Characteristic delay networks of US airlines

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Network effects on air traffic delays

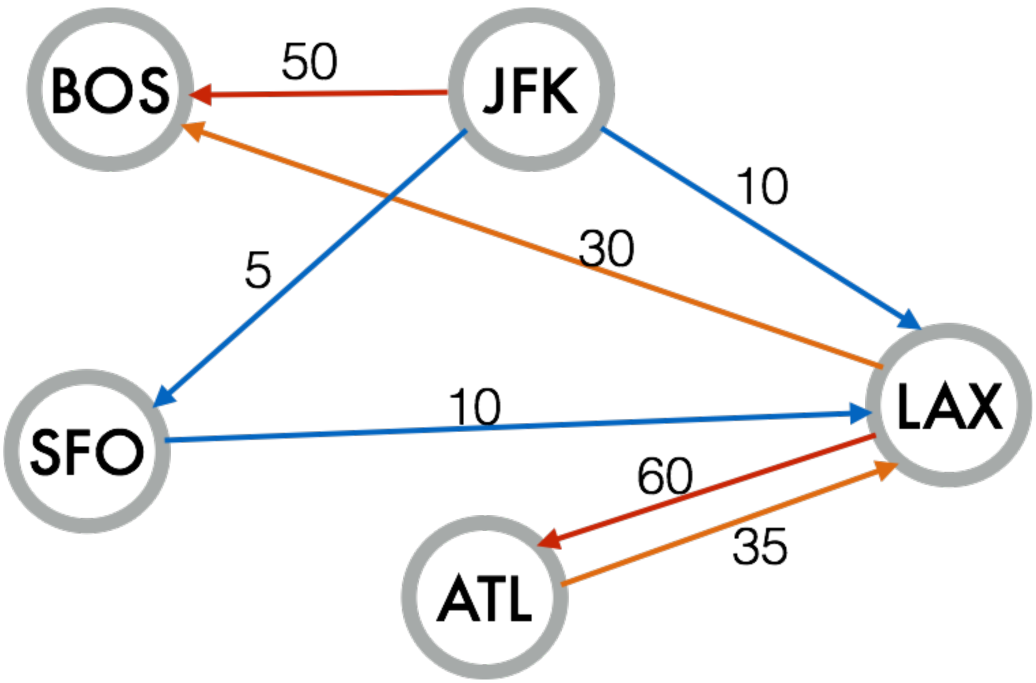
US domestic flights in 2016

- A significant fraction of delays is due to late arrival of incoming aircraft
- Network effects play a role in delay propagation
  - Crew connectivity, same aircraft used for multiple flight legs
- How is the 'network effect' different for each airline ?
  - What are the important factors – scheduling practices, weather pattern correlations etc.

Source: Bureau of Transportation Statistics

First step: Representing delays as a network

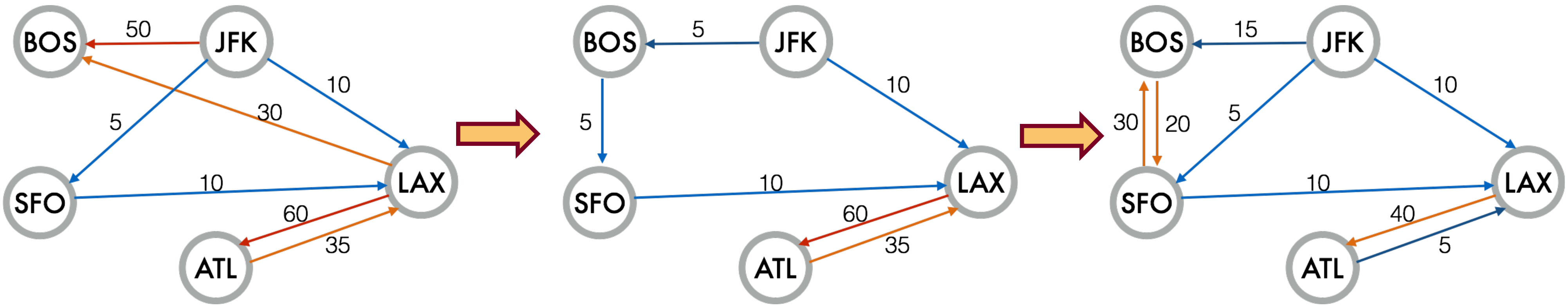
- The delay state of the air transportation system at any time can be represented using a **weighted, directed graph**



Delay state of the system

- Nodes: Airports
- Edges: 'Typical' delay of flights on that link

Delay networks are dynamic

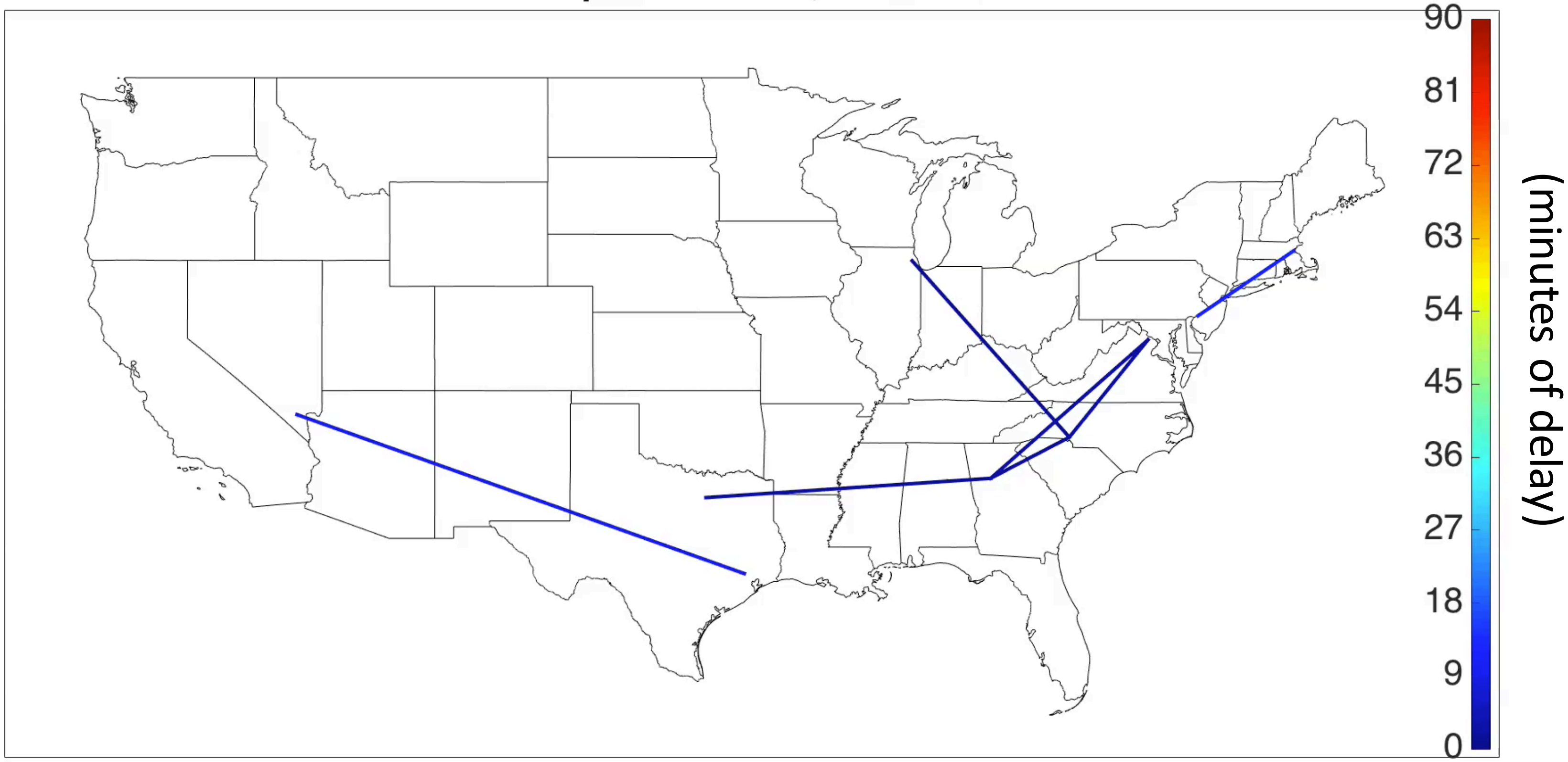


t= 4 pm t= 5 pm t= 6 pm

- The system is represented as a **time series of delay networks**
- Exhibit both temporal and spatial patterns
  - Morning versus evening
  - Congested hub airports versus smaller airports

Example of a high north east delay day

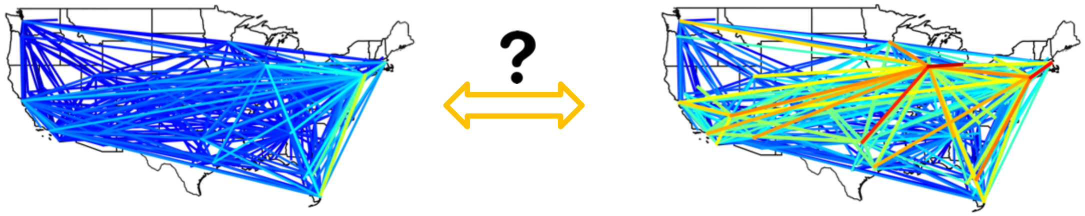
7 September 2011, 4 AM Eastern Time



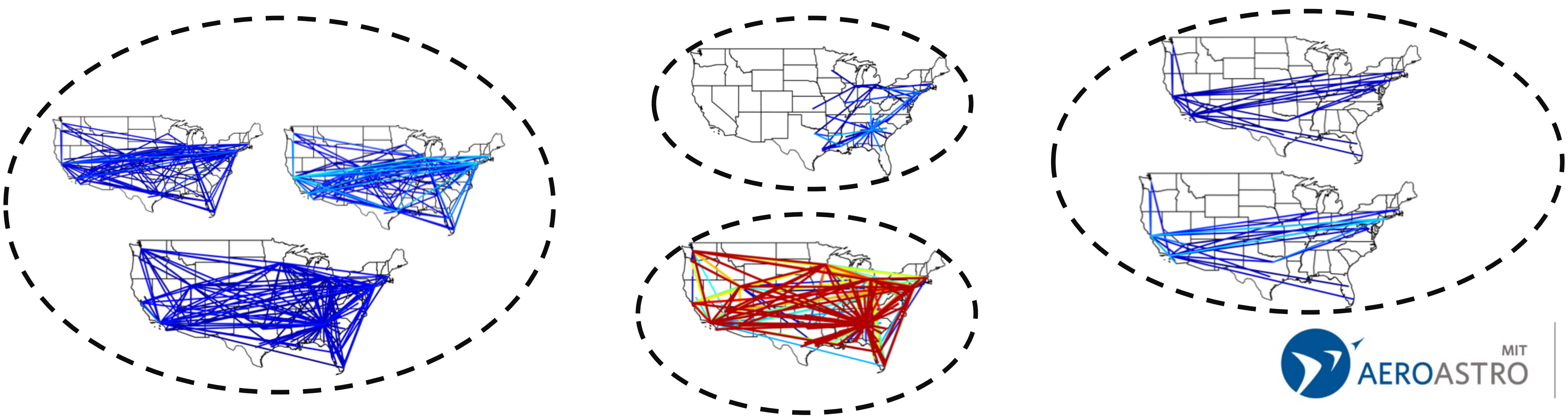
Data: Bureau of Transportation Statistics

Two related problems

- Given two networks, when do we say that they are similar i.e when can we say that the delay patterns are similar?



- What are the similar groups of delay networks
  - This is the network clustering problem



Focus of this talk

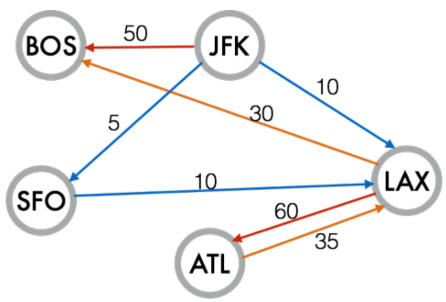
- The question of network similarity and clustering can be asked for
  - Hourly networks
  - Time series of networks that represent a day

- Delay networks can
  - Consider the total system state (across all airlines)
  - Be airline-specific

- In this talk we focus on ‘daily patterns’ and will look at both the total system and some of the individual carriers

What is the feature vector for the network

- A feature vector is a succinct representation of a network
- For every network G_i, we construct a feature vector f_i



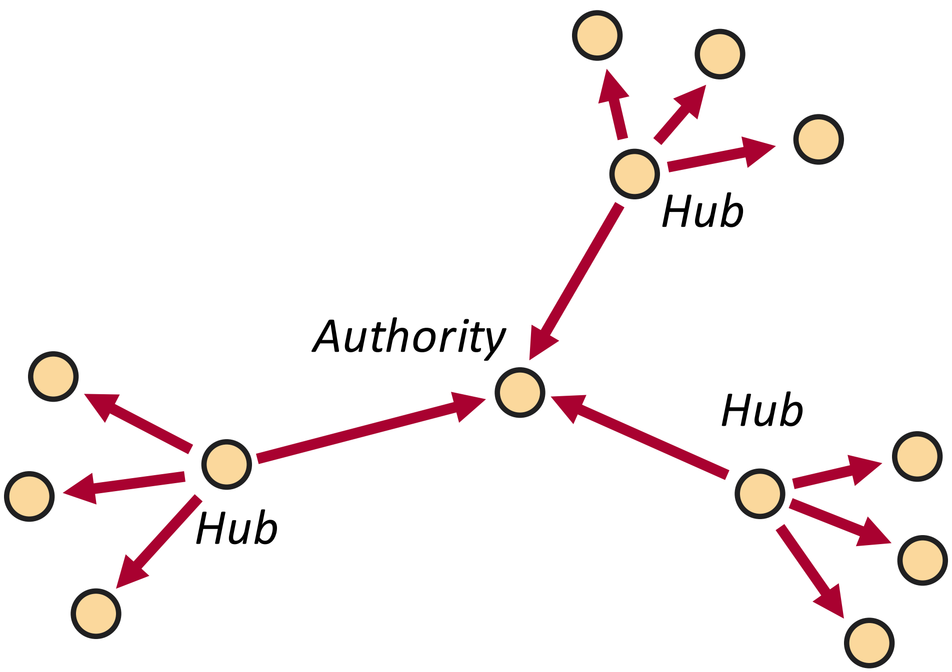
Compute $f_i = \begin{pmatrix} \vdots \\ \vdots \end{pmatrix}$

Dimensionality reduction of the data

- The feature vector f_i should capture
  - Delay connectivity
  - Magnitude of delays

Network centrality: Hub and authority scores

- Hub and authority scores measure important nodes in a network
- A good hub points to good authorities
- A good authority is pointed to by good hubs



Every node has a hub and authority score that indicates its connectivity in the network [Kleinberg 1997]

Data source

- Bureau of Transportation Statistics, US DoT
- Contains delay of all domestic flights of major carriers
  - 12 airlines
  - Publicly available

- Simplification of this large data set 2016 (5.6 million flights)
  - Eliminate cancelled or diverted flights
  - Consider only OD pairs with at least 5 flights/day (on average)

- Our simplified network has
  - 113 airports (Nodes)
  - ~900 OD pairs (Edges)

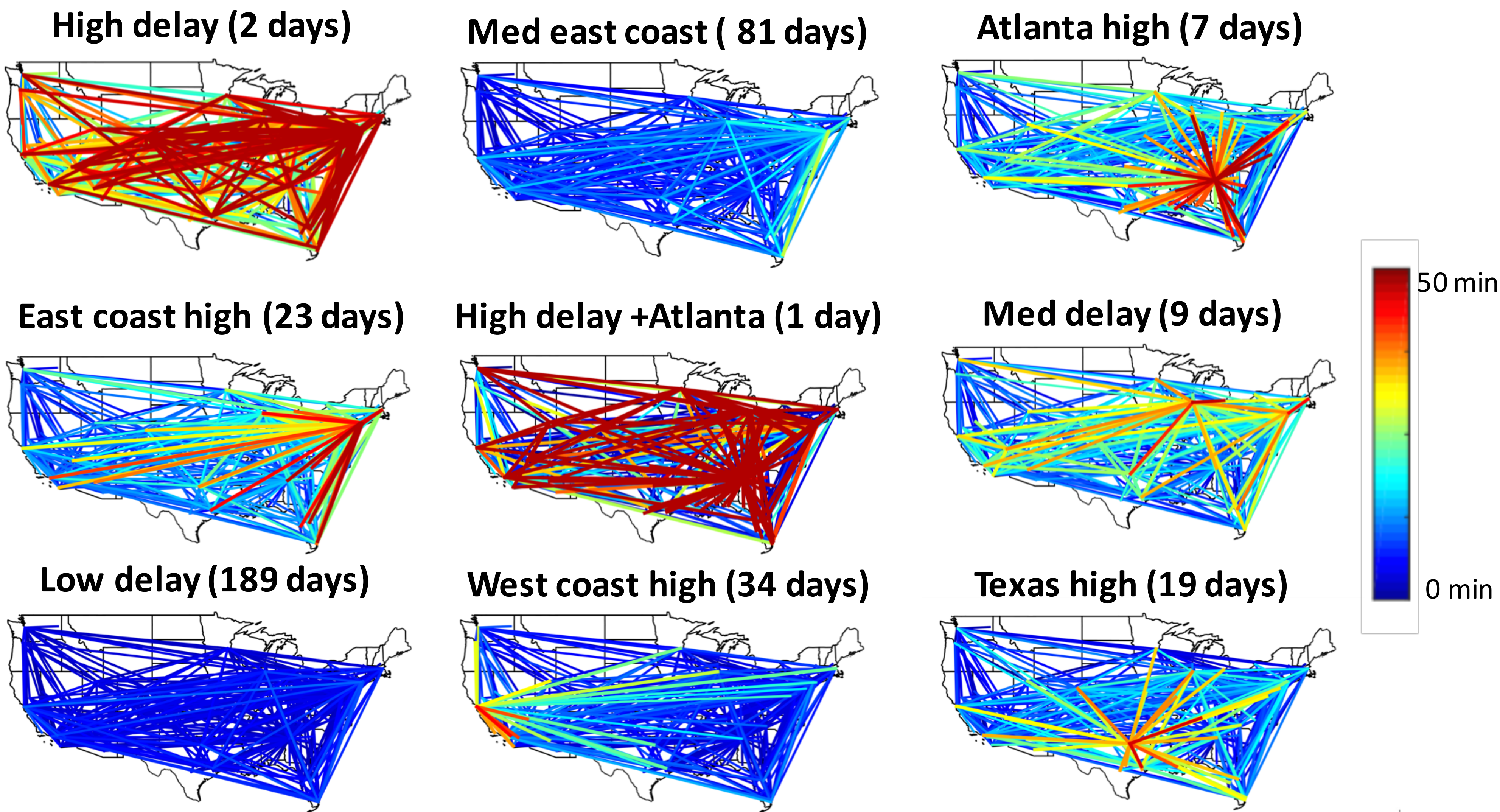
Identifying characteristic delay type-of-days

- What are the most representative days in terms of how the network delays looked
- Each day is a time series of 24 networks
- Use feature vector that contains **delay-weighted hub-authority scores** for each of the 24 hours

$$f = \begin{bmatrix} (\text{Delay})_1 \begin{pmatrix} \vec{h} \\ \vec{a} \end{pmatrix} \\ \vdots \\ (\text{Delay})_{24} \begin{pmatrix} \vec{h} \\ \vec{a} \end{pmatrix} \end{bmatrix}$$

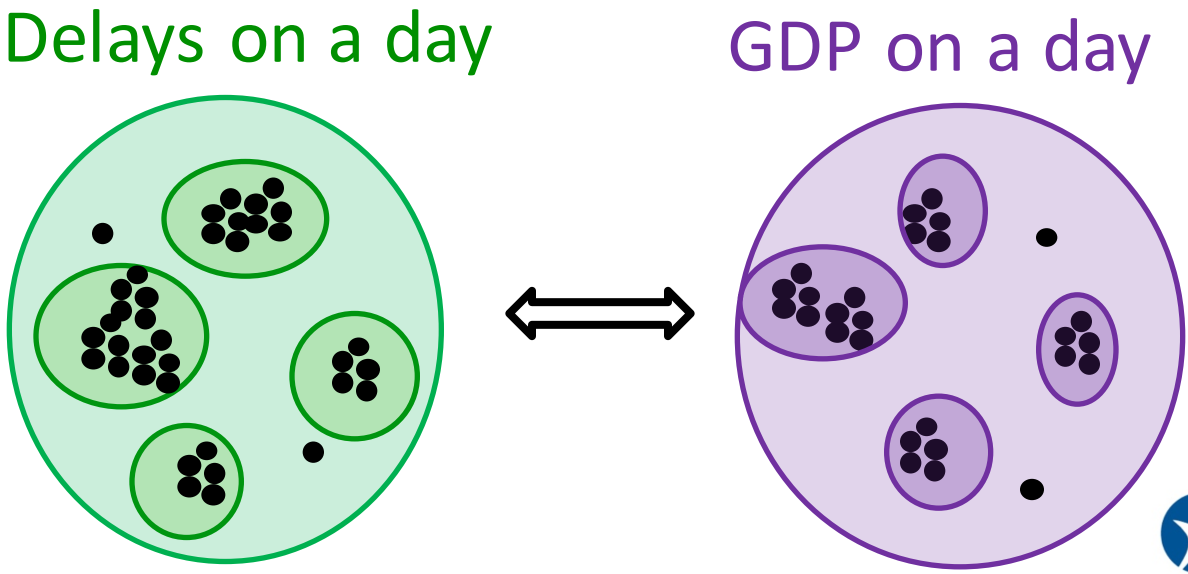
- k-means for clustering
- We identify 9 characteristic type-of-days

Delay type-of-days



Effect of Traffic Management Initiatives (TMI) on network delay

- Ground Delay Programs (GDPs) are common
  - Lead to slot restrictions at an affected airport
  - About 2 to 3 GDPs per day in 2016
- These TMIs are correlated to specific delay patterns
- We can identify the impact of these GDPs on the network delay



Effect of Traffic Management Initiatives (TMI) on network delay

- Ground Delay Programs (GDPs) are common
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  - About 2 to 3 GDPs per day in 2016
- These TMI's are correlated to specific delay patterns
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Delays on a day ⟺ **GDP on a day**

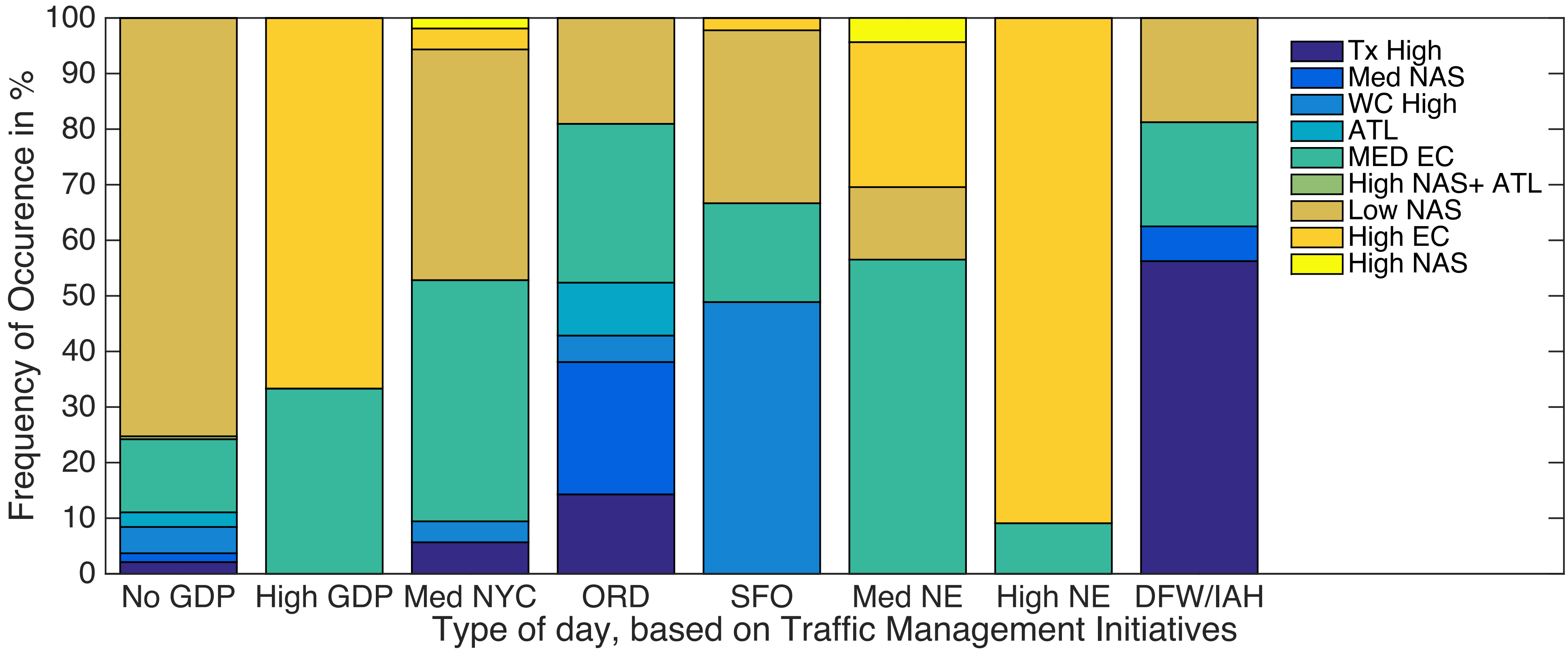
9 types

8 types

1. No GDP
2. High GDP
3. ORD
4. SFO
5. North East

⋮

Delay type-of-day and GDP's



- GDPs and delays are related
  - SFO Delays and GDP
  - Texas delays and GDP
  - North east GDPs with North east delays

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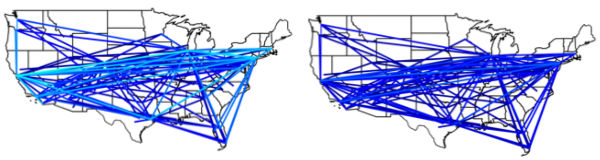
Airline-specific type of days

United

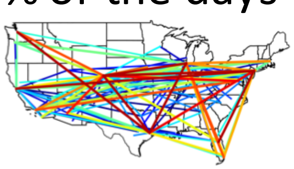
85% low delay



9% East coast delay

5% Chicago delay

< 1% of the days



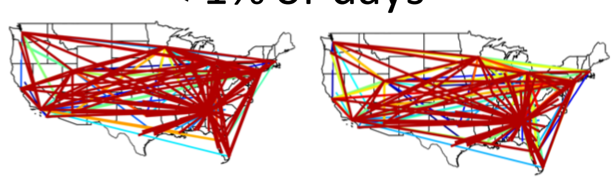
Delta

87% low delay

10% East coast delay

3% Atlanta delay

< 1% of days

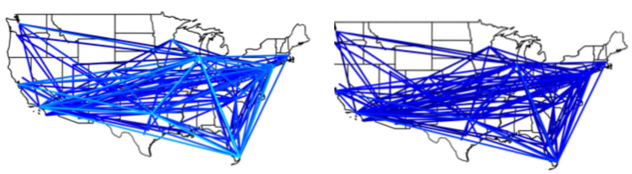


- Most of the days are low delay days
- Each airline has characteristic delay networks that depends on its operational practices

Airline-specific type of days

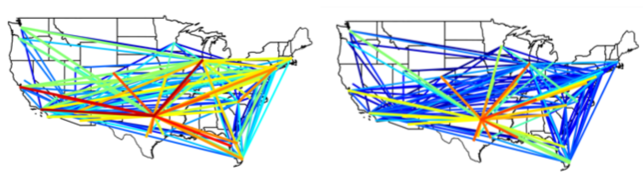
American

85% low delay days



8% East coast delay

6% Dallas delay

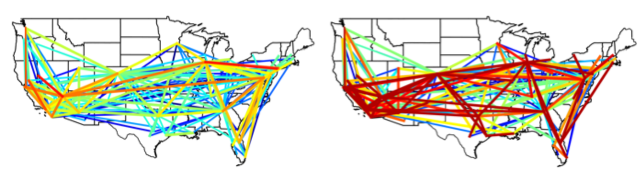


Southwest

87% low delay days

11% West coast delay

2% High delay



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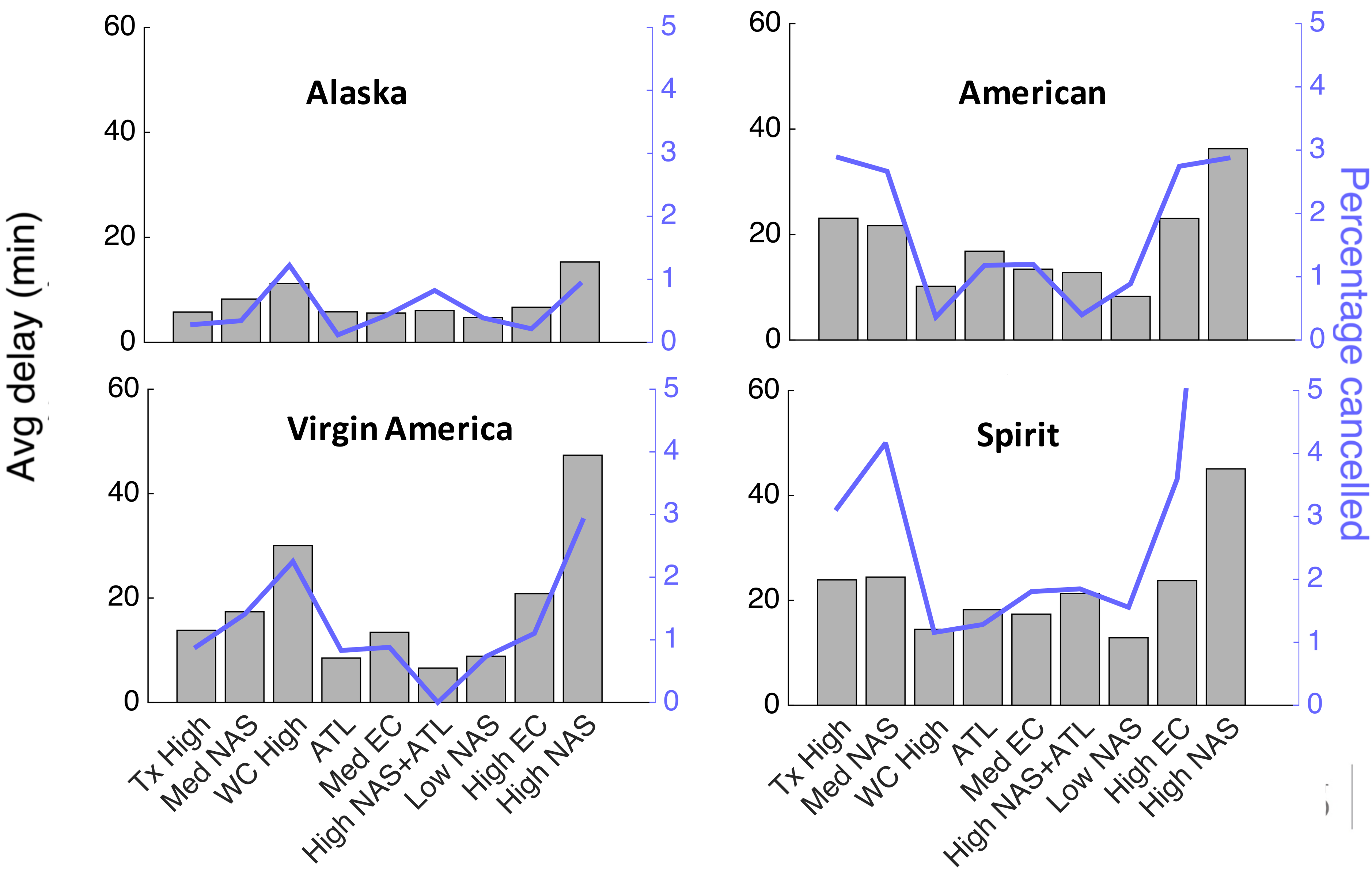
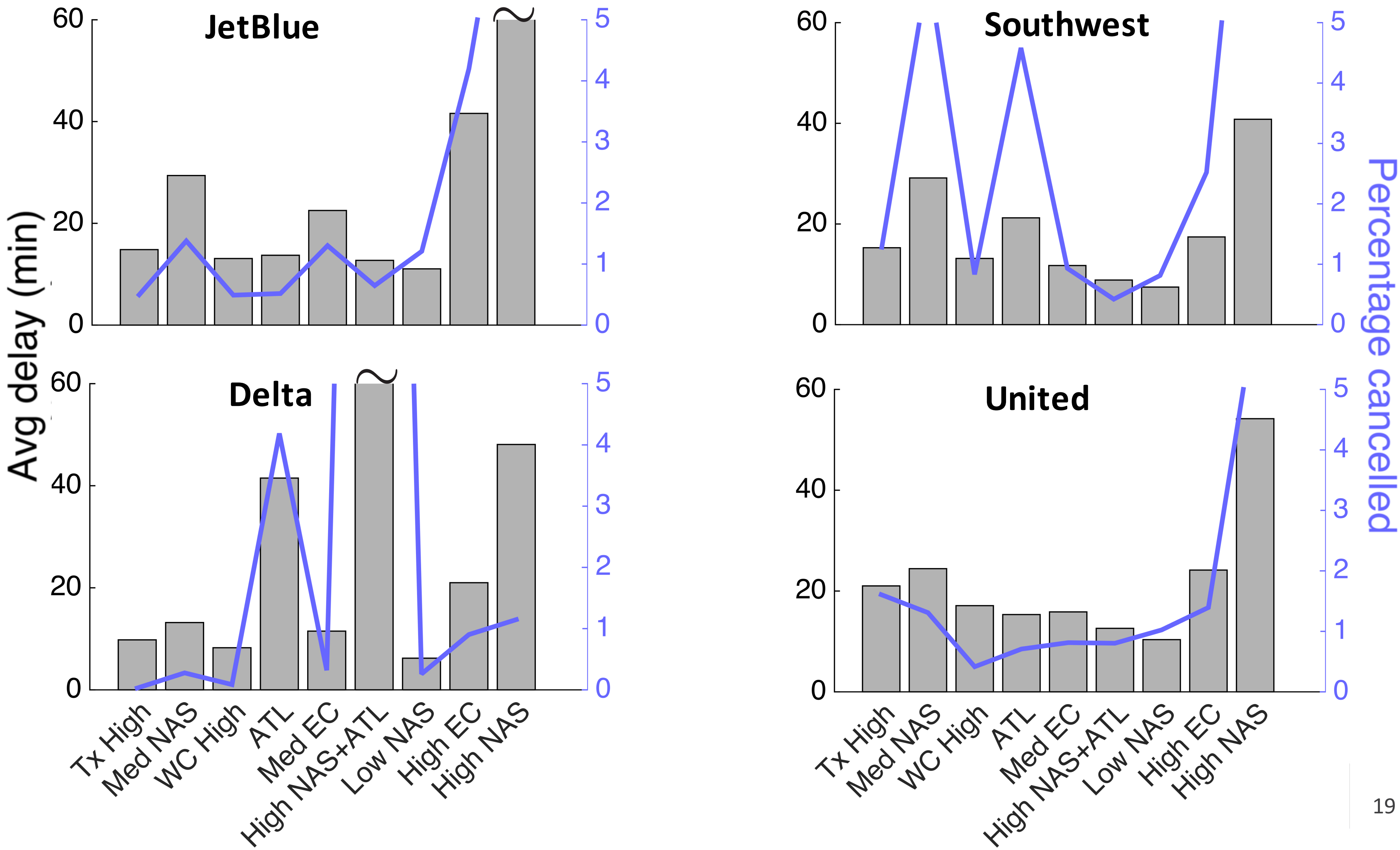
Delay type of day and its impact on airlines

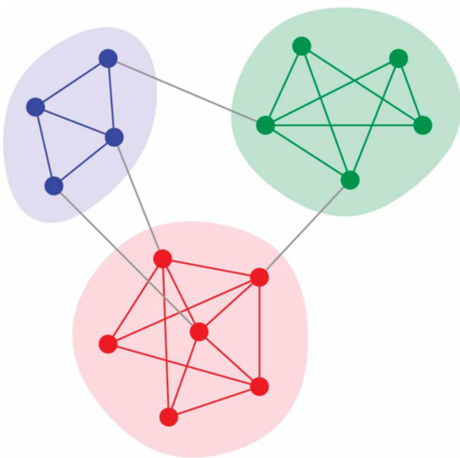


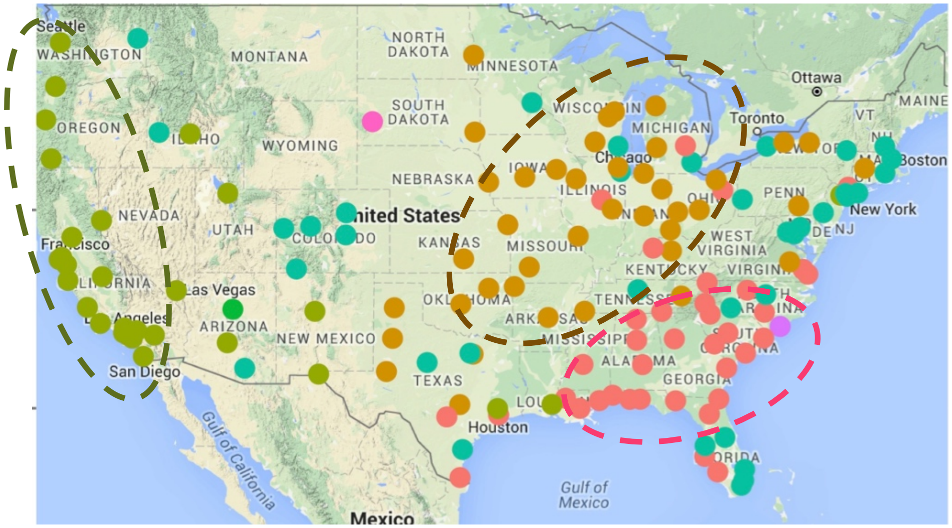
Delay type of day and its impact on airlines



Related work: Communities in networks

- Airports in a community have higher delay edges amongst themselves than to airports in other community

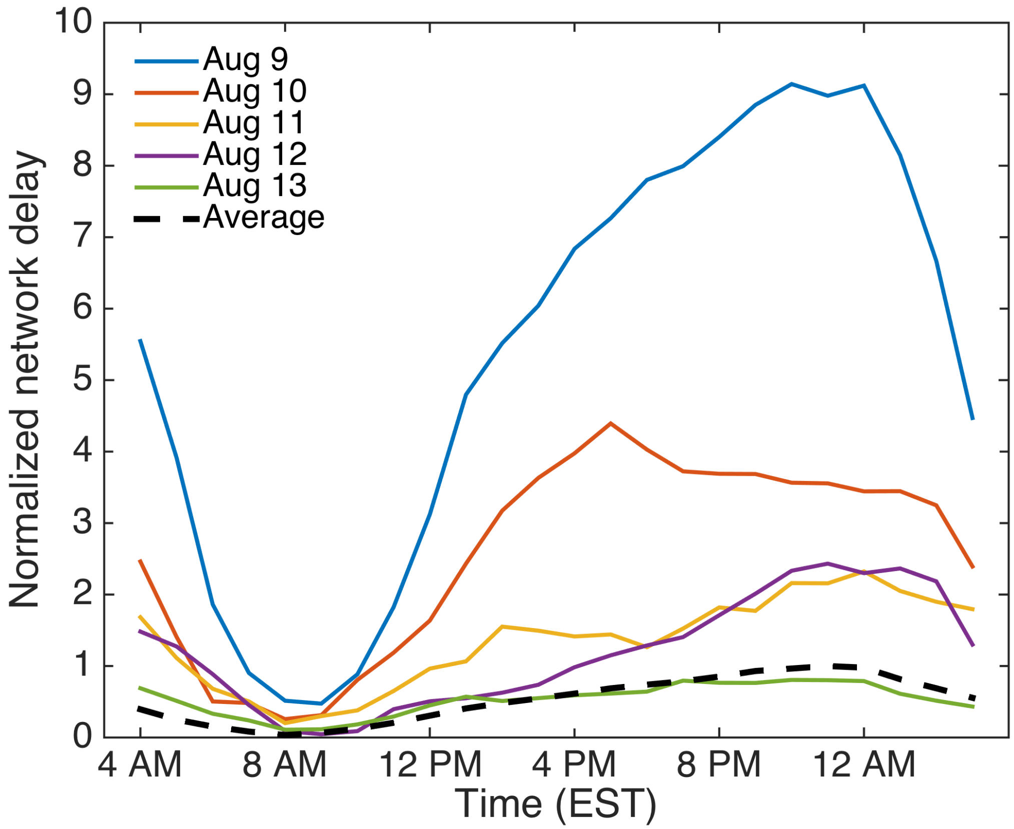




- Strong geographical correlations in the community structure
- Communities are reasonably consistent across types-of-days
- Indicates strong tendency for delays to propagate within these airports

Potential application: Recovery dynamics prediction

- Delta's power outage on 8 August 2016 lead to delays and cancellations
- Potential to predict recovery and network impacts after such events



- Not all carriers were impacted by this incident
- Highlights benefit of carrier level network clustering

Summary

- Identifying characteristic delay patterns is important for developing predictive models and planning mitigation strategies [ATM Seminar ‘17]
  - Models/predictions could be carrier specific
  - Performance measurement of airlines
- Extensions:
  - Identified communities of airports with similar delay behavior
  - Correlating the states to weather disruptions, airport closures etc.
  - Multilayer, multi-timescale networks [ICRAT ‘16]
  - Markov Jump Linear System model for delay dynamics [CDC ‘16]