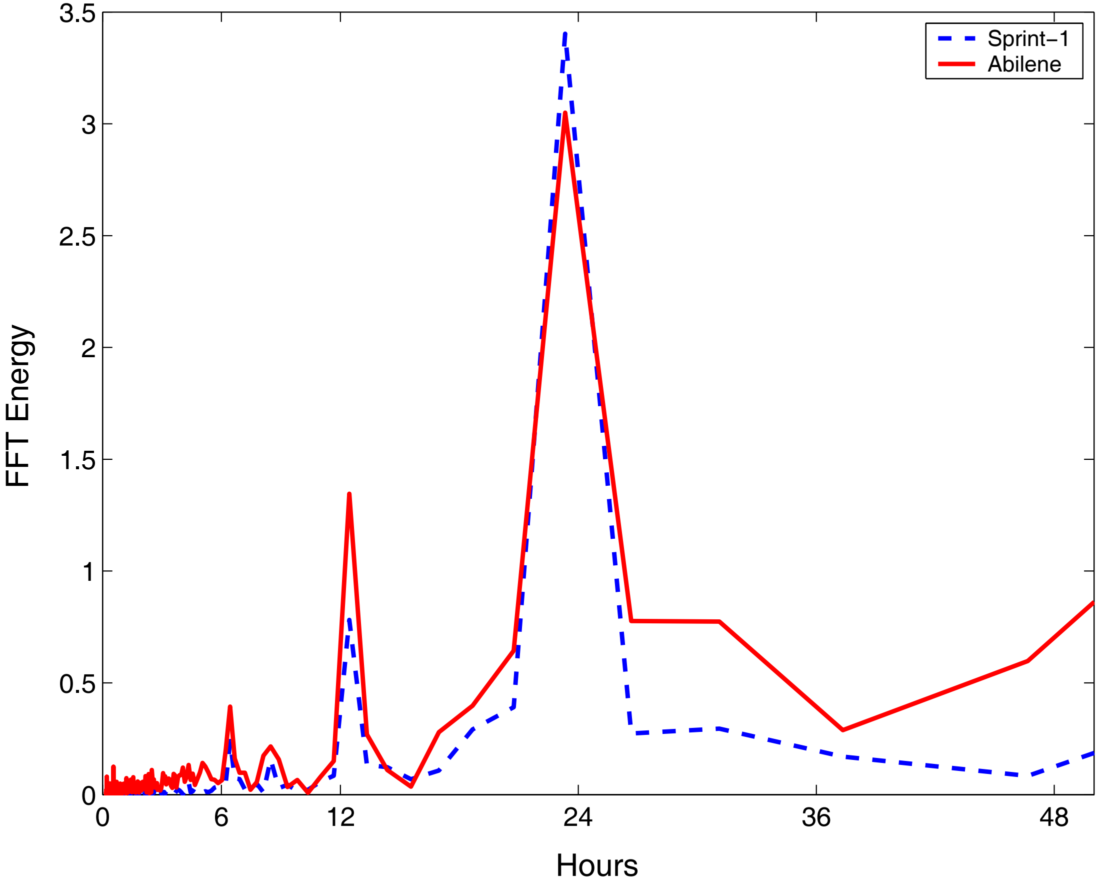
Spike
s-eigenflows

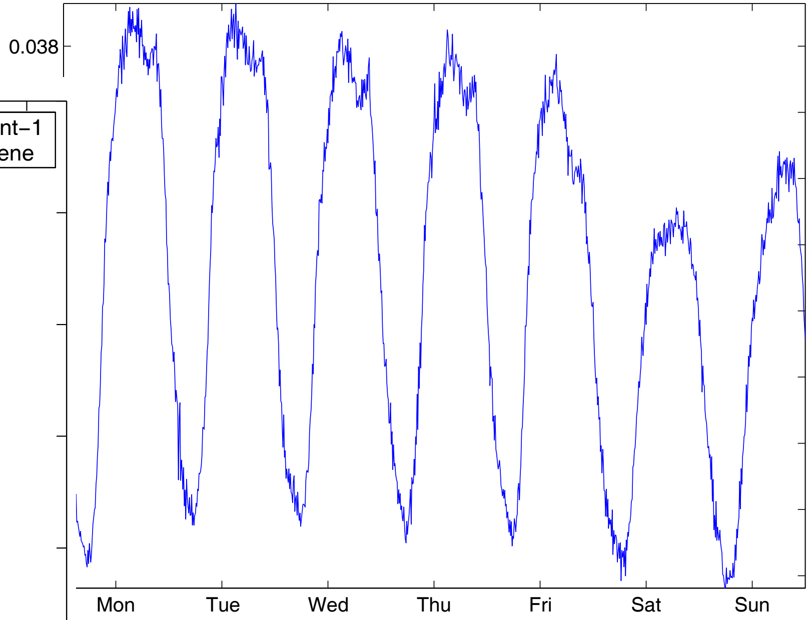
Sudden, isolated spikes and drops

Noise
n-eigenflows

Roughly stationary and Gaussian

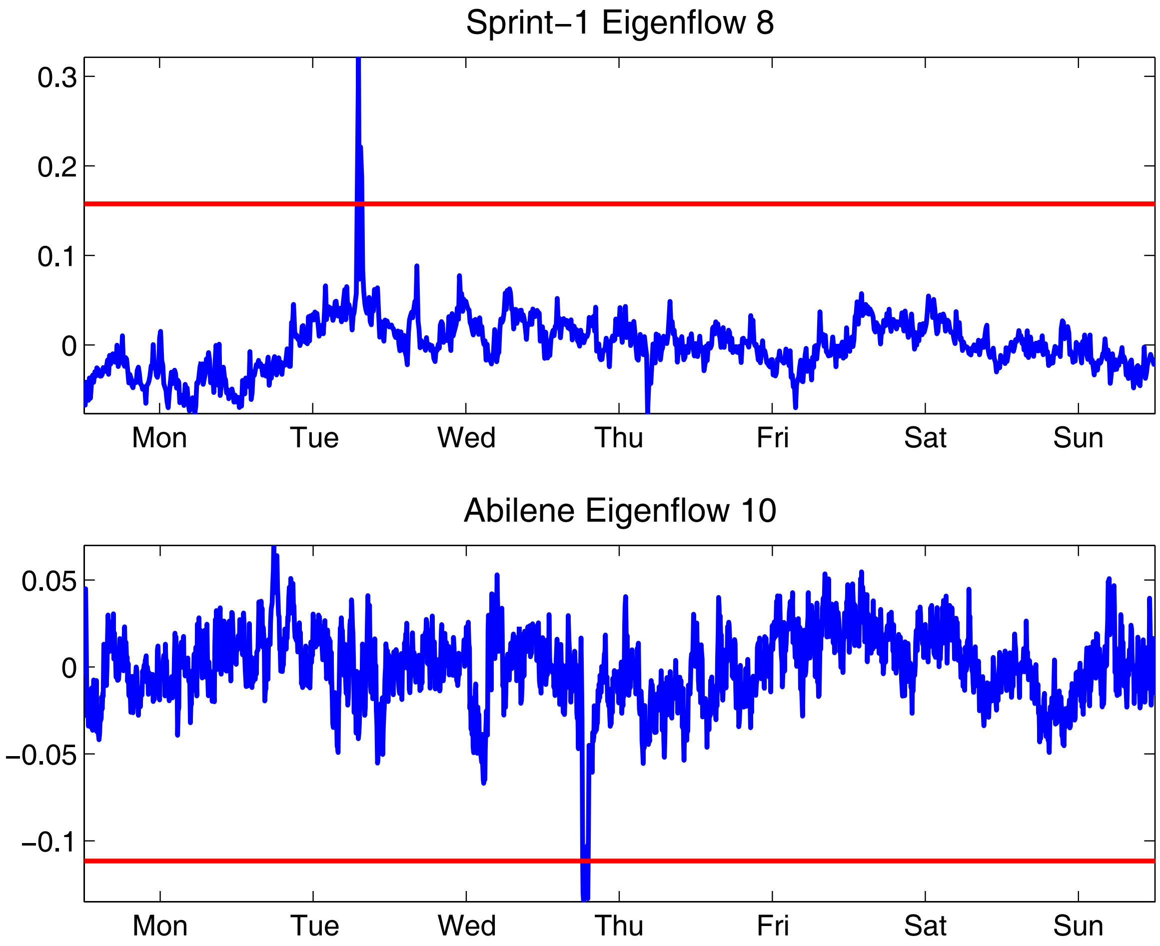
D-eigenflows Have Periodicity





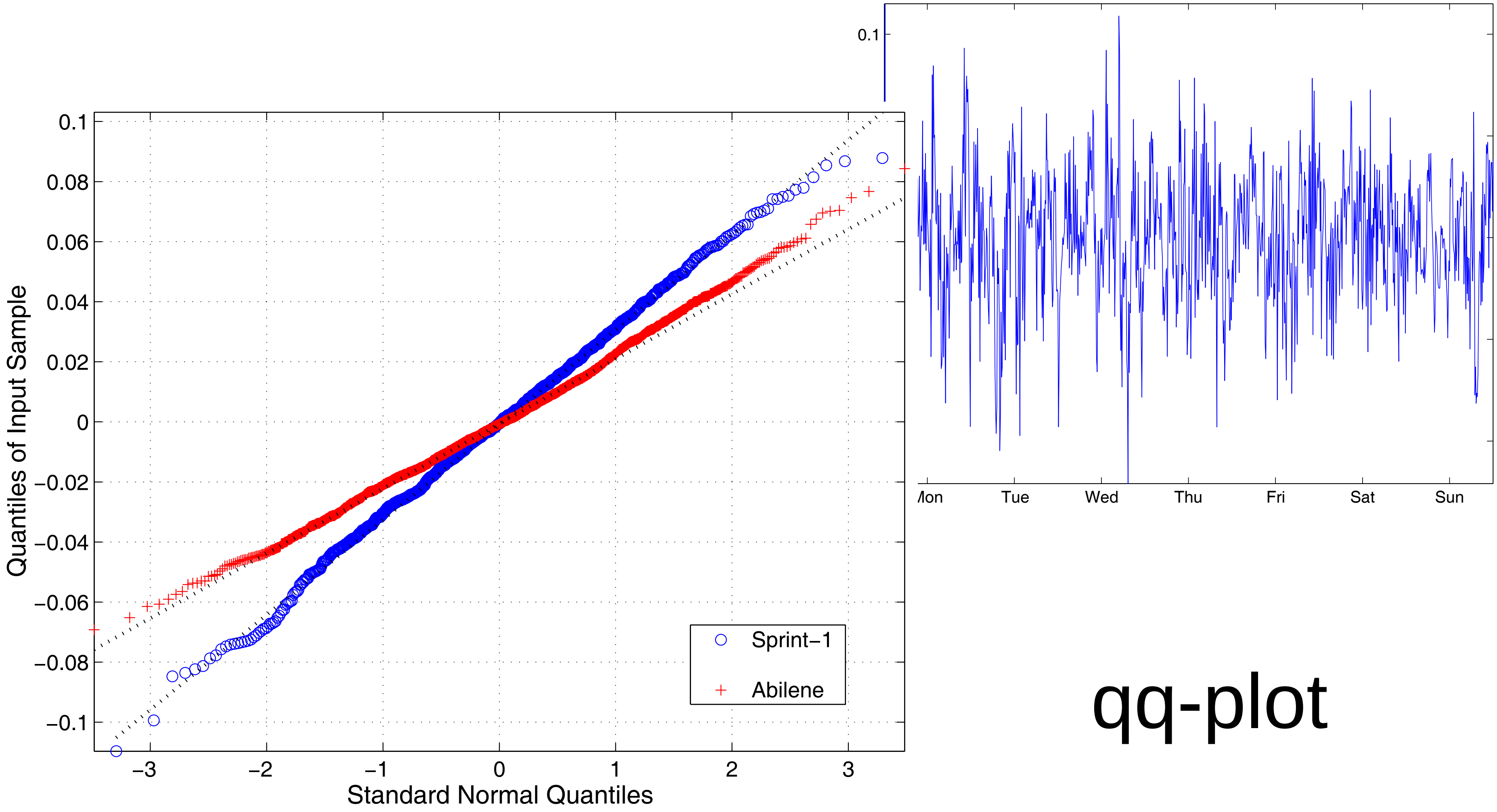
Power spectrum

S-eigenflows Have Spikes



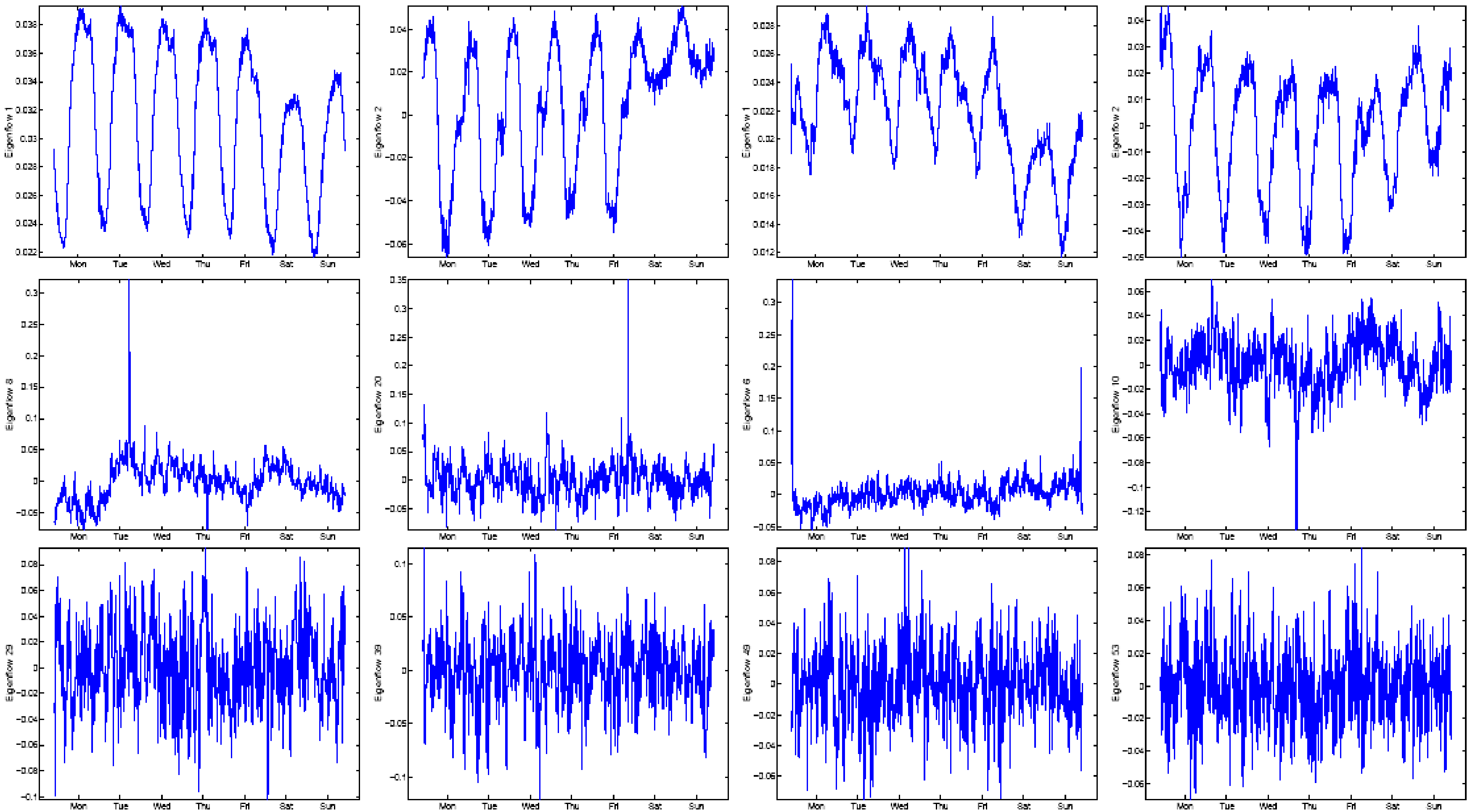
5-sigma threshold

N-eigenflows Are Gaussian



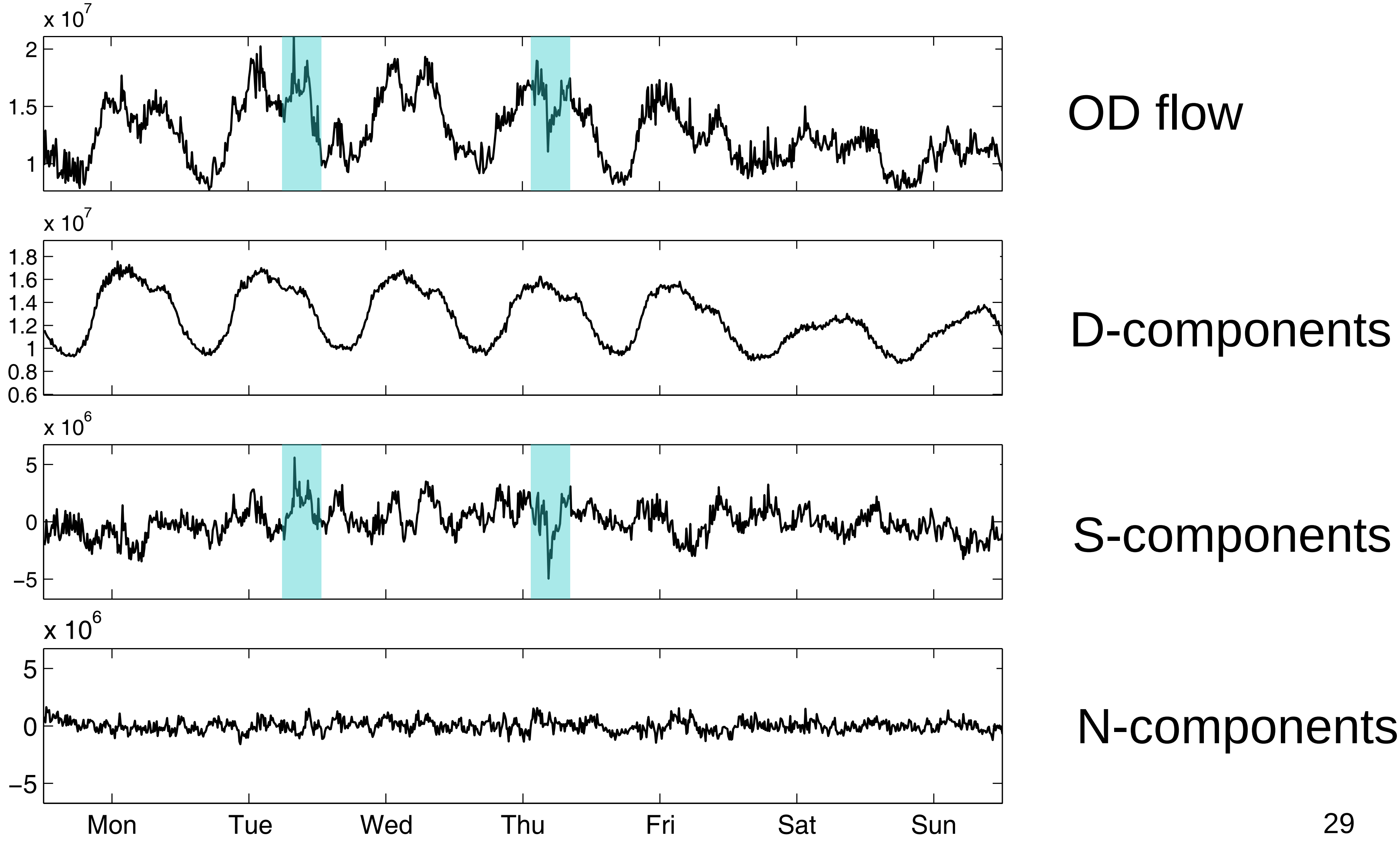
qq-plot

Hundreds of Eigenflows But Only Three Basic Types

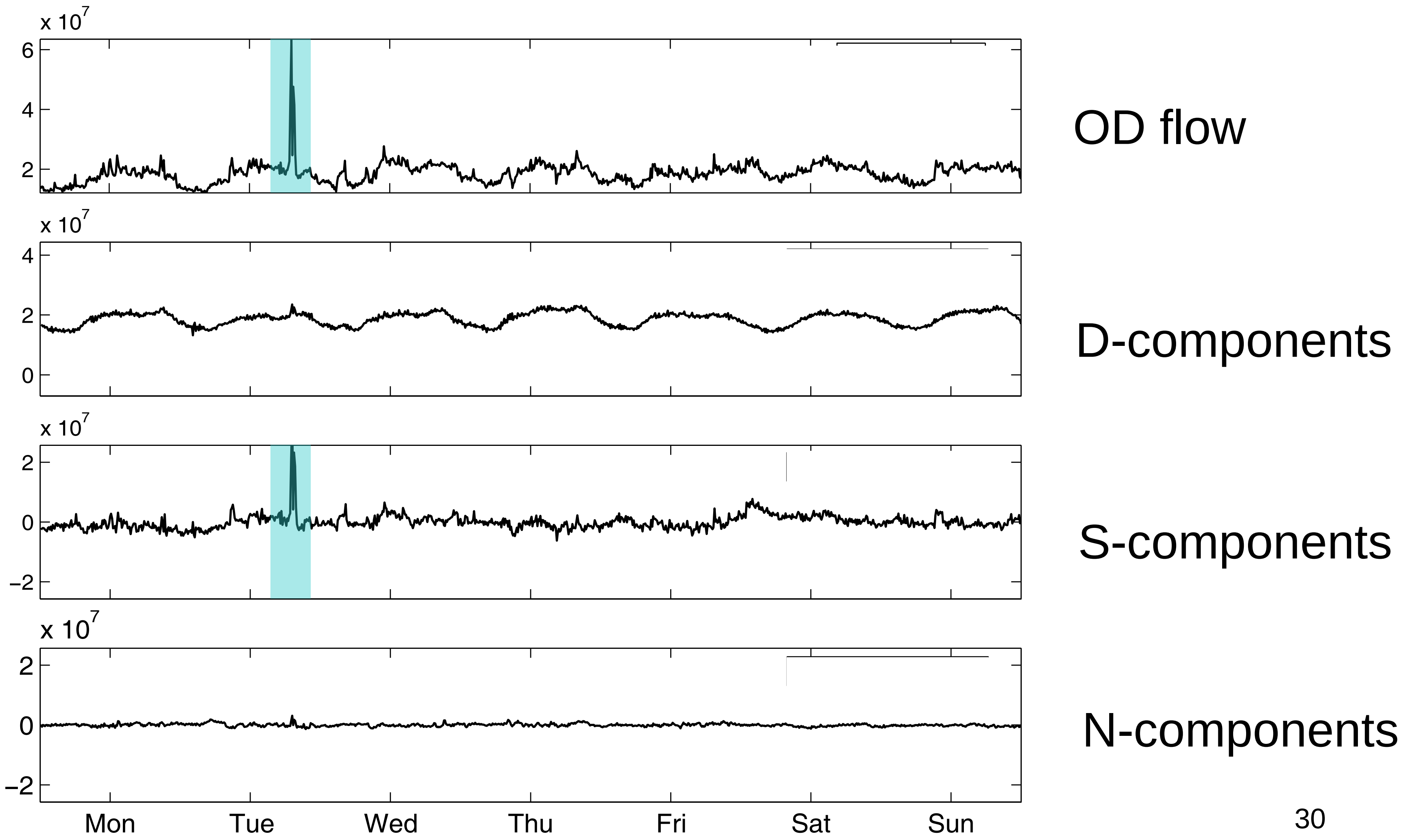


(a) Sprint (b) Abilene

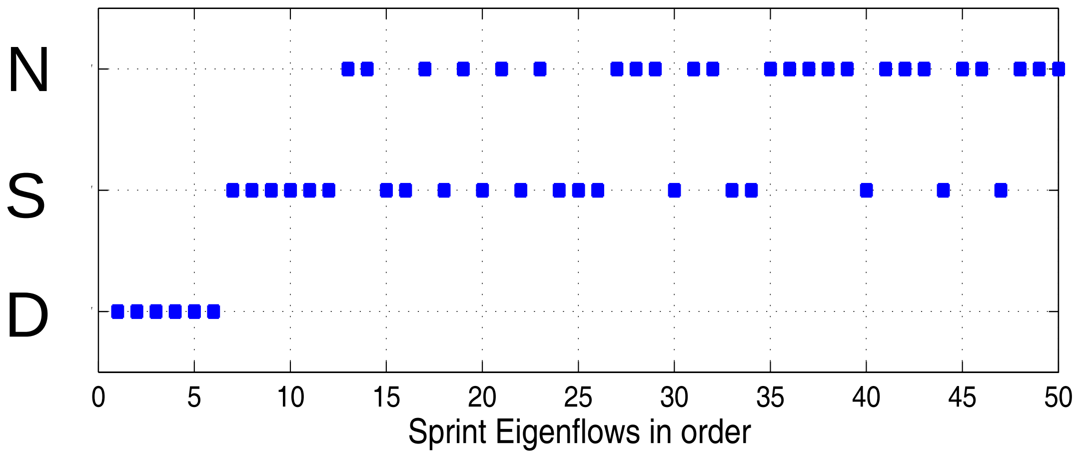
An OD Flow, Reconstructed

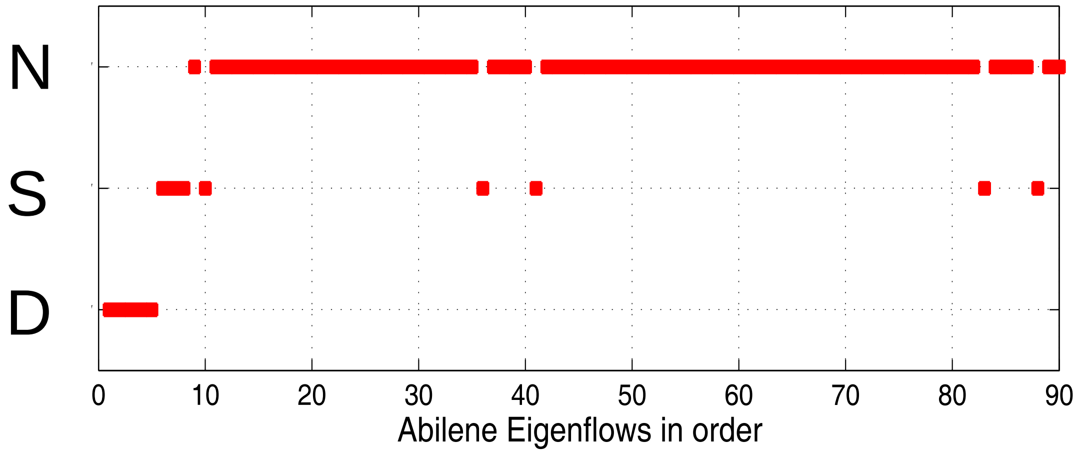


Another OD Flow, Reconstructed



Which Eigenflows Are Most Significant?





1-6: *d-eigenflows* appear to be most significant in both networks.

5-10: *s-eigenflows* are next important.

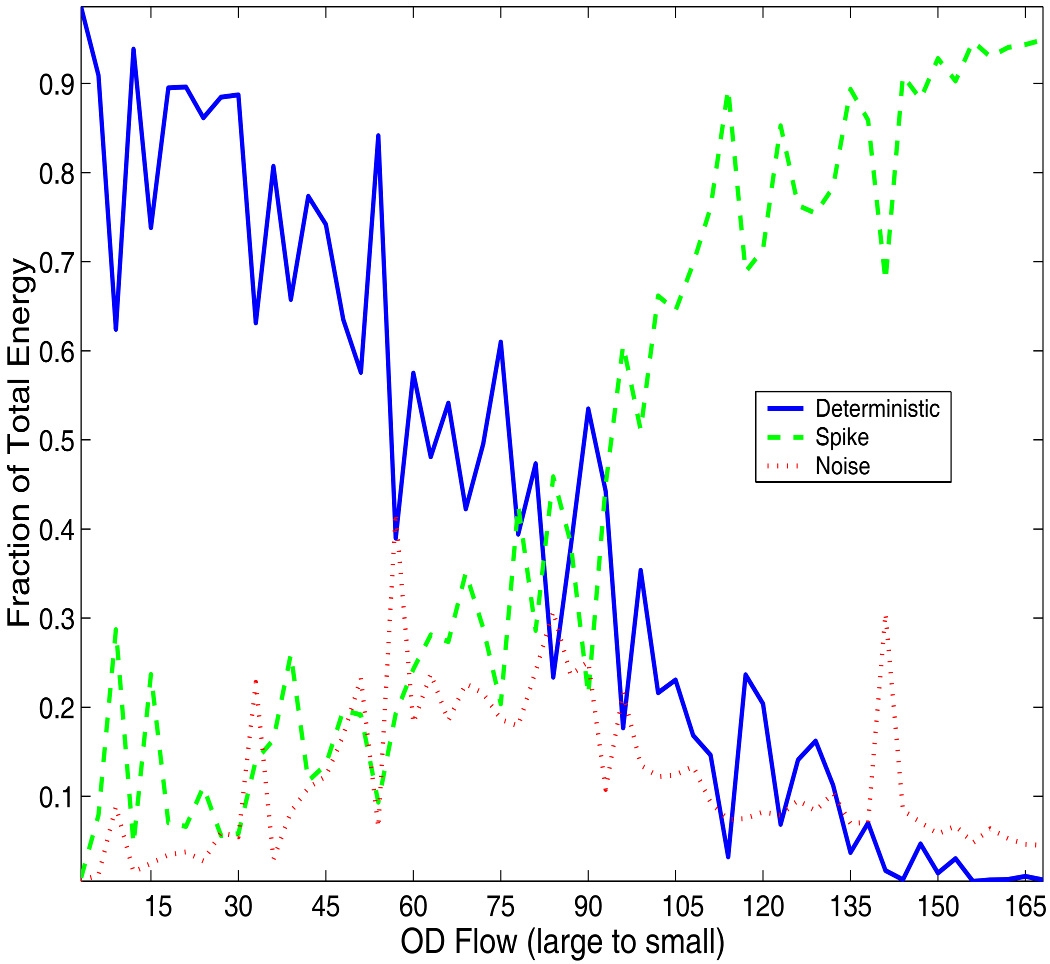
12 and beyond: *n-eigenflows* account for rest.

Contribution of Eigenflow Types

Fraction of total OD flow energy captured by each type of eigenflow

Eigenflow type	Sprint-1	Abilene
d-eigenflow	92.17%	69.79%
s-eigenflow	5.59%	18.60%
n-eigenflow	2.24%	11.61%

Contribution to Each OD Flow (Sprint)

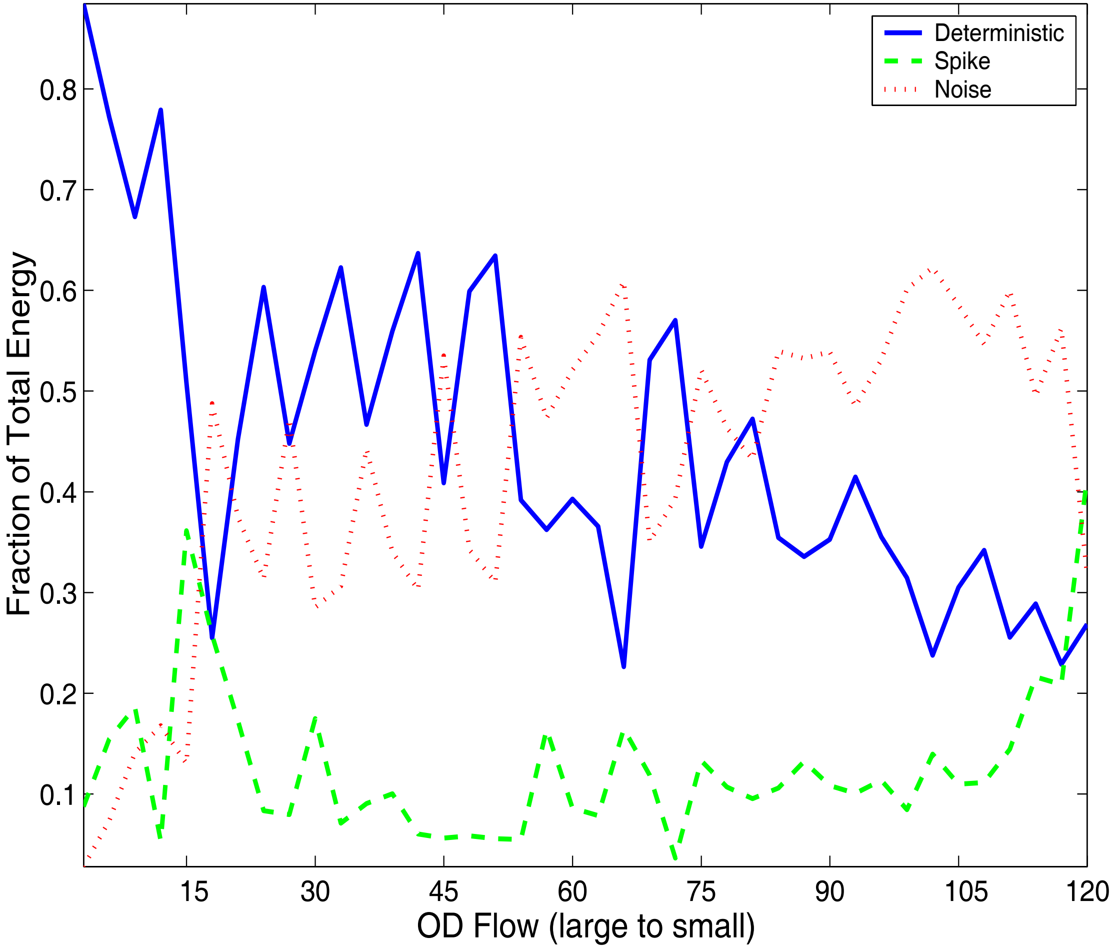


Largest OD flows: Strong deterministic component.

Smallest OD flows: Primarily dominated by spikes.

Regardless of size, n-eigenflows account for a fairly constant portion.

Contribution to Each OD Flow (Abilene)



Largest OD flows: Strong deterministic component.

Smallest OD flows: Dominated by noise, but have diurnal trends also.

Regardless of size, spikes account for a fairly constant portion.

Summary: Specific Questions

- Are there low dimensional representations for a set of OD flows?
  - 5-10 eigenflows is sufficient for good approximation of a set of 100+ OD flows
- Do OD flows share common features?
  - The common features across OD flows are eigenflows
- What do the features look like?
  - Each eigenflow can be categorized as D, S, or N
- Can we get a high-level understanding of a set of OD flows in terms of these features?
  - Both networks: Large flows are primarily diurnal
  - Sprint: Small flows are primarily spikes; noise constant.
  - Abilene: Small flows have N and D; spikes constant.

Outline

- Find intrinsic dimensionality of OD flows

- Decompose OD flows
- Characterize eigenflows
- Reconstruct OD flows

Structural Analysis

- Potential applications

Traffic Matrix Estimation

Problem Statement:
Infer OD flows (X) given link measurements (Y) and routing matrix (A): $Y^T = AX^T$

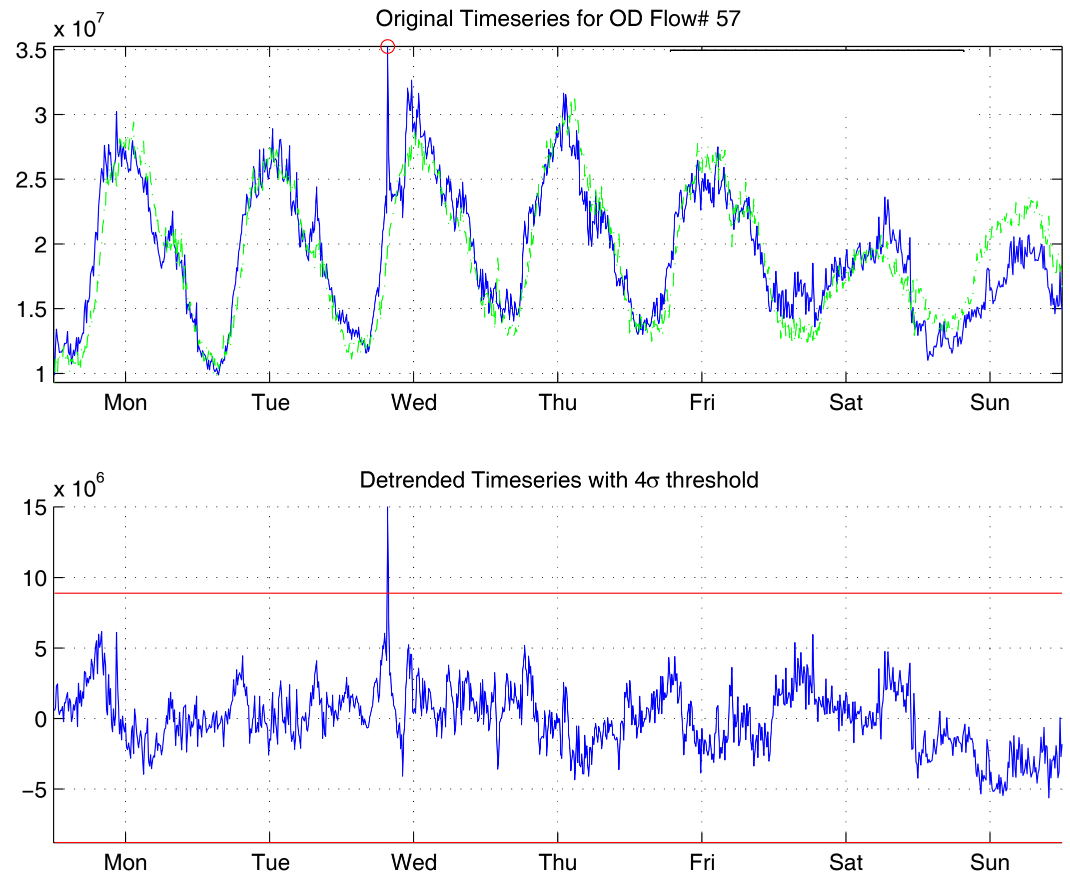
State of the Art:
dim(X) > dim(Y), so treat as ill-posed linear inverse problem.
Infer *Y* on *stationary (short)* timescales.

Possible Approach:
On *longer* timescales, intrinsic dimensionality of OD flows is small, so *effective* dim(X) < dim(Y)
TM estimation of *largest eigenflows* now becomes a "well-posed" problem.

Anomaly Detection

State of the art:
Use wavelets to detrend each flow in isolation.
[Barford:IMW02]

Possible approach:
Detrend *all* OD flows simultaneously by subtracting d-eigenflows.



Traffic Forecasting

State of the art:

Treat each flow timeseries independently.
Use wavelets to extract trends.
Build timeseries forecasting models on trends.
[PTZC:INFOCOM03]

Possible approach:

Build forecasting models on d-eigenflows as trends.
Allows simultaneous examination and forecasting for entire ensemble of OD flows.

Traffic Engineering

Problem Statement:
How does one identify important traffic flows, so that they can be treated differently?

State of the art:
Measure all flows on a single link
Find “heavy-hitters” or “elephant” flows based on preset thresholds [PTC:INFOCOM04, PTBTSC:IMW02]

Possible approach:
Look across all flows and extract common features
Taxonomize each flow into D, S, or N

Final thoughts

OD flows a useful primitive to engineer networks

Set of OD flows have low dimensional representations

A *Structural Analysis* approach can provide useful insight into nature of OD flows

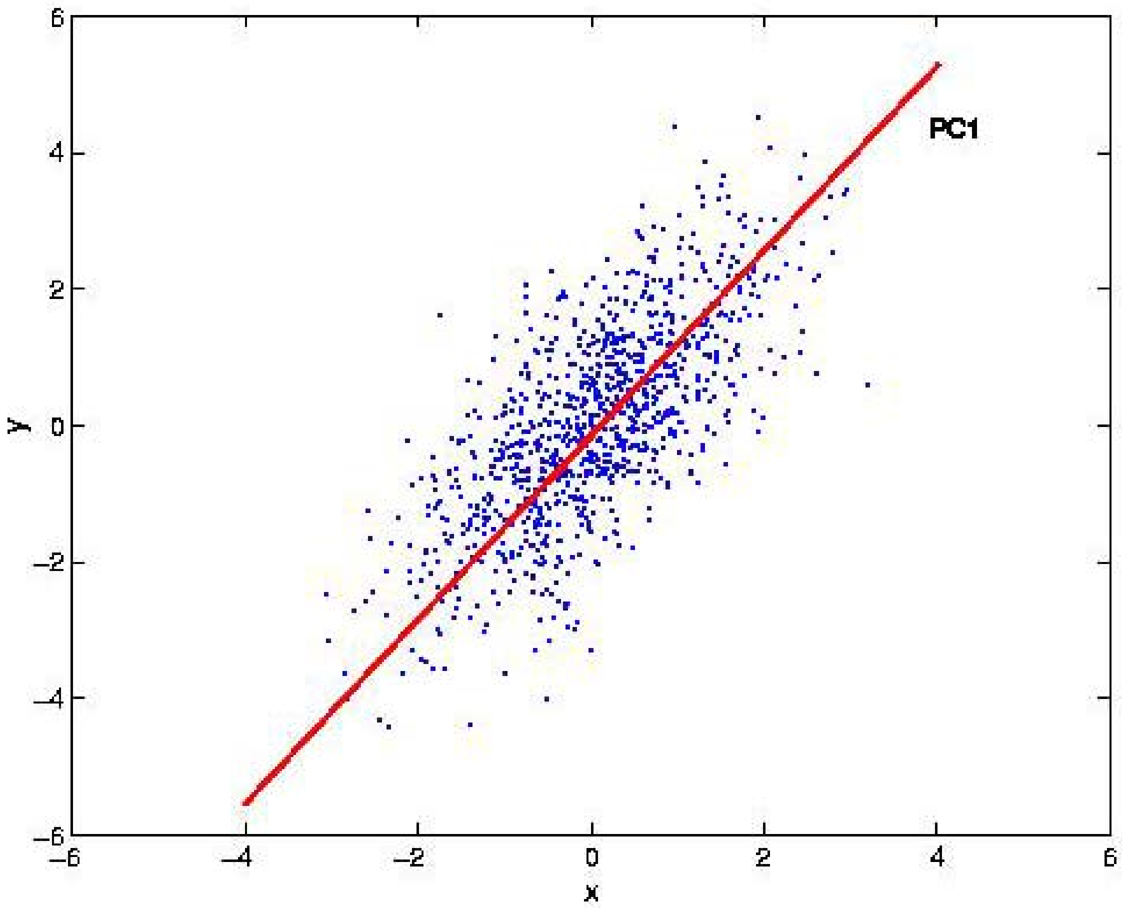
Thanks!

- **Help with Abilene Data**
  - Rick Summerhill, Mark Fullmer (Internet2)
  - Matthew Davy (Indiana University)

- **Help with Sprint-Europe Data**
  - Bjorn Carlsson, Jeff Loughridge (SprintLink),
  - Richard Gass (Sprint ATL)

Backup slides

Principal Component Analysis



For any given dataset, PCA finds a new coordinate system that maps maximum variability in the data to a minimum number of coordinates

New axes are called Principal Axes or Components

Properties of Principle Components

- Each PC in the direction of maximum (remaining) energy in the set of OD flows
  - Ordered by amount of energy they capture

$$v_1 = \arg\max_{\|v\|=1} \|\overbrace{Xv}^{\text{mapping of X onto one PC}}\|$$

and,

$$v_k = \arg\max_{\|v\|=1} \|\underbrace{(X - \sum_{i=1}^{k-1} X v_i v_i^T)}_{\text{difference between original and data mapped onto first } k\text{-}1 \text{ PCs.}} v\|.$$

- ***Eigenflow***: set of OD flows mapped onto a PC; a common trend
  - Ordered by most common to least common trend

Energy captured by each PC