

Non-negative Matrix Factorization for Methylation Data Deconvolution

Update on the Data Challenge and
the related paper: Lutsik et al

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➤ Concept of NMF

➤ Update on the Data Challenge

➤ Paper

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Genome Biology

METHOD

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MeDeCom: discovery and quantification of latent components of heterogeneous methylomes



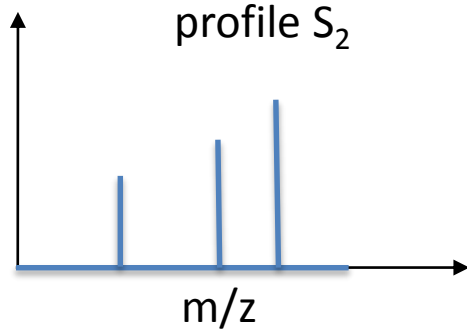
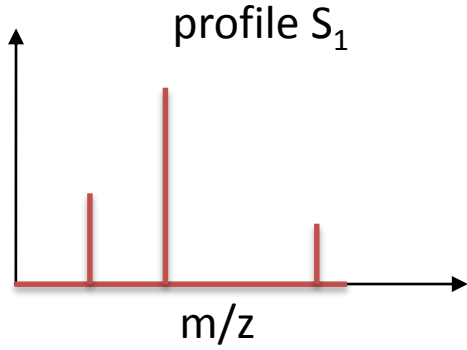
Pavlo Lutsik^{1,4†}, Martin Slawski^{2,3,5†}, Gilles Gasparoni¹, Nikita Vedeneev², Matthias Hein^{2*} and Jörn Walter^{1*}

Abstract

It is important for large-scale epigenomic studies to determine and explore the nature of hidden confounding variation, most importantly cell composition. We developed MeDeCom as a novel reference-free computational framework that allows the decomposition of complex DNA methylomes into latent methylation components and their proportions in each sample. MeDeCom is based on constrained non-negative matrix factorization with a new biologically motivated regularization function. It accurately recovers cell-type-specific latent methylation components and their proportions. MeDeCom is a new unsupervised tool for the exploratory study of the major sources of methylation variation, which should lead to a deeper understanding and better biological interpretation.

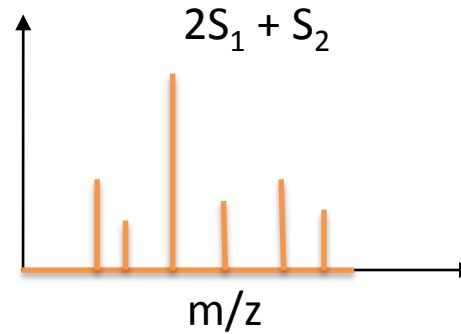
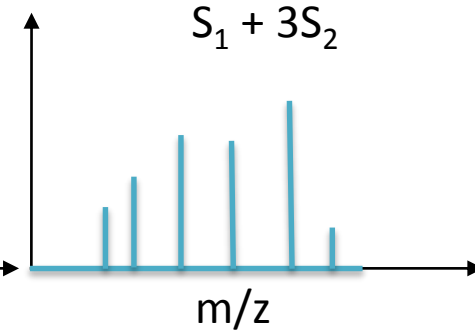
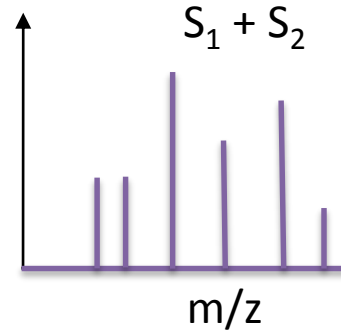
Keywords: DNA methylation, DNA methylome, Cell heterogeneity, Deconvolution, Matrix factorization, Epigenetics

Concept: NMF



$$X = S \times M$$

$$M = \begin{bmatrix} 1 & 2 & 1 \\ 1 & 1 & 3 \end{bmatrix}$$



Non-negative

Non-negative

Non-negative

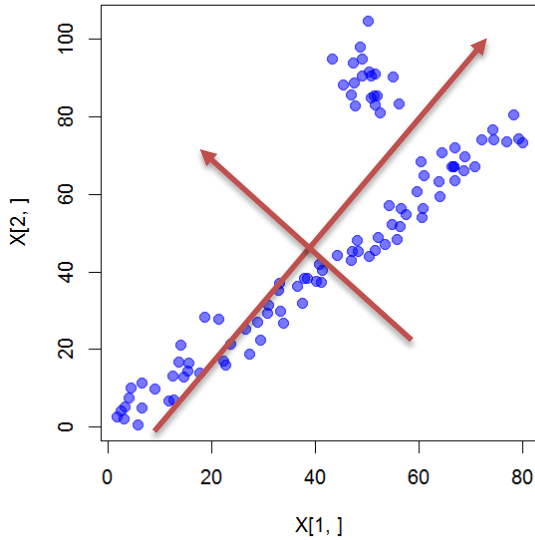
$$X \approx T \times A$$

$\sim S$

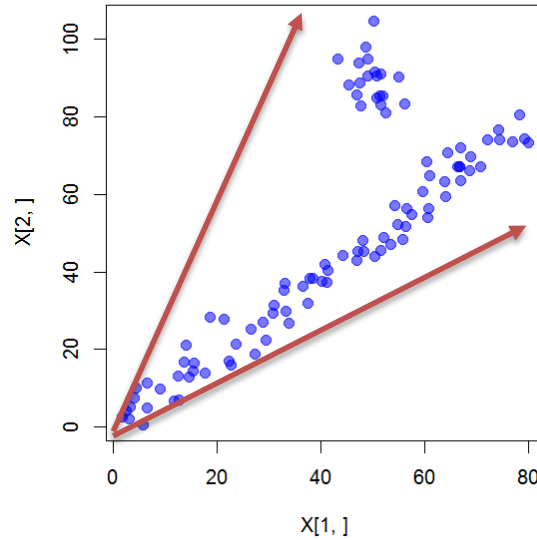
$\sim M$

Concept: NMF

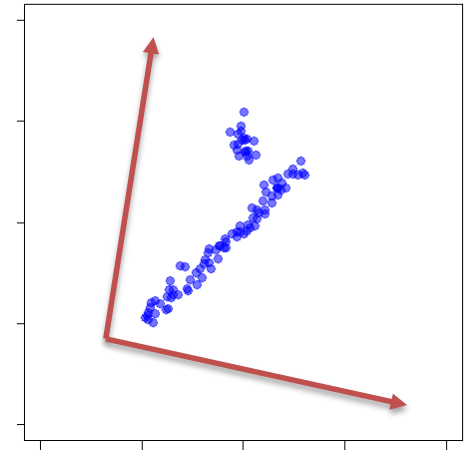
PCA



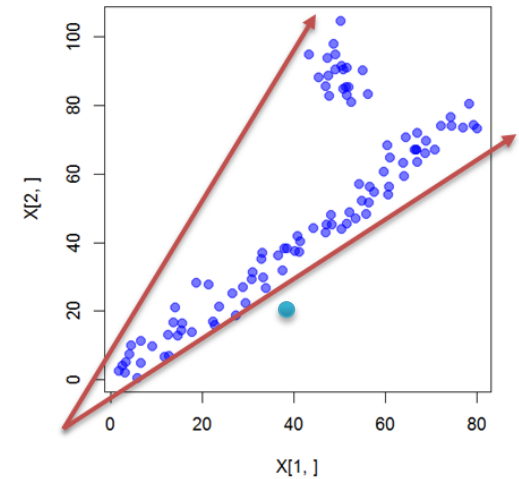
NMF



NMF: issue 1



NMF: issue 2



- Multiple solutions
- Is the minimal description stable?

⇒ we need:

- additional restrictions
- regularizations during fitting

Place & Participants



Aussois, Dec 2018

Invited speakers:

- E. Andres **Houseman**, independent data scientist, USA, **RefFreeEWAS**
- Pavlo **Lutsik**, from DKFZ, Heildeberg, Germany, **MeDeCom**
- Eugene **Lurie**, from BCM, Houston, USA, **Edec**

Participants:

- 9 (10) commands 3-4 members: FR, DE, US, RU, LU, NL, ... ?

Data Challenge

Structures

2 sub-challenges: $X = S \times M + \text{noise}$

- **Training:** 3 cell types, 100 synthetic samples, no confounding variables
- **Main:** k cell types ($k=5$), 100 synthetic samples, y confounding variables

Our team:

- Fabian Bergmann (MSc student) – IT, submits, fine tuning, RefFreeEWAS
- Tony Kaoma – wide search for alternative algorithms, MeDeCom
- Petr Nazarov – ICA, moderating FB 😊

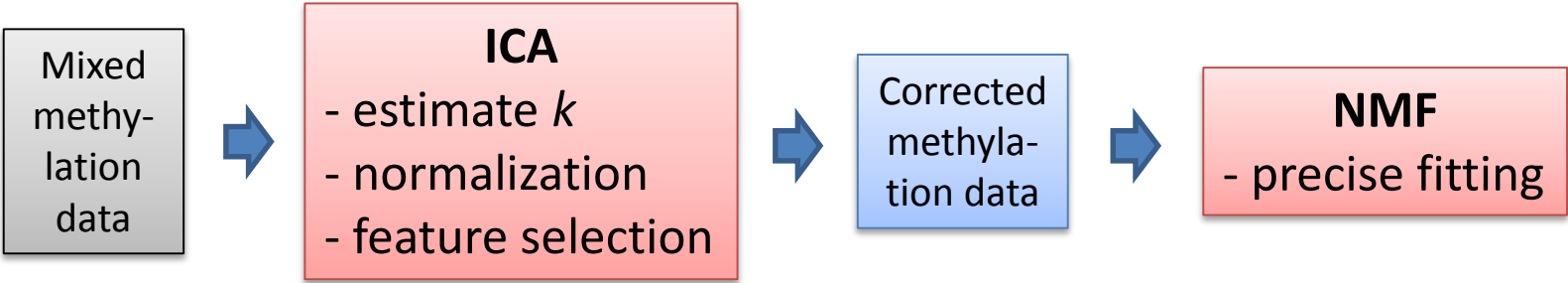
Reasons why we won sub-challenge 1:

- our tuning of the parameters was more efficient – RefFreeEWAS overfits!
- search for methods for initial estimation by TK helped

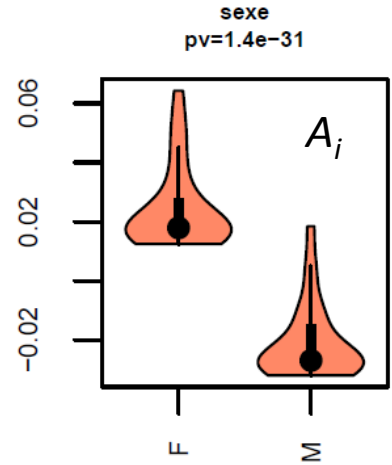
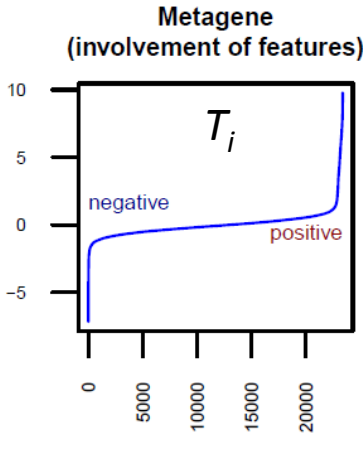
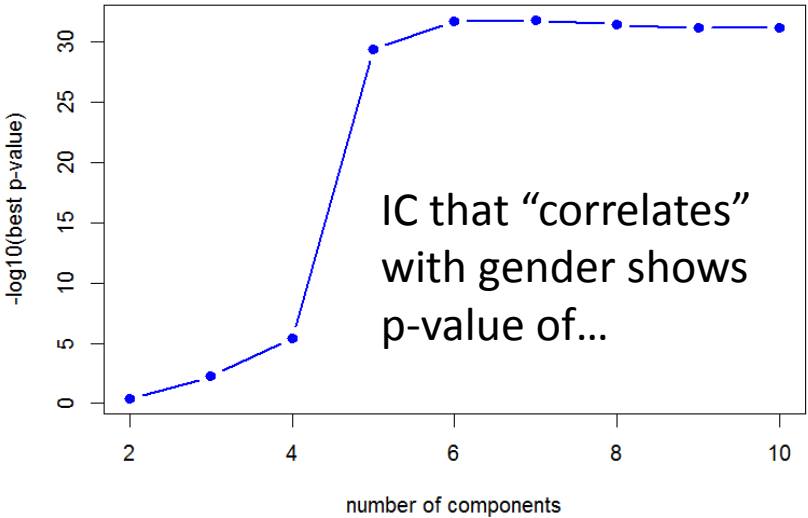
...and ICA was not needed at all 😊!

Data Challenge

Winning strategy for sub-challenge 2



Gender was one of the confounders



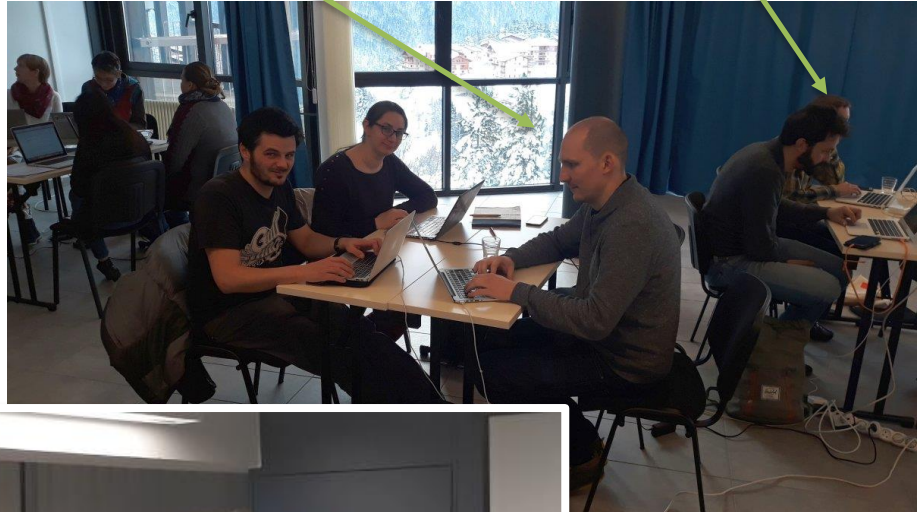
$$X = T \times A$$

Data Challenge

Teams

Pavlo Lutsik: MeDeCom

Eugene Lurie: Edec



Almost the only biologist 😊

Conclusions & Results

- Even the top methods on NMF must be fine-tuned in order to give good results
- ICA is of no help for simple tasks. But can be useful in more complex situations (e.g. confounders)
- Pavlo Lutsik, the developer of MeDeCom and co-author of RnBeads, was “astonished” by Tony’s results on his own tool and proposed to work together on the protocols paper
- The general paper based on the challenge was planned, but i.m.h.o., the chances are vague
- It brings new knowledge and simply... a lot of fun 😊

E.Andreas Houseman:
RefFreeEWAS



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Abstract

It is important for large-scale epigenomic studies to determine and explore the nature of hidden confounding variation, most importantly cell composition. We developed MeDeCom as a novel reference-free computational framework that allows the decomposition of complex DNA methylomes into latent methylation components and their proportions in each sample. MeDeCom is based on constrained non-negative matrix factorization with a new biologically motivated regularization function. It accurately recovers cell-type-specific latent methylation components and their proportions. MeDeCom is a new unsupervised tool for the exploratory study of the major sources of methylation variation, which should lead to a deeper understanding and better biological interpretation.

Keywords: DNA methylation, DNA methylome, Cell heterogeneity, Deconvolution, Matrix factorization, Epigenetics

MeDeCom Paper

$$D = T \times A + E$$

Main idea (sorry, it is simple but... 😊)

Standard NMF:

$$\min_{T,A} \|D - TA\|_F^2 = \sum_{i=1}^m \sum_{j=1}^n (D_{ij} - (TA)_{ij})^2$$

subject to

$$0 \leq T_{is} \leq 1 \quad \forall i, s$$

$$A_{sj} \geq 0 \quad \forall s, j$$

$$\sum_{s=1}^k A_{sj} = 1 \quad \forall j.$$

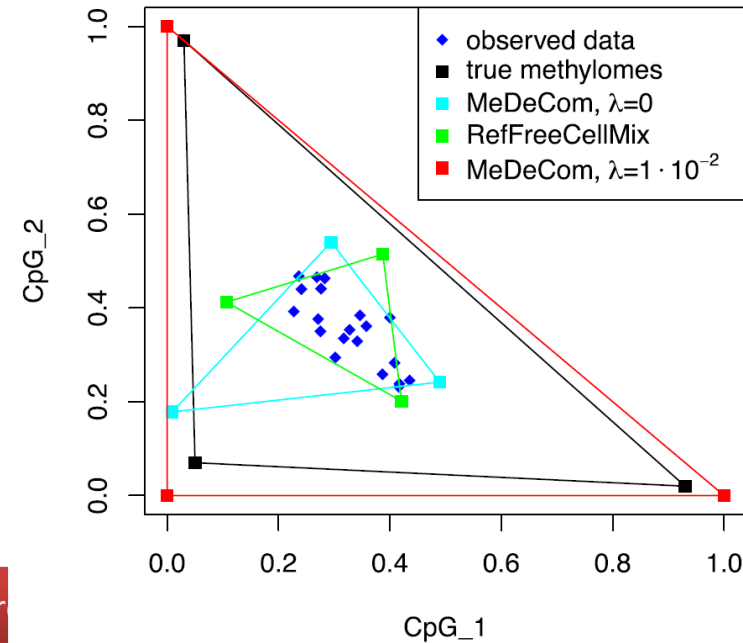
MeDeCom's regularization:

$$\min_{T,A} \|D - TA\|_F^2 + \lambda \sum_{i=1}^m \sum_{s=1}^k \omega(T_{is}), \text{ with } \omega(x) = x(1-x)$$

subject to $0 \leq T_{is} \leq 1 \quad \forall i, s$

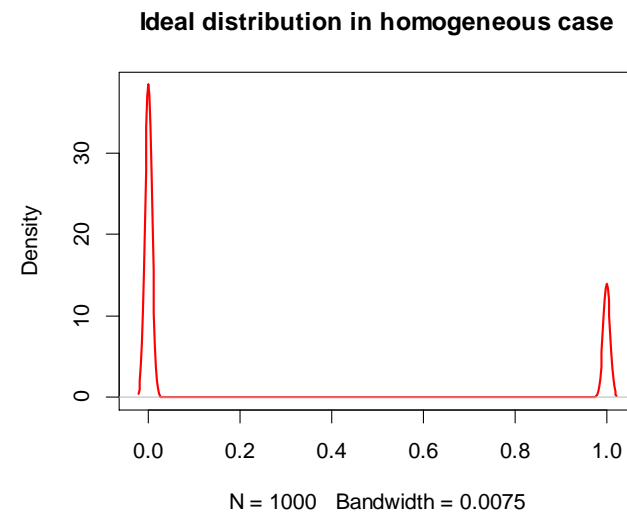
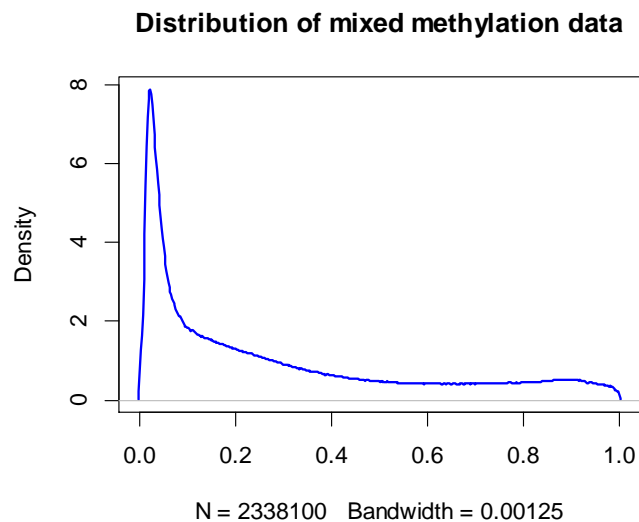
$$A_{sj} \geq 0 \quad \forall s, j$$

$$\sum_{s=1}^k A_{sj} = 1 \quad \forall j,$$



Assumptions / Requirments

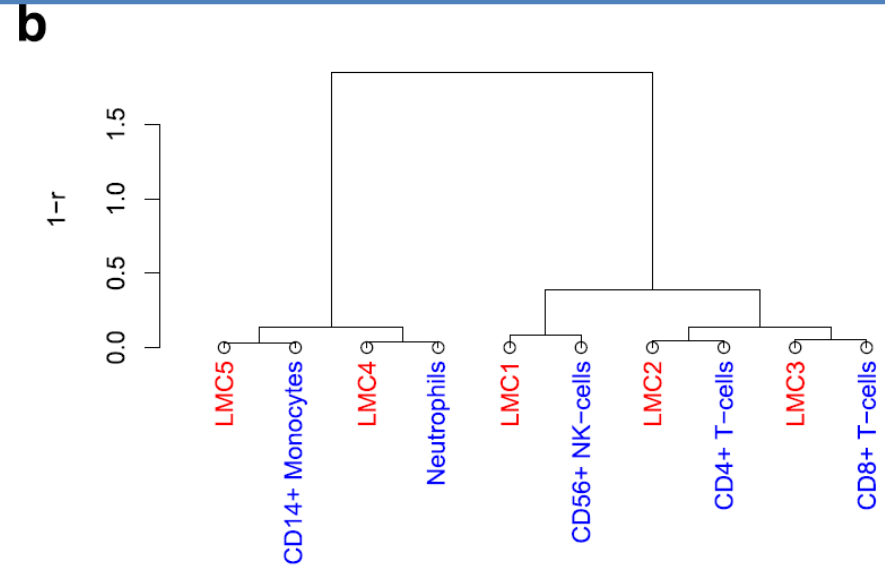
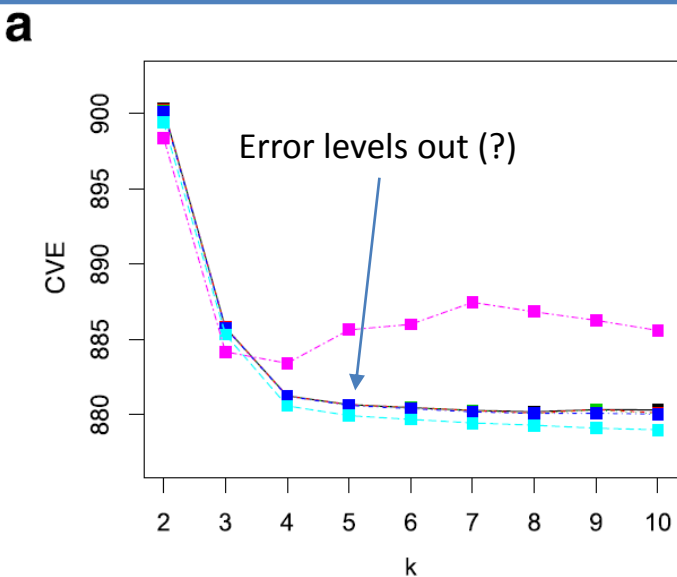
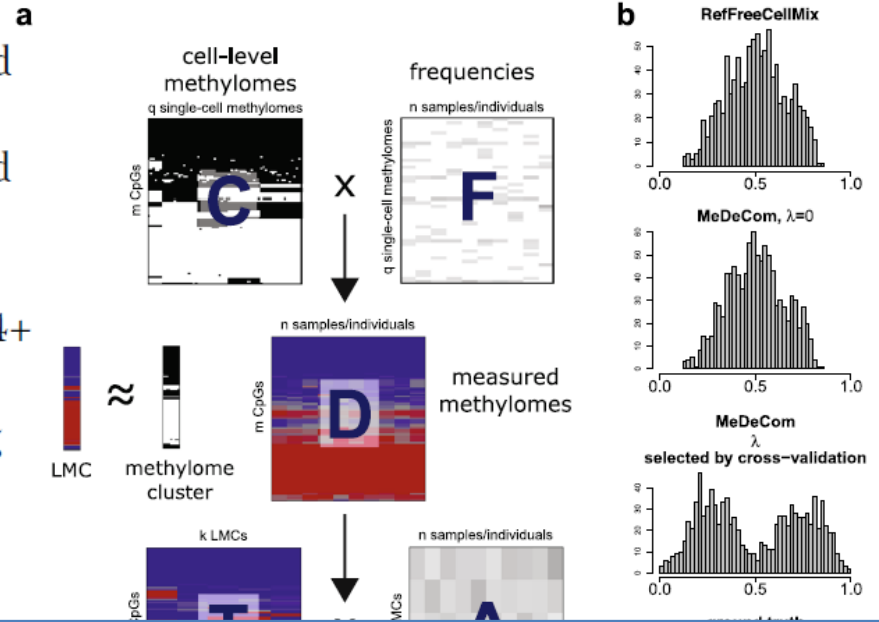
- (1) Cell population consists of finite (and small) number of sub-populations.
- (2) Each cell subpopulation have homogenous methylome profile => \forall CpG can be either 0 or 1.
- (3) Population mixtures are variable b/w samples.
- (4) Low level of technical noise and high level of biological variability.



MeDeCom Paper

Synthetic data

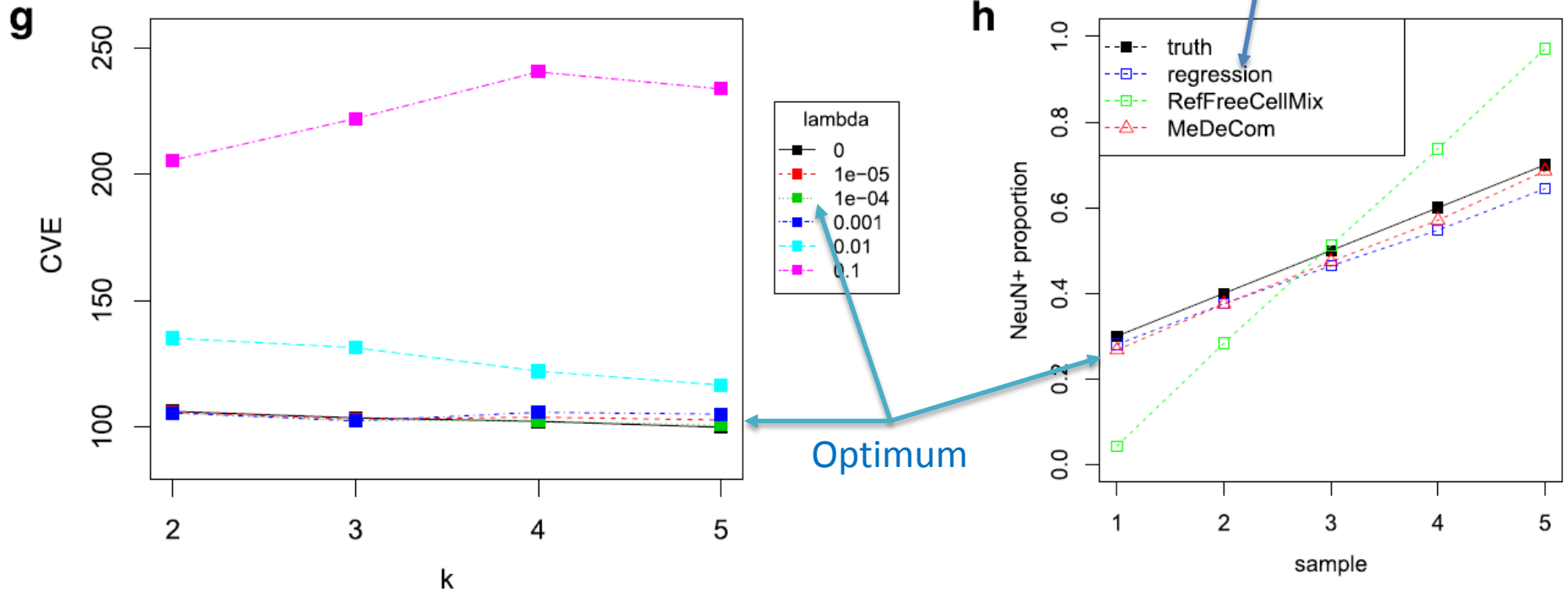
- $k_{sim} = 2$ with two distant cell types (neutrophils and CD4+ T cells).
- $k_{sim} = 2$ with two similar cell types (neutrophils and monocytes).
- $k_{sim} = 3$ with two similar cell types and one distant from the first two (neutrophils, monocytes and CD4+ T cells).
- $k_{sim} = 5$ with all major blood cell types, excluding eosinophils and B cells.



MeDeCom Paper

Cell mixture

Dataset ArtMixN: cell sorting into NeuN+ and NeuN- cells.
NeuN = RBFOX3 protein

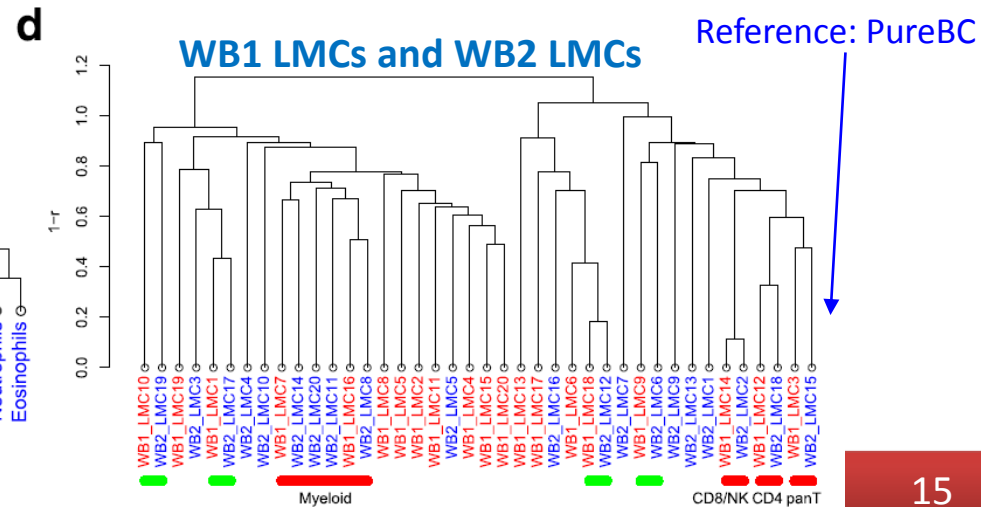
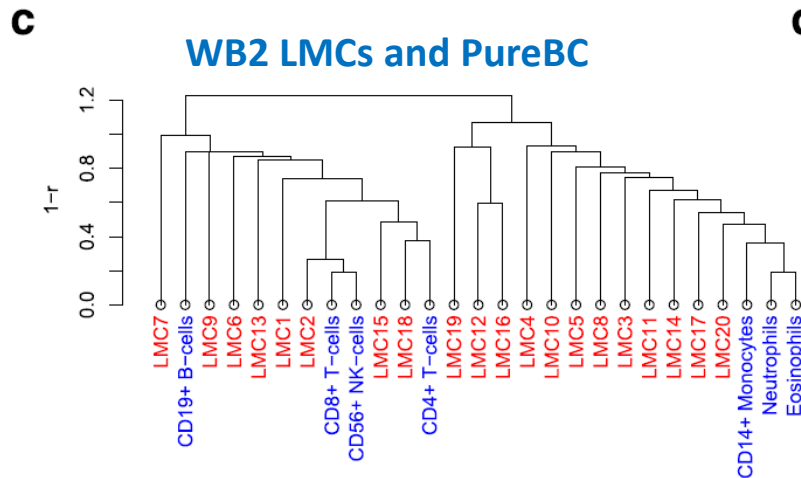
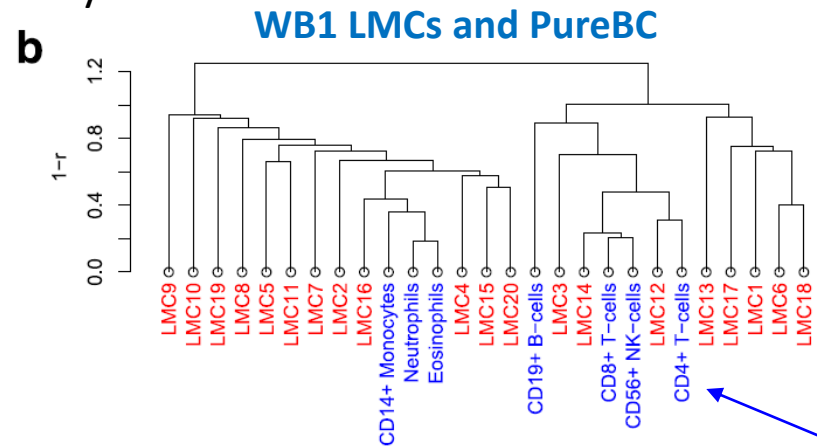
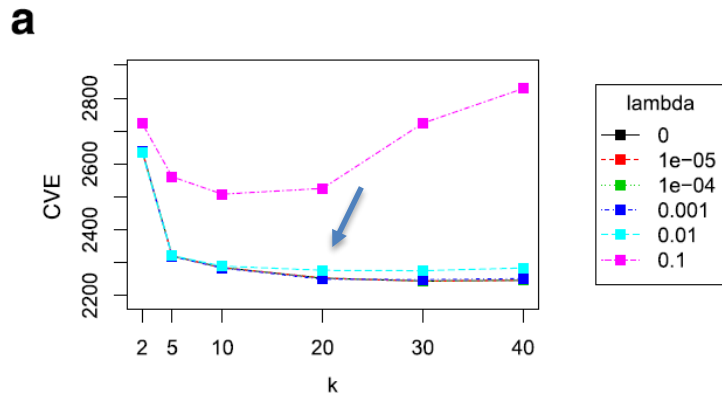


MeDeCom Paper

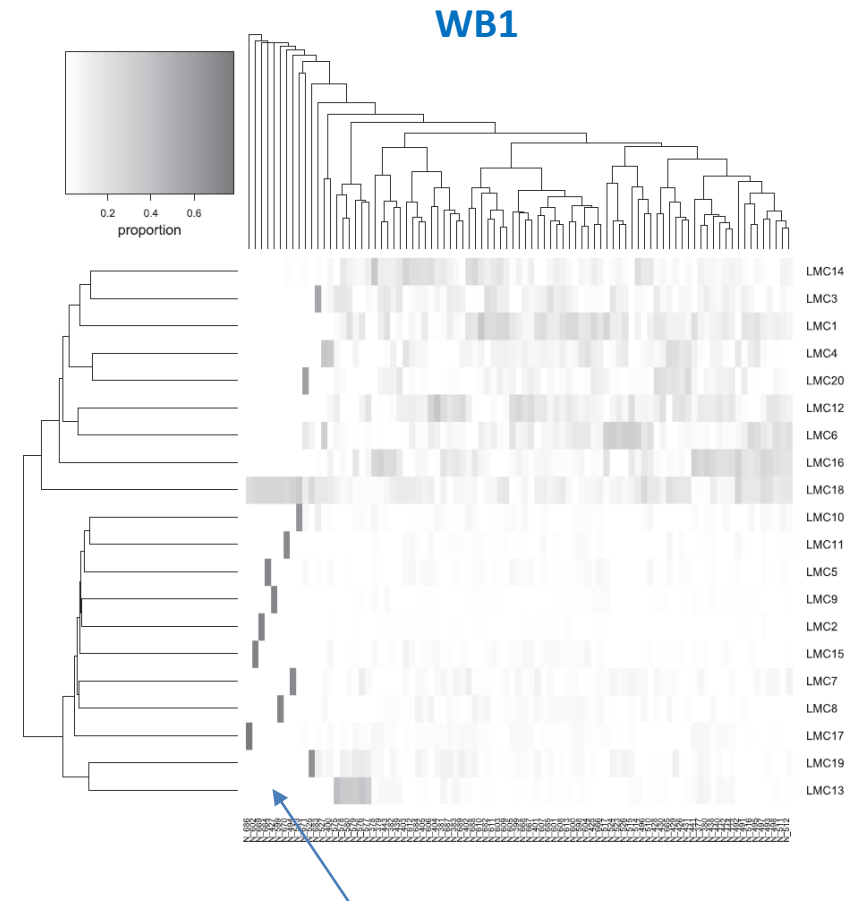
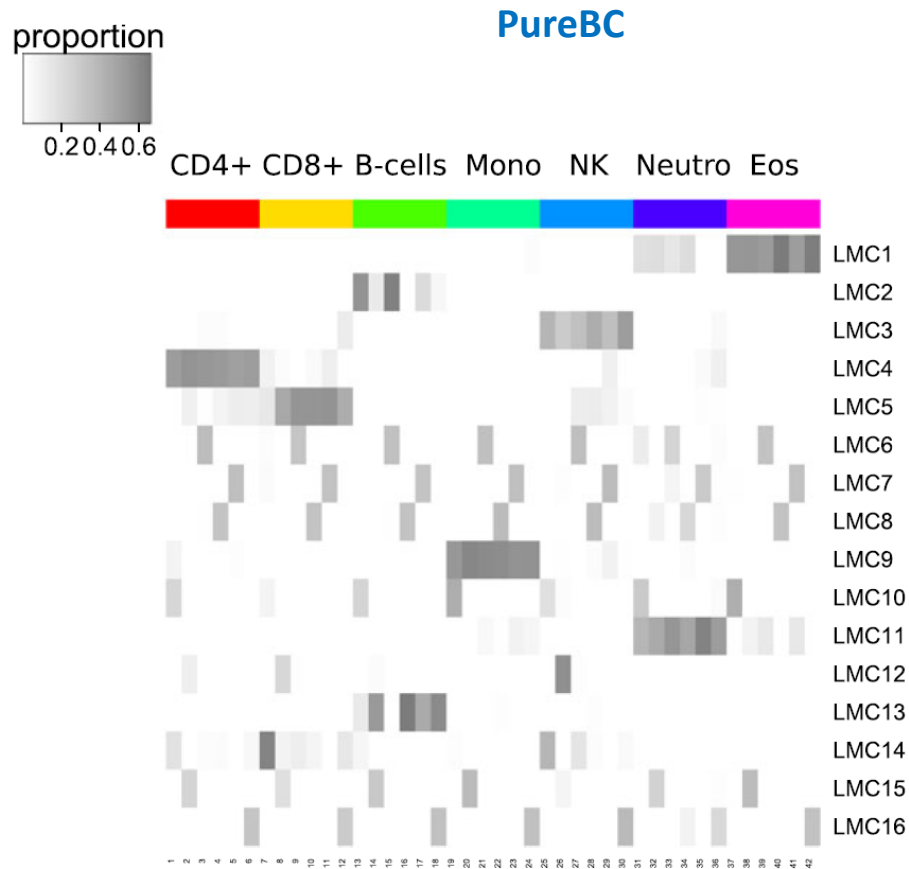
Blood samples

Whole blood samples were used.

- **PureBC** – 7 MACS-purified cell types: neutro, mono, B cells ,CD4+, CD8+, NK, eosinophils
- WB1 – 87 rheumatoid arthritis patients
- WB2 – 442 cancer-free patients from EPIC Italy



PureBC samples



Specific to a single donor? Mutations?

MeDeCom Paper

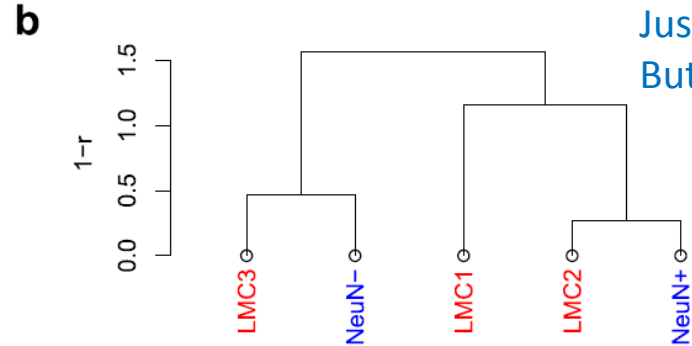
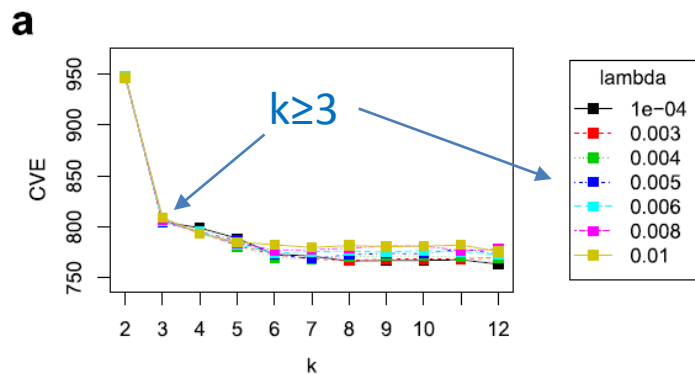
Brain samples

Whole blood samples were used.

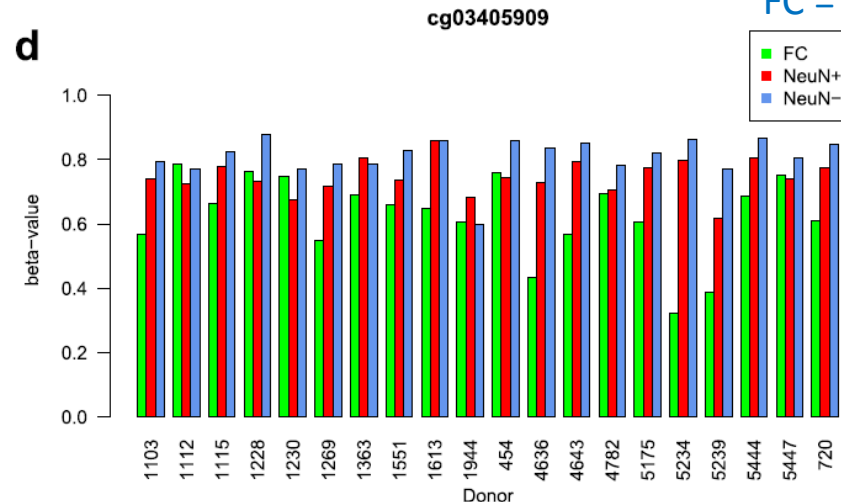
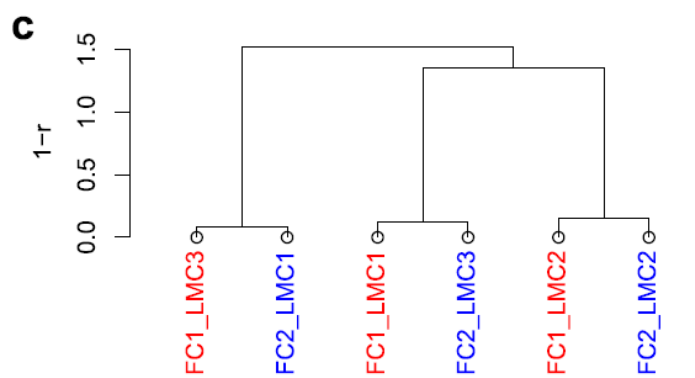
- **PureN** – 2x29 NeuN+/- fractions of 29 healthy controls
- FC1 – 2x10 frontal cortex of MDD (major depression disorder) patients
- FC1 – 114 frontal cortex of AD (Alzheimer's disease) patients

Why $k=3$?

Just to have stable result...
But it is not enough.



frontal cortex
FC = NeuN⁺ + NeuN⁻



MeDeCom Paper

Conclusions

MeDeCom

- (1) provides significant advances compared to other methods;
- (2) uses with biologically relevant constrains and its LMCs are more interpretable;
- (3) acts robustly on artificial and real data;
- (4) identifies key methylation signatures;
- (5) (IMHO) Low k is more dangerous than high k.

But: Separation of specific blood cell subtypes (similar methylomes) becomes challenging

