POLITECNICO
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Machine Learning Methods for Communication Networks and Systems

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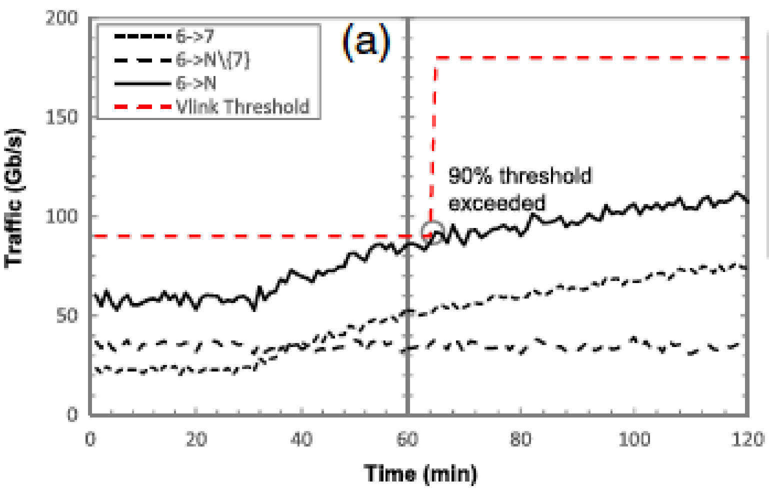
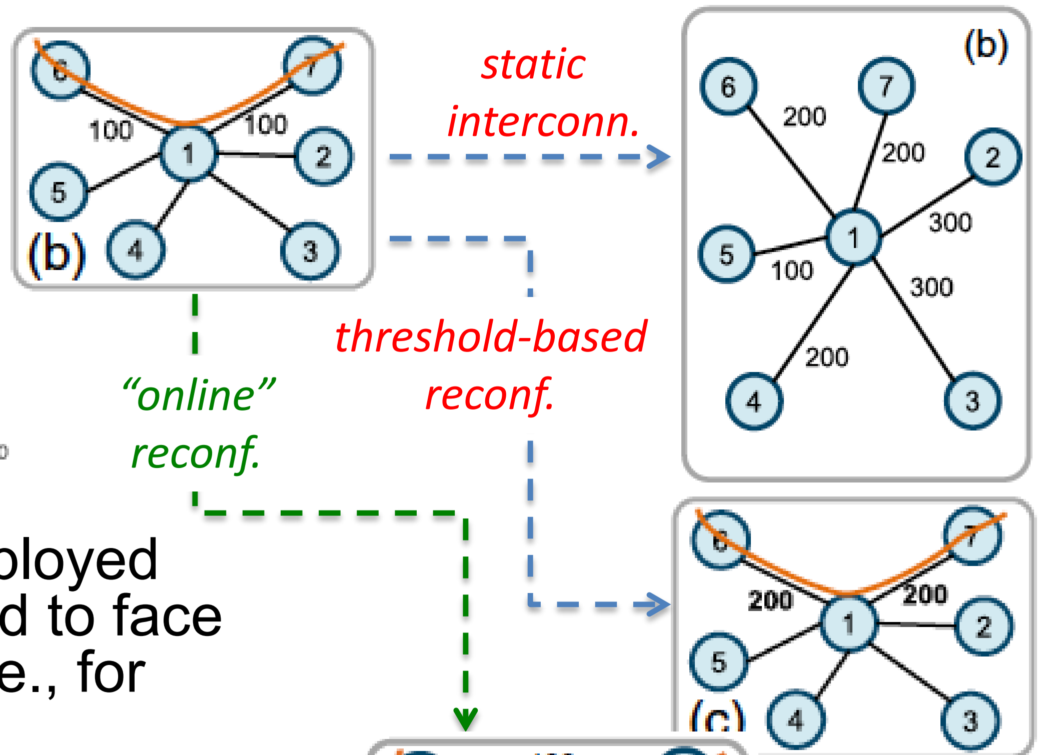
Part II – 7: Traffic prediction

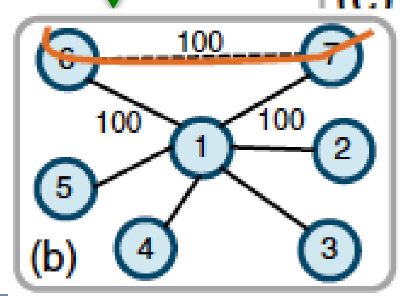
Network layer domain
Traffic prediction

- New network services are featured by high traffic dynamics (variability)





- No reconfiguration: deployed capacity is dimensioned to face worst-case scenario (i.e., for peak-traffic)
- ML leverages *online* (live) traffic monitoring/prediction to efficiently exploit available resources w/o overdimensioning



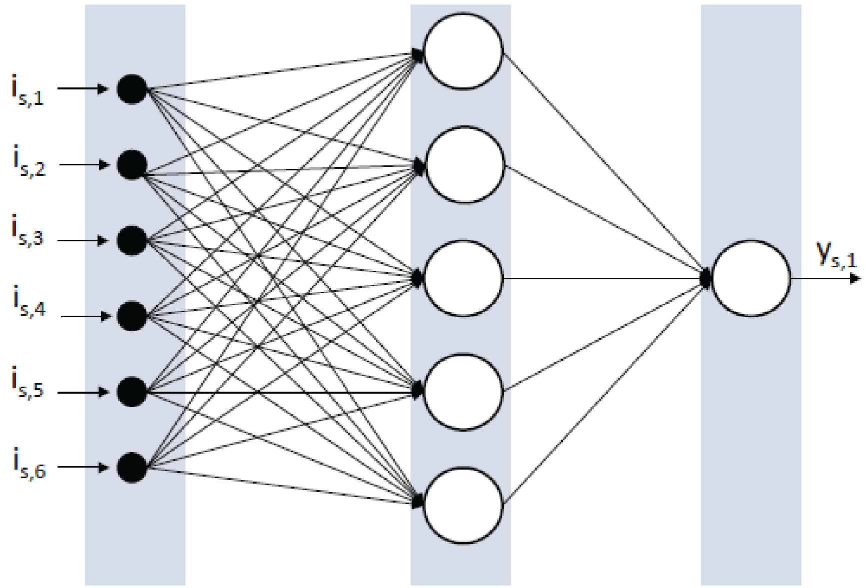
Morales *et al.*, *JOCN*, vol. 9 n. 1, Jan. 2017

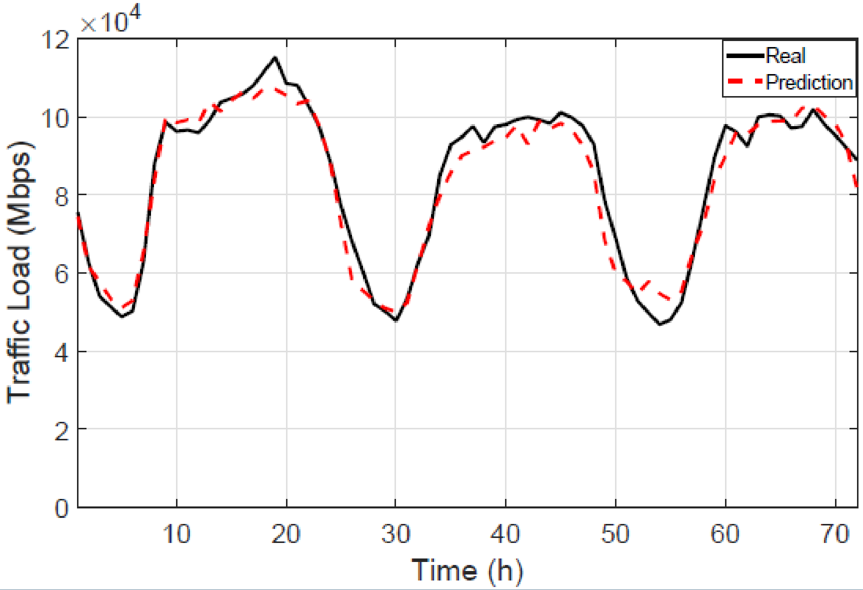
Traffic prediction
Source 1

- Alvizu *et al.*, “Matheuristic with machine learning-based prediction for software-defined mobile metro-core networks”, *Journal of Optical Communication and Networking*, vol. 9 n. 9, Sep. 2017
- Paper objective: periodically predict (i.e., every hour) traffic requirements to perform energy-optimized network resources allocation
  - input
    - Historical traffic data
  - output
    - Traffic requirements for the next period
  - ML algorithm: Neural Network

Traffic prediction
Source 1

- Input features
  - hour of the day
  - day of the week
  - holiday/weekend (flag)
  - prev. day average load
  - prev. day load (same hour)
  - prev. week load (same day, same hour)
- Single hidden layer
  - 5 hidden units
  - sigmoidal activation function
- Error backpropagation with gradient descent
- Data samples: TIM Call Detail Records (CDR)
  - 1 record every 10 mins (144 per day)
  - monitoring during Nov.-Dec. 2013

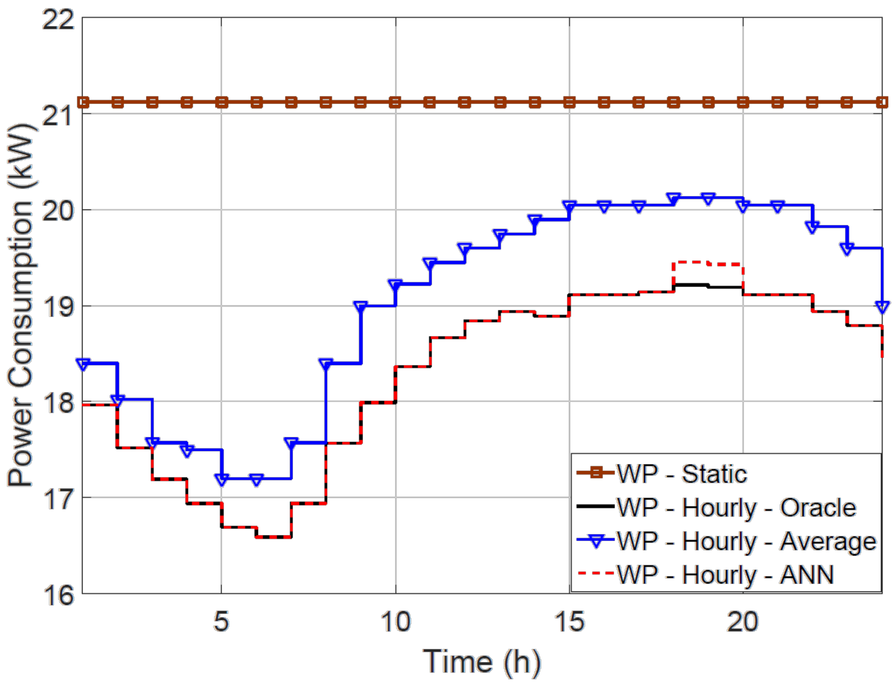




Traffic prediction
Source 1

Power/Energy consumption comparison

- ***Static***: resources allocation based on peak traffic
- ***Hourly-Oracle***: hourly reconfigurations, perfect traffic prediction (oracle)
- ***Hourly-Average***: hourly reconfigurations, considering average traffic pattern, and optimized routing with matheuristic
- ***Hourly-ANN***: hourly reconfigurations, ANN-based traffic prediction and optimized routing with matheuristic



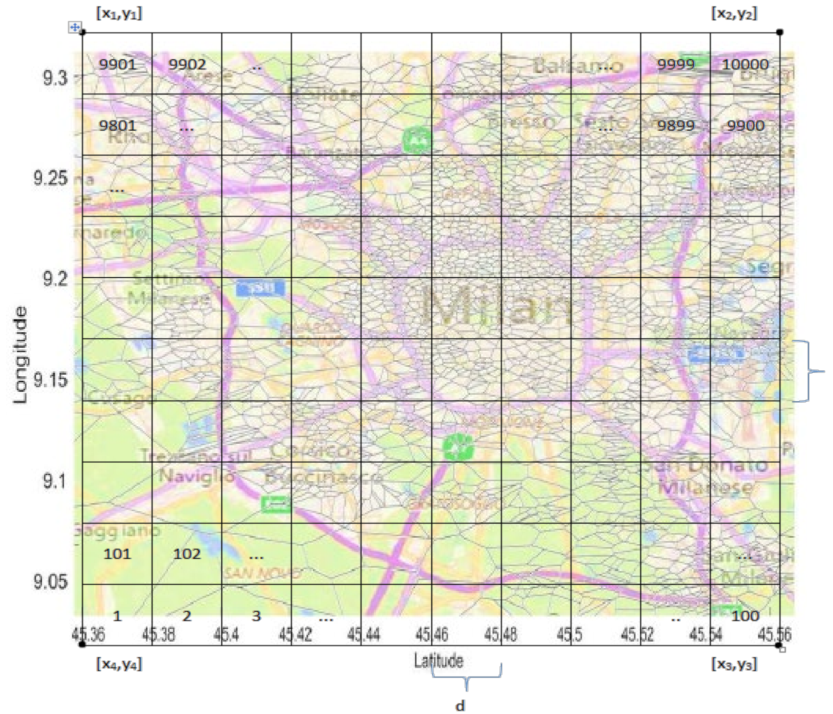
	WP			
16/12/2013	Static	Hourly (Oracle)	Hourly (Average)	Hourly (ANN)
Total Energy (kWh)	506.88	439.28	457.66	439.76
Energy Saving (compared to static)		13.3%	9.7%	13.2%
Optimality Gap (with oracle)			4%	0.1%
17/12/2013	Static	Hourly (Oracle)	Hourly (Average)	Hourly (ANN)
Total Energy (kWh)	506.88	442.62	457.66	444.64
Energy Saving (compared to static)		12.6%	9.7%	12.2%
Optimality Gap (with oracle)			3.2%	0.45%

Traffic prediction
Source 2

- Troìa *et al.*, “Identification of Tidal-Traffic Patterns in Metro-Area Mobile Networks via Matrix Factorization Based Model”, in *PerCom 2017,* Mar. 2017
- <u>Paper objective</u>: extract common traffic patterns in a metropolitan network to characterize Internet traffic
  - input
    - Internet traffic data
  - output
    - Geographic-related traffic patterns
  - ML algorithm: k-means, spectral clustering, non-negative matrix factorization

Traffic prediction
Source 2

- Datasets exploited
  - Call Detail Records (CDRs): measurements of traffic from Milan TIM cellular network
  - TIM base stations location (OpenCell-ID)
    - 1728 base stations
  - Locations of Points of Interests (POIs)
  - DUSAF: Database with types of geographical areas
    - used as “ground truth” for evaluation



Point of Interests

1	ADMINISTRATION
2	RELIGIOUS BUILDINGS
3	COMPANIES
4	CULTURE
5	RESIDENCES FOR SOCIAL ACTIVITIES
6	GOVERNMENT
7	TRANSPORT INFRASTRUCTURE
8	TECHNOLOGY INFRASTRUCTURE
9	ISTRUCTION
10	HEALTH
11	SOCIAL SERVICE
12	SECURITY
13	SPORT
14	TURISM
15	UNIVERSITY AND RESEARCH

Traffic prediction
Source 2

- Different clustering approaches have been used
  - k-means alone does not provide well-separated clusters
  - Non-negative Matrix Factorization (NMF) + k-means
  - Spectral clustering + NMF
  - Collective NMF (C-NMF) + k-means
- NMF and C-NMF aim at reducing the dimension of data points before applying clustering
  - C-NMF goal: use information on POIs to capture similarities between different cells

Traffic prediction

Source 2

- **CDR Matrix** ***V*** *[NxT]*: traffic information
  - N: number of base stations
  - T : number of time intervals
- **POI Matrix** ***P*** *[NxM]*: POIs information
  - N: number of base stations
  - M: number of different types of POI
- H_u *[KxT]*, H_s *[KxM]*: basis matrices of CDR and POI

- ***W [NxK]*: coefficients matrix**
  - captures information from matrices V and P
- Obj. function:

  minimize $$O(W, H_u, H_s) = \beta||V - WH_s||^2 + \alpha||P - WH_u||^2 + \lambda\left(||W||^2 + ||H_u||^2 + ||H_s||^2\right)$$

- when *W* is found, k-means is performed on it

Traffic prediction

Source 2

- Clustering performance metrics*
  - *Davies-Bouldin (D&B)*: based on the ratio between intra-cluster and inter-cluster distances (the lower, the better)
  - *Calinski Harabasz (CH)*: based on the ratio between inter-cluster and intra-cluster distances (the higher, the better)
  - *Dunn index*: measures the clusters "compactness" (the higher, the better)

TABLE II
CLUSTERING INDEXES: *Davies-Bouldin (D&B)*, *Calinski Harabasz (CH)* AND *Dunn*.

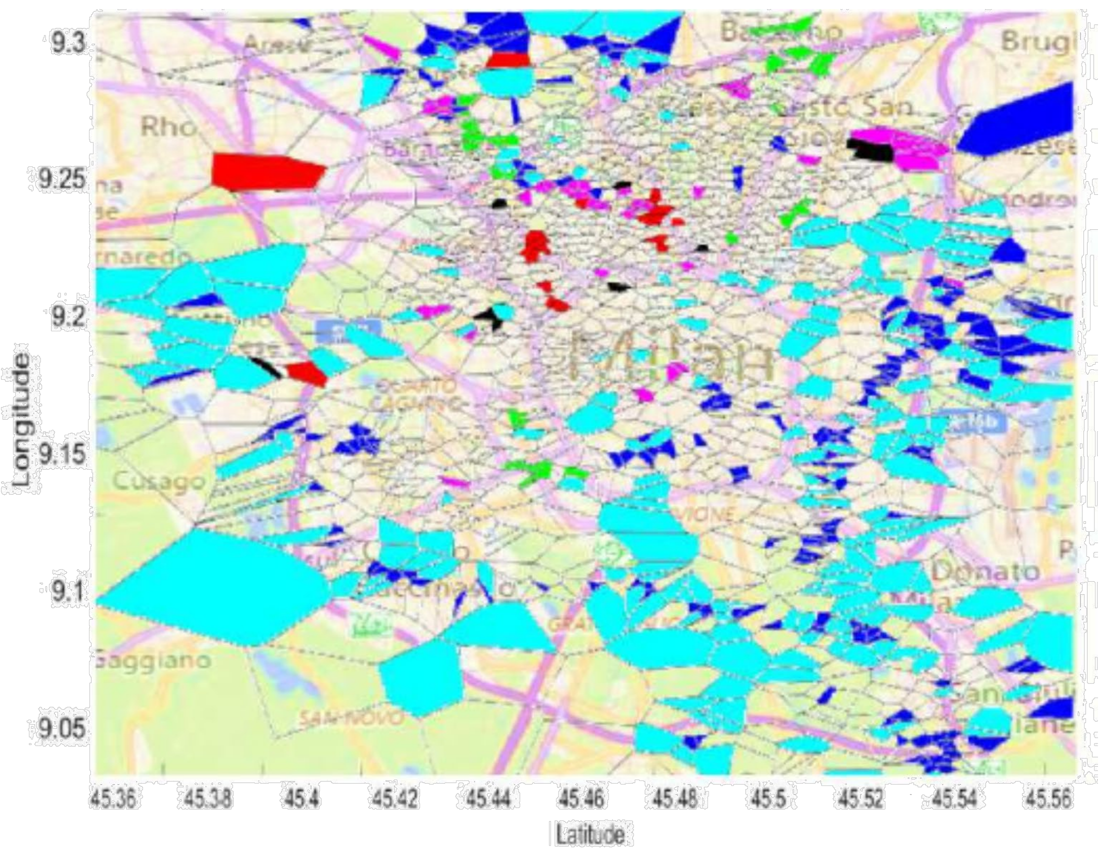
	D&B	CH	DUNN
KMEANS	1.22(12)	8894(8)	0.028(8)
SPECTRAL CLUSTERING	2.85(8)	6.92(15)	$1.93 \cdot 10^{-7}(29)$
NMF	0.91(38)	798(4)	0.031(38)
C-NMF	1.29(30)	1663(5)	0.069(52)

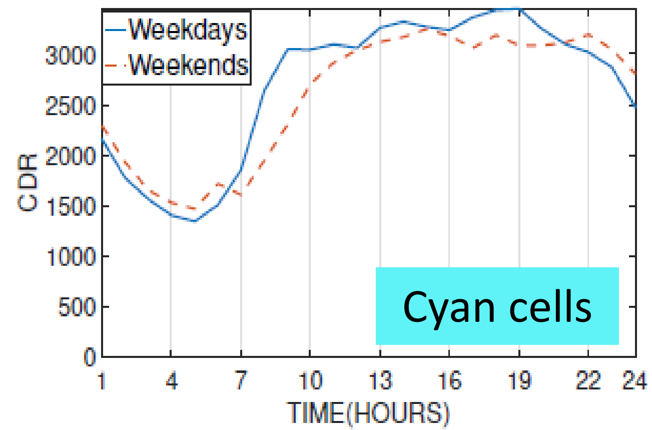
*source: Evgenia Dimitriadou and Dolnicar, Sara and Weingessel, Andreas. An examination of indexes for determining the number of clusters in binary data sets. Psychometrika, 67(1):137–159.

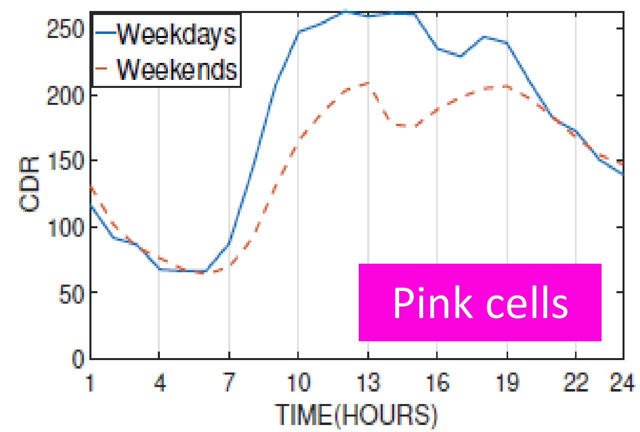
Traffic prediction

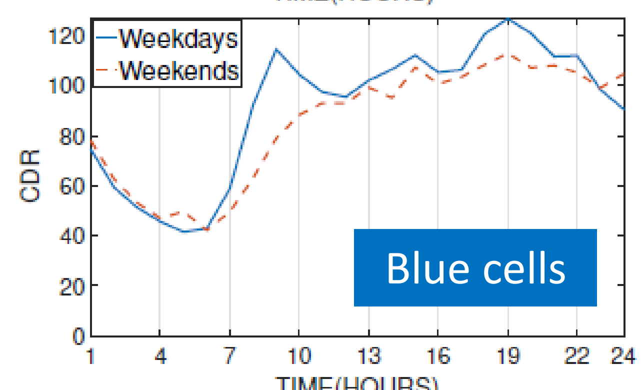
Source 2

- Pattern analysis









Traffic prediction
Source 2

- Pattern analysis