1 Vaccination Dataset

Load data

- > data(bloodCellMarkersIRISDMAP)
- > data(svmMarkers)
- > data(canonicalPathways)
- > data(vacData)

Construct a joint pathway matrix by merging canonical Pathways, blood Cell-Markers IRISDMAP and symMarkers and select genes appearing in both gene expression profile and the joint pathway matrix.

- > allPaths=combinePaths(bloodCellMarkersIRISDMAP, svmMarkers,canonicalPathways)
- > cm.genes=commonRows(allPaths, vacData)

Normalize the data and count the number of latent variables in the data by num.pc(). The result is 24. Then set max.iter = 250, k = 24 and all other parameters to be default.

- > vacDataN=rowNorm(vacData)
- > num.pc(vacDataN[cm.genes,])

> plierResult=PLIER(vacDataN[cm.genes,], allPaths[cm.genes,],k=24, trace=T, max.iter=150)

```
[1] "L2 is set to 82.0573187891353"
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- [1] "L1 is set to 41.0286593945677"
- [1] "L3 is set to 0.0111182399988254"

We correlate the decomposition result with SPVs from CellCODE. We have nice one-to-one correspondence, though the "DendriticCell" signature from Cell-CODE is more closely related to the Type-I interferon transcriptional response so it is probably not cell-type induced variation.

- > data(SPVs)
- > plotMat(cor(t(plierResult\$B), SPVs))

Visualize the cross-validation results

> plotMat(plierResult\$Uauc)

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Plot all of U and visualize the top genes
> plotU(plierResult,auc.cutoff = 0.5, pval.cutoff = 1)
> plotTopZ(plierResult, vacDataN, allPaths, top = 10)
The "PID_ATF2_PATHWAY" looks a little tenuous and we can check its statistics.
> plierResult$summary[which(plierResult$summary$`LV index`==3),]
\end{Sinput}
\begin{Soutput}
           pathway LV index
                                   AUC
                                         p-value
5 PID_ATF2_PATHWAY
                    3 0.5718064 0.0536596
\end{Soutput}
\end{Schunk}
The association with "PID_ATF2_PATHWAY" is not significant: this pathway has only 42 genes t
\begin{Schunk}
\begin{Sinput}
> plotTopZ(plierResult, vacDataN, allPaths, index=c(3), top=50)
\end{Sinput}
\end{Schunk}
\section{HCC Dataset}
Load data
\begin{Schunk}
\begin{Sinput}
> data(HCCdataTumor)
> data(canonicalPathways)
> data(chemgenPathways)
> data(oncogenicPathways)
\end{Sinput}
\end{Schunk}
Construct a joint pathway matrix by merging canonicalPathways, chemgenPathways and oncogenic
\begin{Schunk}
\begin{Sinput}
> CancerPath=combinePaths(canonicalPathways, chemgenPathways, oncogenicPathways)
> cmHCC=commonRows(HCCdataTumor, CancerPath)
\end{Sinput}
\end{Schunk}
Remove small pathways, not strictly necessary but saves computation time by making the pathw
\begin{Schunk}
\begin{Sinput}
> ii=which(colSums(CancerPath[cmHCC,])<20)</pre>
> HCCpath=CancerPath[, -ii]
\end{Sinput}
\end{Schunk}
Prescale the data
\begin{Schunk}
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\begin{Sinput}
> HCCdataN=rowNorm(HCCdataTumor[cmHCC,])
\end{Sinput}
\end{Schunk}
Precompute Chat, which is used to define active pathways and is expensive for large pathway
\begin{Schunk}
\begin{Sinput}
> HCCchat=computeChat(CancerPath[cmHCC,])
\end{Sinput}
\end{Schunk}
Compute the number of latent variables by num.pc(HCCdataUse) and the result is 52. Then set
\begin{Schunk}
\begin{Sinput}
> plierResultHCC=PLIER(HCCdataN, CancerPath[cmHCC,], k = 52, Chat = HCCchat, trace=T)
\end{Sinput}
\begin{Soutput}
[1] "L2 is set to 132.670764279278"
[1] "L1 is set to 66.3353821396389"
[1] "L3 is set to 0.00807273868235351"
\end{Soutput}
\end{Schunk}
Plot the result with a high AUC cutoff so it is not too busy
\begin{Schunk}
\begin{Sinput}
> plotU(plierResultHCC, auc.cutoff = 0.9)
\end{Sinput}
\end{Schunk}
We found two immune components, interferon alpha and genes related to interferon gamma/CD8/1
\begin{Schunk}
\begin{Sinput}
> plotTopZ(plierResultHCC, HCCdataN, CancerPath, index=c(26, 40), top = 20)
\end{Sinput}
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