Smart Card in Public Transportation: Designing a Analysis System at the Human Scale

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LIP6 - UPMC - Sorbonne Universités

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Urban mobility – many issues & sensors

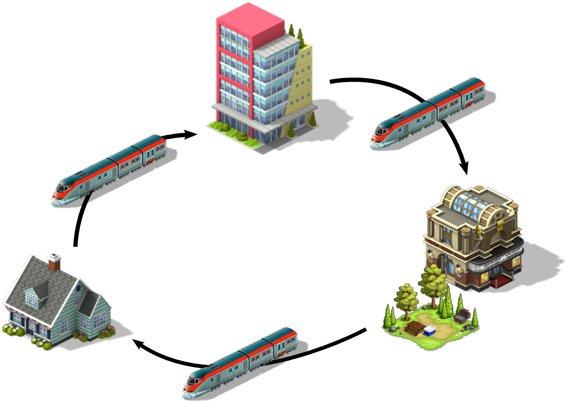
- Data sources
  - City / Smart City: cellphones, GPS, smart street furnitures ...
  - Explosion of available data, rich literature over the last decade

- Development policies [Black et al., 2002, Golias, 2002]
- Global view on traffic [Ceapa et al., 2012, Louail et al., 2014]
- Regularity of users
  - Trip prediction [Song et al., 2010, Foell et al., 2013]
  - Users representations [Poussevin et al., 2014]

Urban mobility – *User-centered study*

- Temporal patterns, habits

⇒ at the individual scale
⇒ for a standard week day



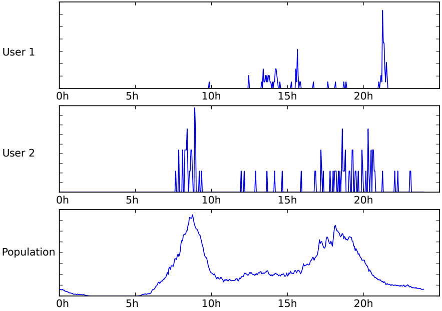
Illustrations from CityVille

Contributions and challenges

- Logs = entries of **10k users** during **13 weeks**

CONTRIBUTIONS AND CHALLENGES

- Logs = entries of **10k users** during **13 weeks**



- Characterize **noisy** users
  - Aggregation / Clustering
  - Habits modeling of week days:

8am Week days | 7pm Week days | 11pm Thursdays

⇒ Variance overestimate

Contributions and challenges

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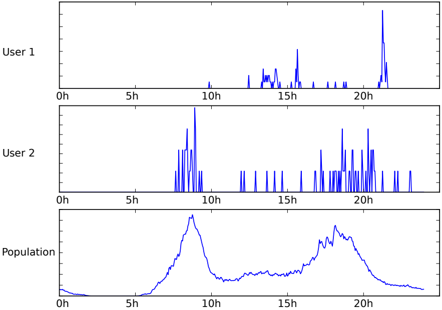

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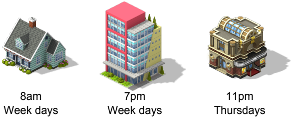


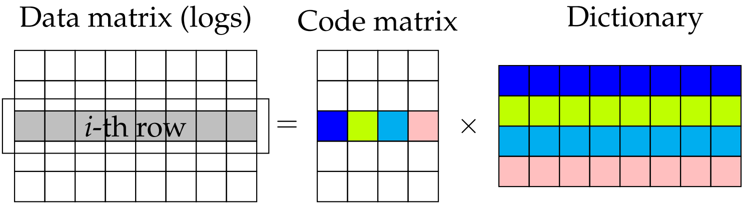
$\Rightarrow$ Variance overestimate

New hypothesis:

Habits are shared...
but with individual schedule

Matrix factorization

User decomposition = Habit extraction



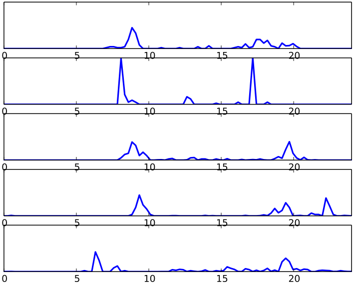
Goal: optimizing both **code & dictionary**

- Variations SVD [Golub and Van Loan, 1996]
  - Non-negative matrix factorization [Lee and Seung, 2000]
  - Sparseness [Hoyer, 2002]

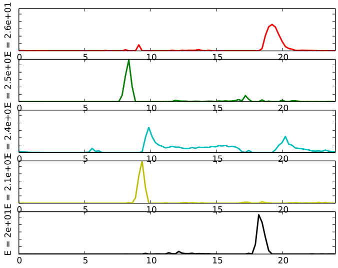
NMF ON AN EXAMPLE

5 random users

- 24h = 96 intervals of 15min



Dictionary: (most used atoms)



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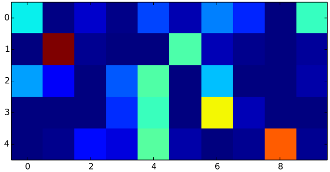

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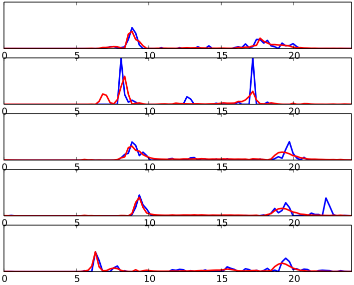

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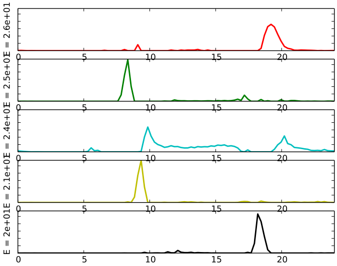

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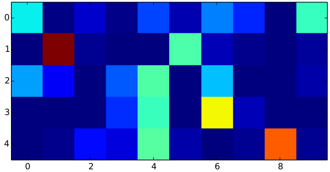

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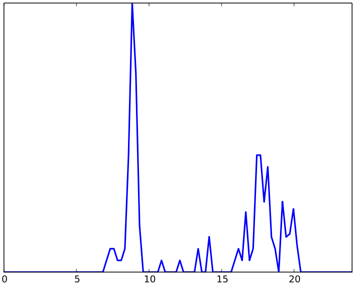
Focusing on user #1



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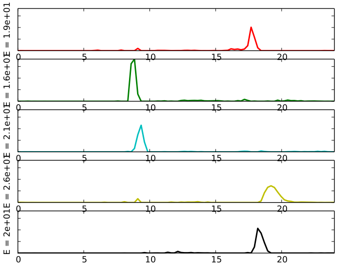

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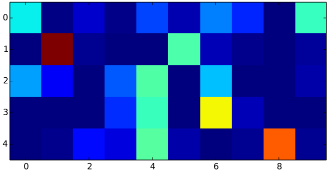

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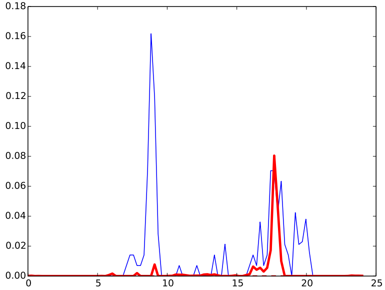

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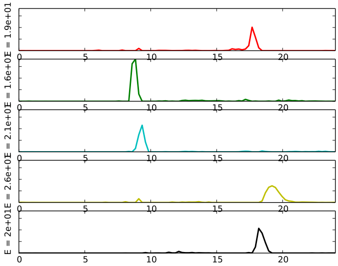

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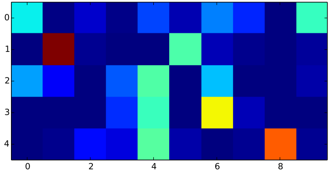

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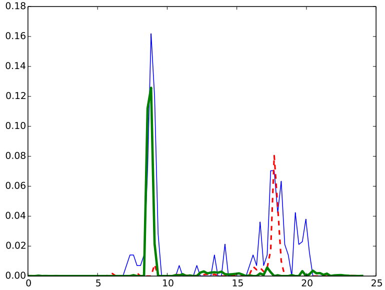

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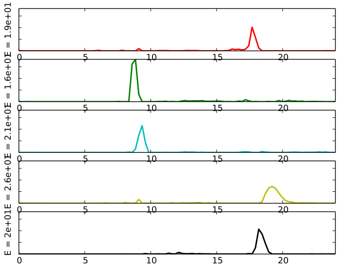

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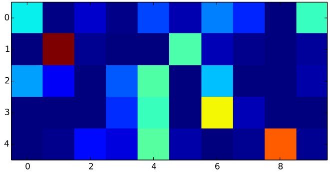

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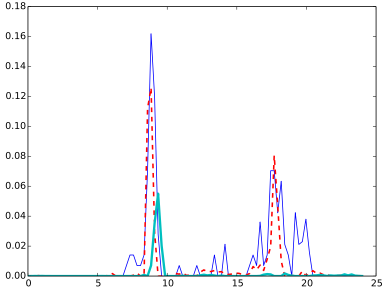

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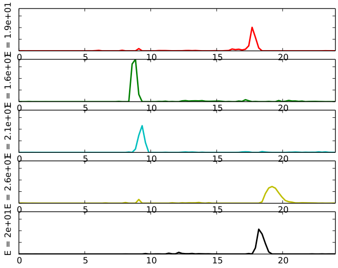

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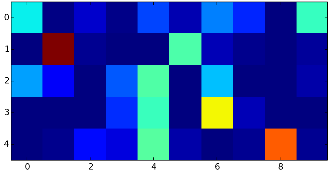

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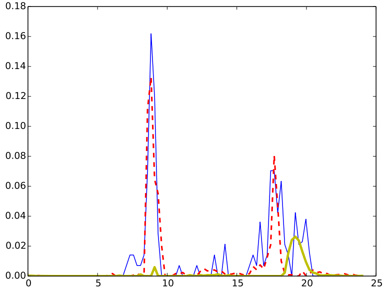

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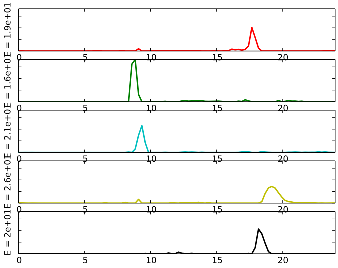

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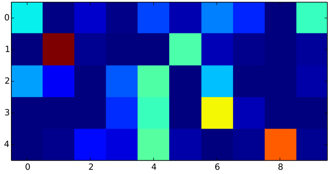

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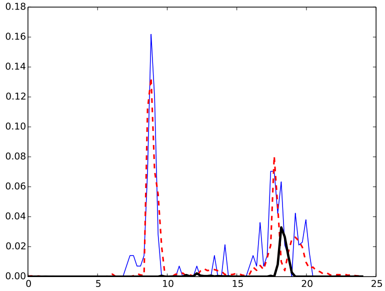

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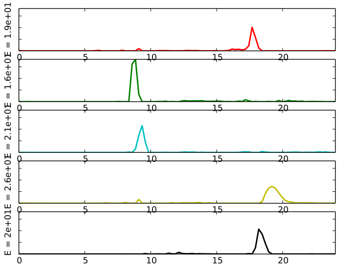

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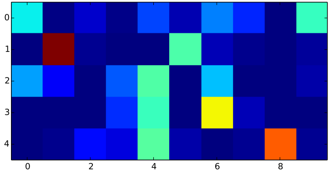

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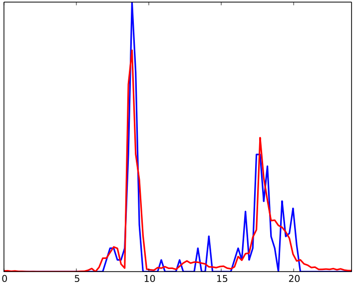

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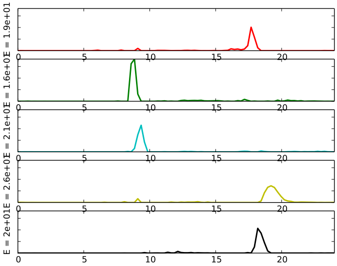

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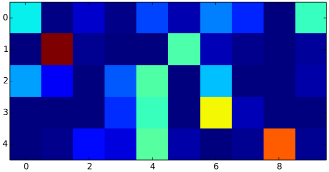
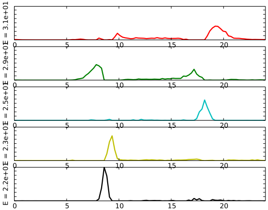


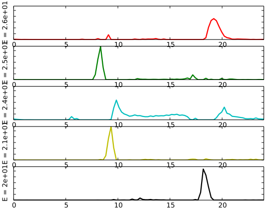
NMF: analysis

- Number of atoms in the dictionary (rank constraint)

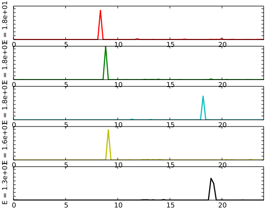
5 atoms



5 best atoms among 10



5 best atoms among 40



  - More atoms = finer reconstruction...
    +reconstruction of the noise...
    + meaningless atoms
  - Less atoms = no longer local event modeling (variance overestimate)
- Parameters are wasted modeling translated events
- Evaluation ?

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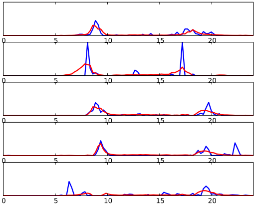
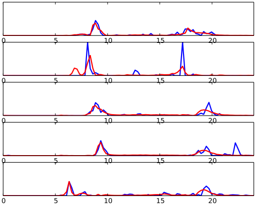
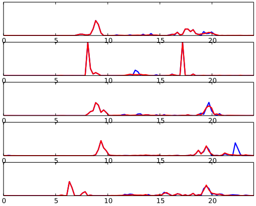
Reconstruction (poor dictionary)



Reconstruction (standard dictionary)



Reconstruction (rich dictionary)

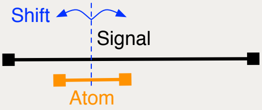


- Parameters are wasted modeling translated events
- Evaluation ?

Contribution: TS-NMF

Idea:

- Keeping the NMF framework
- Defining **compact atoms**
  which **shapes are learned on all users** (=NMF)
  which can be **positioned for each user**



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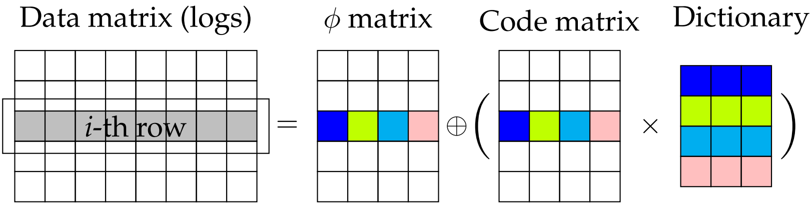
$$u = \sum_z \tau_{u,z}(w_{u,z} d_z) = w_{u,z} d_z(t + \phi_{u,z})$$



Algorithm

Algorithm 1: TS NMF learning algorithm

Data: $X \in \mathbb{R}_+^{U \times T}$, Z, max_{iter}, α_Φ

max_{iter}: to reach convergence
α_Φ: window of search in the atom shift procedure

Result: Optimized matrix Φ, D and W

$D, W, \Phi = init(X, Z)$

D and W randomly initialized, Φ regularly scattered along time band

for $it \in 0...max_{iter}$ **do**
    for $u \in range(0, U)$ **do**
        $\mathbf{x}_u = X[u, .]$
        $atoms = descendingEntropy(D)$

return atoms indexes sort in descending order

Algorithm

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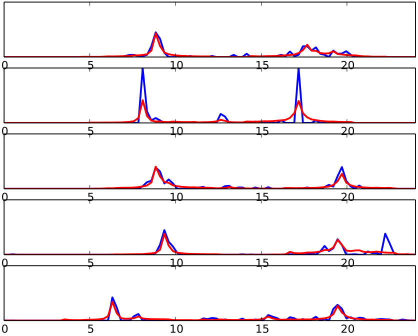
```
for it ∈ 0...max_iter do
    for u ∈ range(0, U) do
        x_u = X[u, .]
        atoms = descendingEntropy(D)
            [return atoms indexes sort in descending order]
        for a ∈ atoms do
            Φ_{u,a} = minimizeLocalCost_t(x_u, D_a)
                [finding optimal time-shift t in a window of size α_Φ]
            W_{u,a} = update_W(x_u, W_{u,.}, D, Φ_{u,a})
                [Simple gradient descent]
            x_u = x_u − f(D_a, Φ_{u,a}) W_{u,a}
                [Matching pursuit like update]
    D = update_D(W, D, Φ)
    D = centerAtoms(D)
        [Centering procedure to make atoms comparable]
```

TS-NMF: outputs

Reconstructed users:



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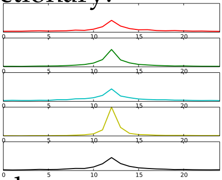

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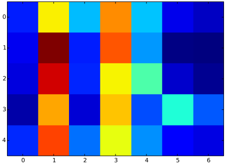

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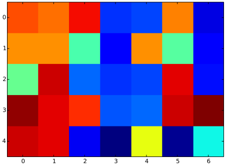
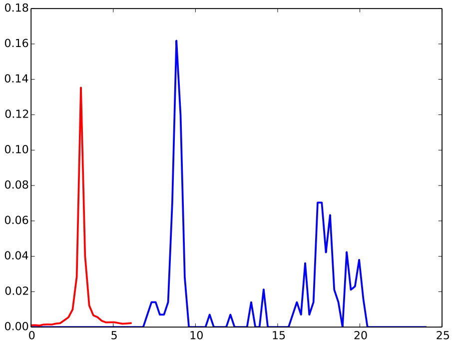


TS-NMF: OUTPUTS

Reconstruction process:

Atom selection ...



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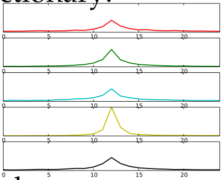

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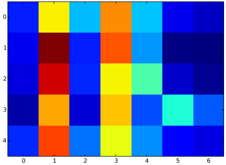

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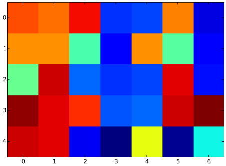
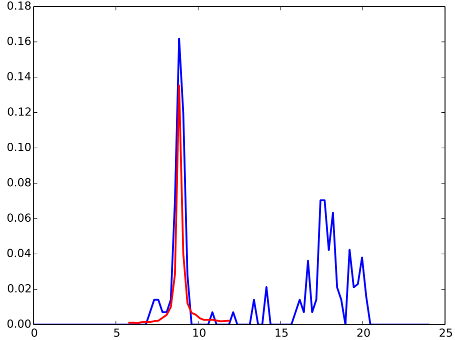


TS-NMF: outputs

Reconstruction process:

+ shift



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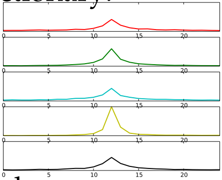

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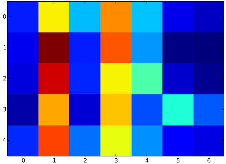

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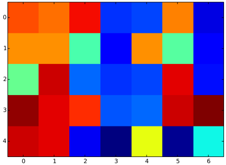

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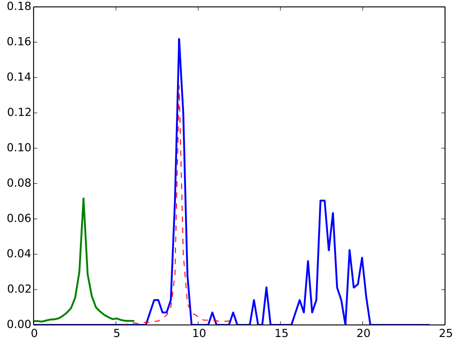

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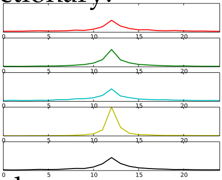

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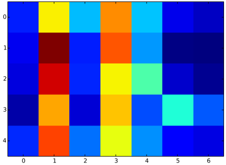

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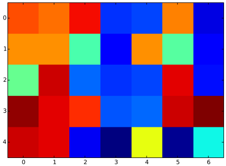

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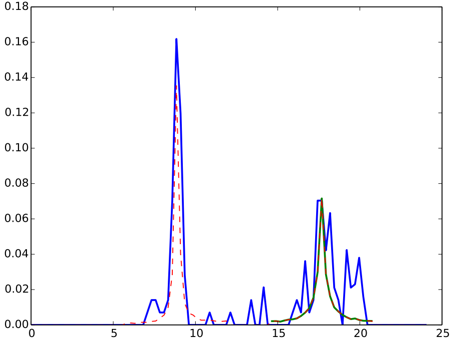

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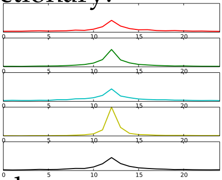

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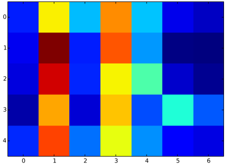

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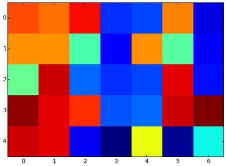
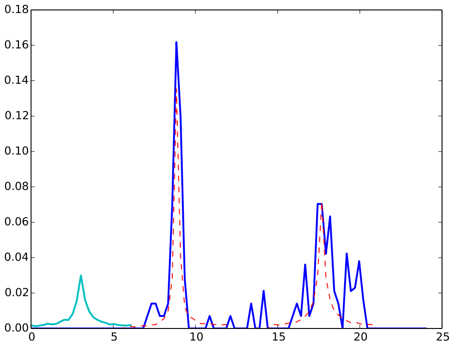
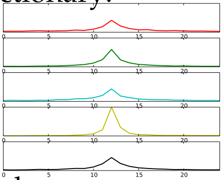


TS-NMF: outputs

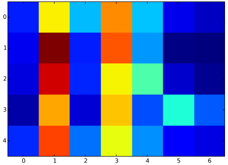
Reconstruction process:



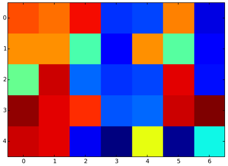
Dictionary:



Code:

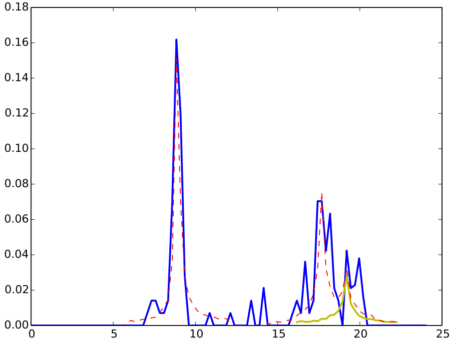


ϕ:



TS-NMF: outputs

Reconstruction process:



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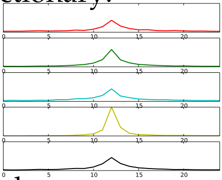

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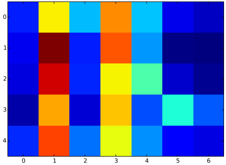
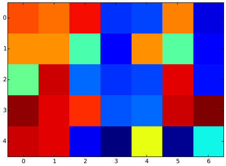


ϕ:



Evaluation

- Impossible on training data:
  - more degrees of freedom ⇒ less reconstruction error
- 9 weeks for learning, 4 weeks for testing
  - Random initialization + non convex optimization ⇒ averaging performance on 5 runs
  - Reconstruction of unseen data (=predictive skills)
  - Necessary but not sufficient
- ⇒ meaning/interpretation of the model is required
  - link with the number of parameters

Baselines & dimensionality

- 10k users
- 480 time intervals (3 minutes)

\# parameters

- General model = 1-mean model $\Rightarrow 0$
- k-means, $k = 16$:
  - 16 prototypes $\in \mathbb{R}^{480}$ + 10k assignments $\Rightarrow$ 17,680
- NMF, $Z = 16$:
  - 16 prototypes $\in \mathbb{R}^{480}$ + $10k \times 16$ weights $\Rightarrow$ 167,680
- GMM = 3 Gaussian atoms (μ, σ_1), (μ, σ_2), (μ, σ_3) centered on each of the 480 time interval & weighted $\Rightarrow$ 14,400,003
- TSNMF = 16 atoms of size 60, weighted & shifted $\Rightarrow$ 320,960

Comparison

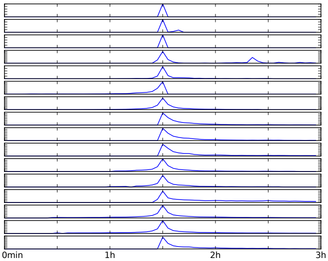
2 metrics

- MSE Mean Squared Error (between real & estimated pdf)
- ML Likelihood of the logs according to the model

Model	# param.	MSE -train- (mean (std))	MSE -test- (mean (std))
General model	0	0.033 (0)	0.040 (0)
KMeans (16 clusters)	17,680	0.027 (6.3e-6)	0.038 (1.5e-5)
NMF	167,680	0.024 (7.7e-5)	**0.036 (6.7e-5)**
GMM	14,400,003	0.023 (0)	0.050 (0)
TS-NMF	320,960	**0.016 (5.8e-4)**	0.042 (8.9e-4)
Model	**# param.**	**ML -train- (mean (std))**	**ML -test- (mean (std))**
General	0	0.0038 (0)	0.0036(0)
KMeans (16 clusters)	17,680	0.010 (6.3e-6)	0.008 (5.7e-6)
NMF	167,680	0.013 (8.3e-5)	0.009 (3.8e-5)
GMM	14,400,003	**0.027 (0)**	**0.018 (0)**
TS-NMF	320,960	**0.026 (9.3e-4)**	0.016 (4.8e-4)

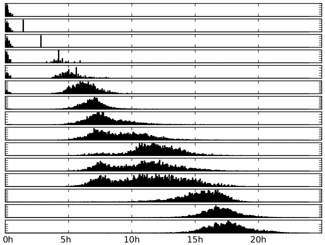
Qualitative analysis

Shapes of the atoms



- +/- variance
- Different shapes

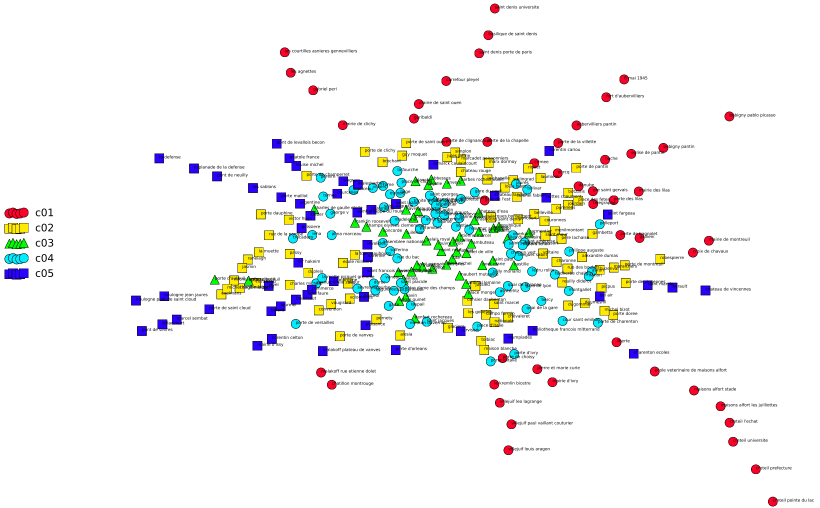
Atoms Positions (distrib. over the population)



- Most atoms correspond to a defined period of the day

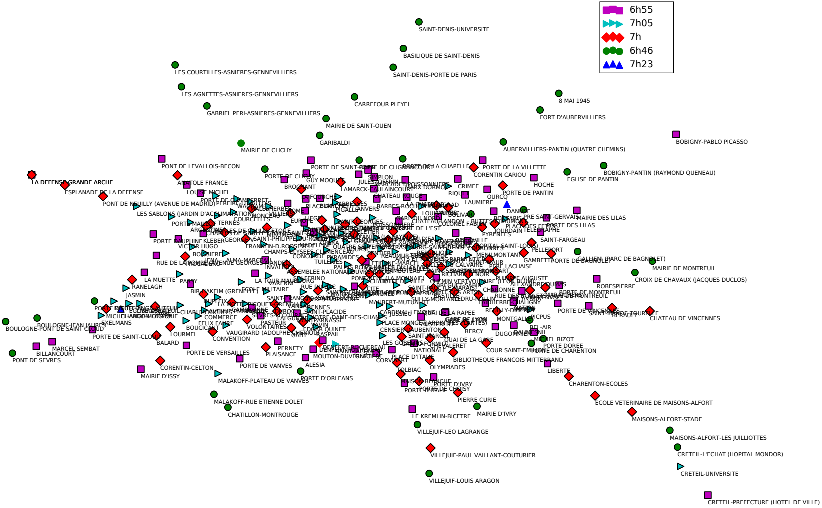
User mapping on Paris map

According to the **shapes of the atoms** [Poussevin et al., 2014]



User mapping on Paris map

According to the **time positions of the atoms** (morning = departure to work)



Conclusion

Characterizing both **habits** and **their schedules**

- ... at the individual scale
- $\Rightarrow$ valuable information on users
- Costly, but scalable for a transportation system

Perspective

- Work on the cost function...
- ... to discover less compact atoms (more meaningful)

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