

# Global-Sigma

immediate

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## Contents

### 1 Gaussian kernel width $\sigma$

The other important parameter for `DiffusionMap` is the Gaussian kernel width  $\sigma$  that determines the transition probability between data points. The default call of `destiny - DiffusionMap(data)` aka `DiffusionMap(data, 'local')` - uses a local  $\sigma$  per cell, derived from a local density estimate around each cell.

Using the 1.0 default, `sigma = 'global'`, estimates  $\sigma$  using a heuristic. It is also possible to specify this parameter manually to tweak the result. The eigenvector plot explained above will show a continuous decline instead of sharp drops if either the dataset is too big or the  $\sigma$  is chosen too small.

The  $\sigma$  estimation algorithm is explained in detail in ?. In brief, it works by finding a maximum in the slope of the log-log plot of local density versus  $\sigma$ .

```
In [2]: library(destiny)
        data(guo_norm)
```

#### Using `find_sigmas`

An efficient variant of that procedure is provided by `find_sigmas`. This function determines the optimal  $\sigma$  for a subset of the given data and provides the default  $\sigma$  for a `DiffusionMap` call. Due to a different starting point, the resulting  $\sigma$  is different from above:

```
In [3]: sigmas <- find_sigmas(guo_norm, verbose = FALSE)
        optimal_sigma(sigmas)
```

10.8945955274194

The resulting diffusion map's approximation depends on the chosen  $\sigma$ . Note that the  $\sigma$  estimation heuristic only finds local optima and even the global optimum of the heuristic might not be ideal for your data.

```
In [4]: par(pch = 20, mfrow = c(2, 2), mar = c(3,2,2,2))
        palette(cube_helix(6))

        for (sigma in list('local', 5, round(optimal_sigma(sigmas), 2), 100))
          plot(DiffusionMap(guo_norm, sigma), 1:2,
               main = substitute(sigma == s, list(s = sigma)),
               col_by = 'num_cells', draw_legend = FALSE)
```

