Linear Relations between Gene Expression in Several Tissues

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Notation, Model

Notation:

 $Y_{iu} :=$ Gene Expression for patient u in tissue i

 $S_u :=$ Euclidean vector representation of patient u

h := Dimensionality of patient representations

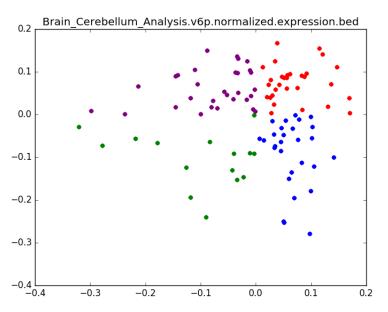
d := Dimensionality of expression representations

 $F_i := \text{Linear transform } (\mathbb{R}^{d \times h})$ associated with tissue i

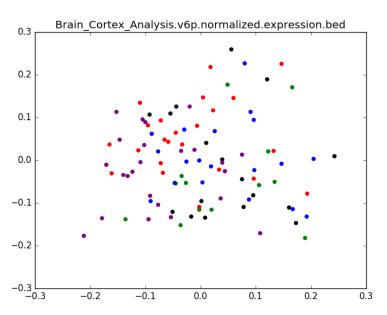
Model:

$$Y_{iu} \sim F_i S_u + \mathcal{N}(0, \sigma^2)$$

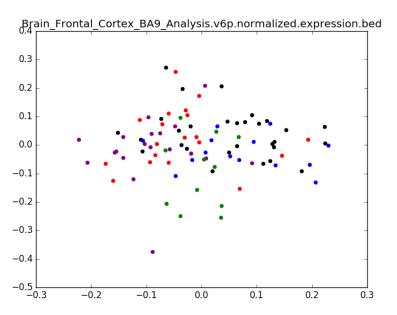
Comparing Tissues by Patients (Cerebellum)



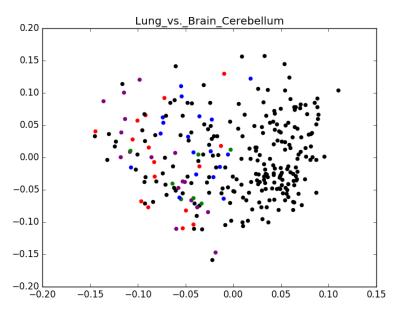
Comparing Tissues by Patients (Cortex)



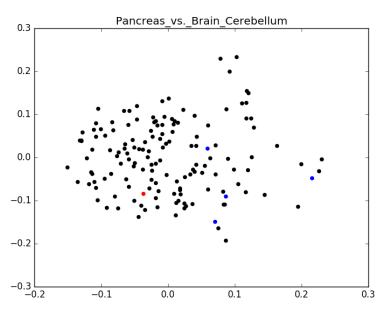
Comparing Tissues by Patients (Frontal Cortex)



Comparing Tissues by Patients (Lung)



Comparing Tissues by Patients (Pancreas)



Our algorithm

Recall our model:

$$Y_{iu} \sim F_i S_u + \mathcal{N}(0, \sigma^2)$$

Given either F_i or S_u , looks like least-squares linear regression! Alternate:

set
$$F_i \leftarrow Y_i S^T (SS^T)^{-1}$$
 $\forall i$
set $S_u \leftarrow \frac{1}{|I_u|} \sum_{i \in I_u} (F_i^T F_i)^{-1} F_i^T Y_{iu}$ $\forall i$

BIC evaluation

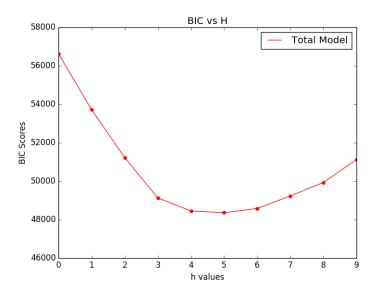
Since F is derived from S in closed form, so F is not a free parameter.

S has nh parameters, where n is the number of patients and h is dimensionality of representation

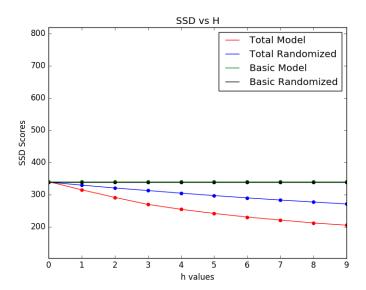
But every solution is rotationally equivalent with solutions along h degrees of freedom, leaving us (n-1)h free parameters.

$$\Rightarrow \mathsf{BIC} = \ln n(n-1)h - 2\ln p(Y:S)$$
$$= (\ln n)(n-1)h + n\ln(2\pi\sigma^2) + \frac{\mathsf{SSD}}{\sigma^2}$$

BIC score across *h* settings



SSD score across *h* settings



Applications

Filling gaps in data: if missing gene expression for some patient for some tissue, can just model it.

Comparing patients: Can calculate cosine similarity between patients' vector representations to compare their similarity.

Deciding on patients: Since all patient representations are in the same vector space, we may solve any decision problem there.