

# kNN-LWPLSR

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kNN : k Nearest Neighbors

LWPLSR : Locally Weighted Partial Least Squares  
Regression

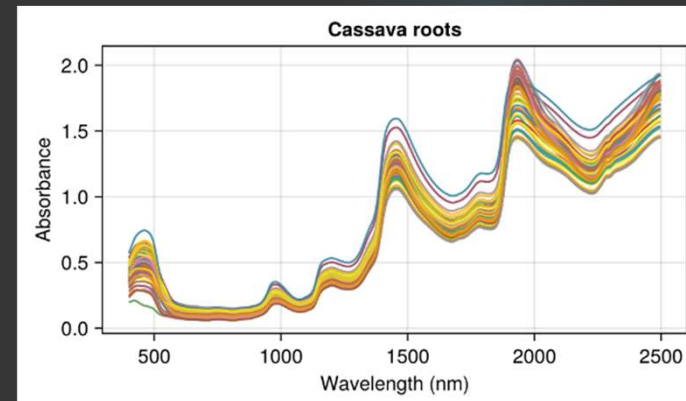
(LWPLSDA  $\Rightarrow$  Discrimination)

Algorithm useful when non-linearity  
between  $X$  and  $Y$  (data heterogeneity, etc.)

- Globally non linear
- Locally linear

# kNN-LWPLSR

- Very performant for NIR data



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## Available pipelines

Journal of  
**CHEMOMETRICS**

RESEARCH ARTICLE

### Comparison of locally weighted PLS strategies for regression and discrimination on agronomic NIR data

Matthieu Lesnoff , Maxime Metz, Jean-Michel Roger

First published: 16 January 2020 | <https://doi.org/10.1002/cem.3209> | Citations: 30



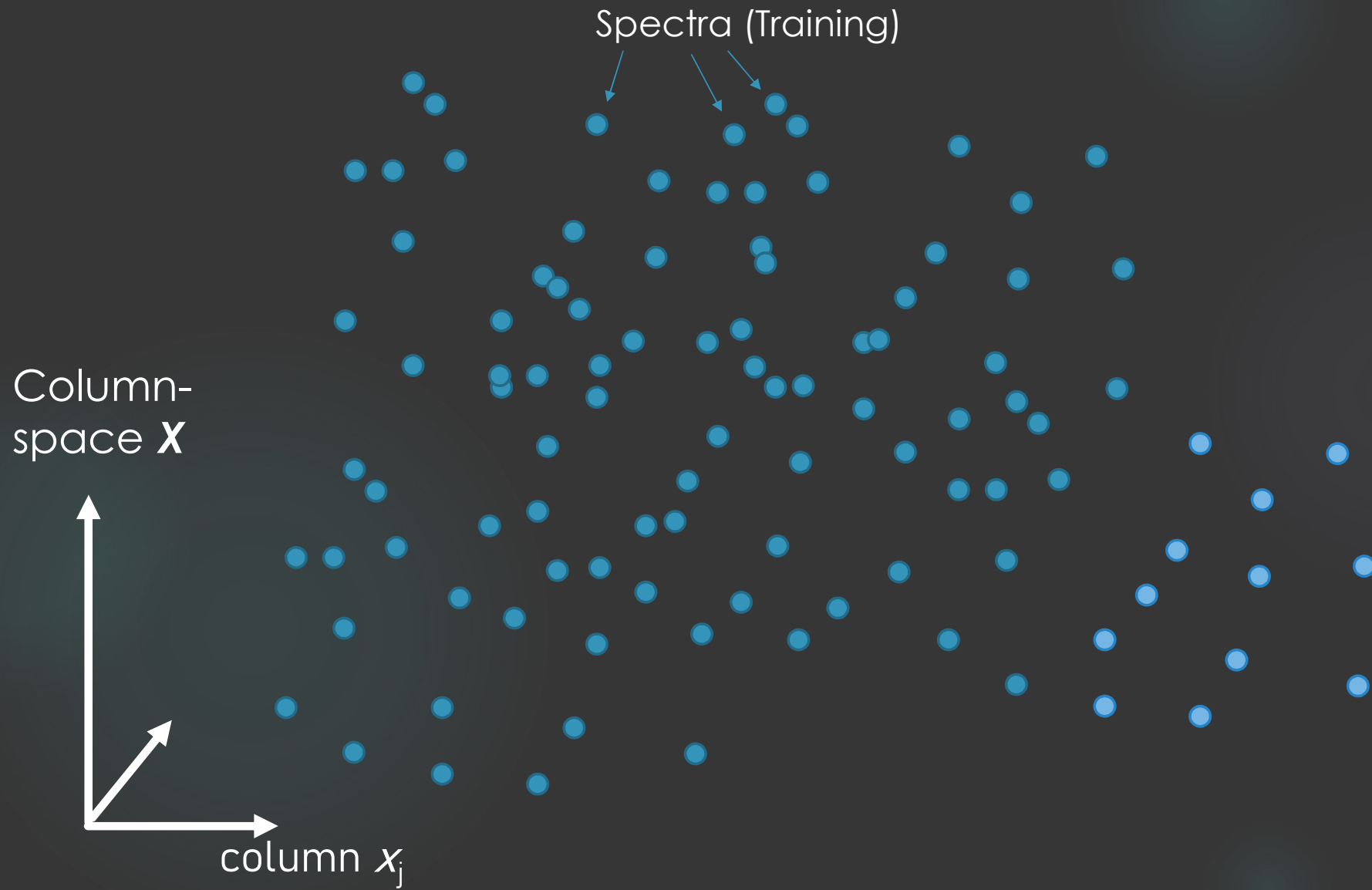
Chemometrics and Intelligent Laboratory  
Systems

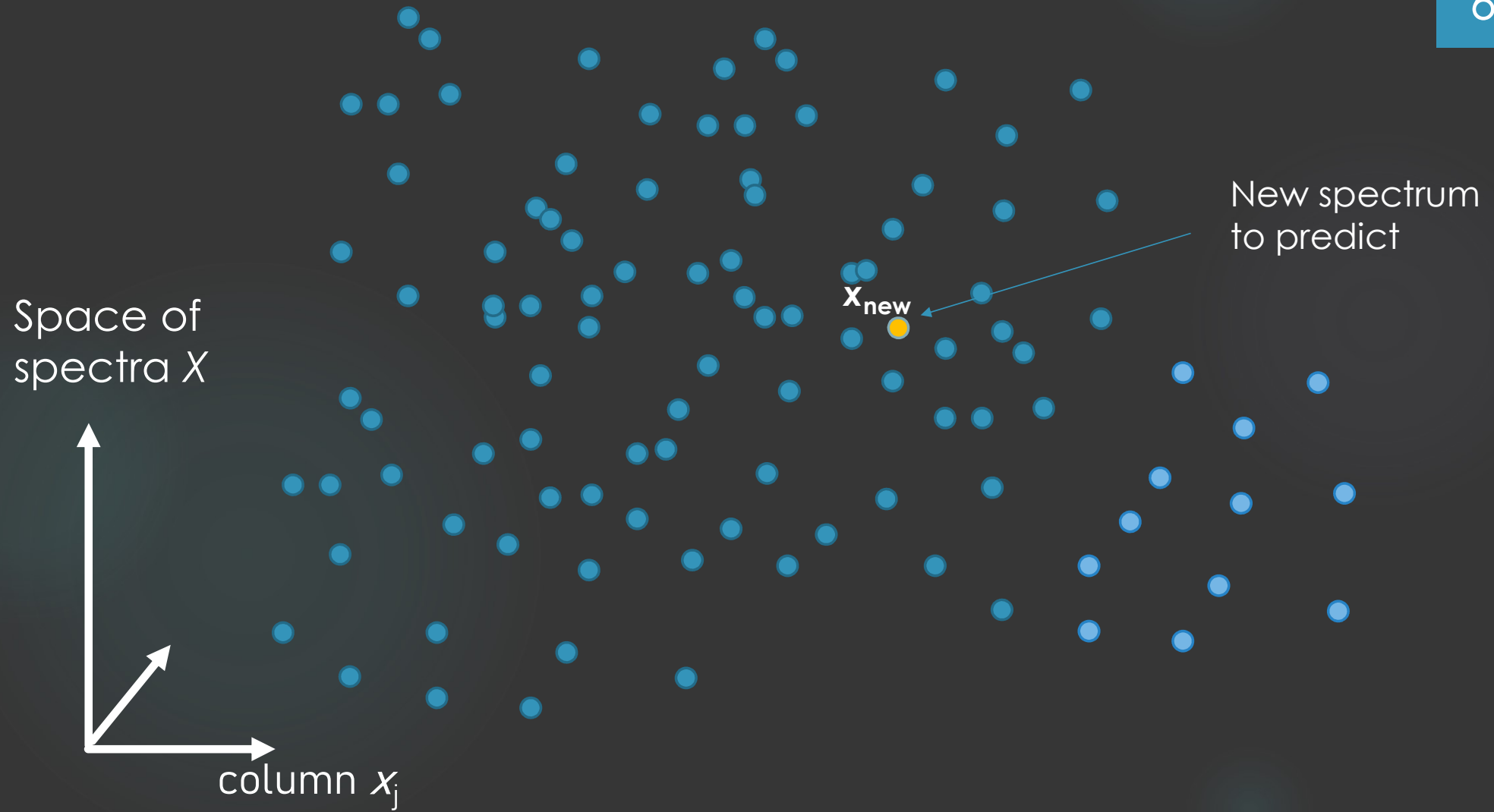
Volume 244, 15 January 2024, 105031

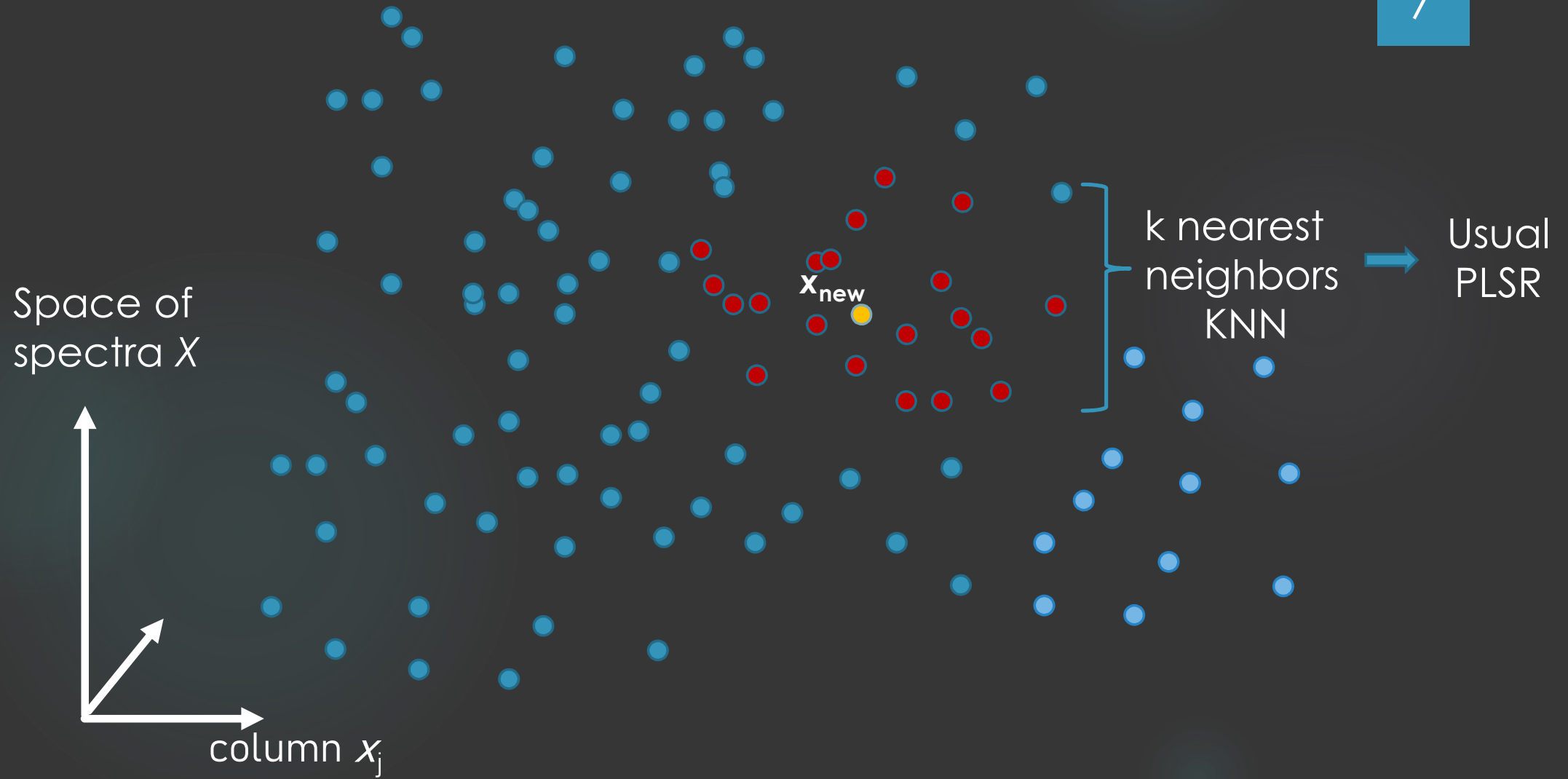


Averaging a local PLSR pipeline to predict chemical compositions and nutritive values of forages and feed from spectral near infrared data

Matthieu Lesnoff <sup>a b c</sup>  

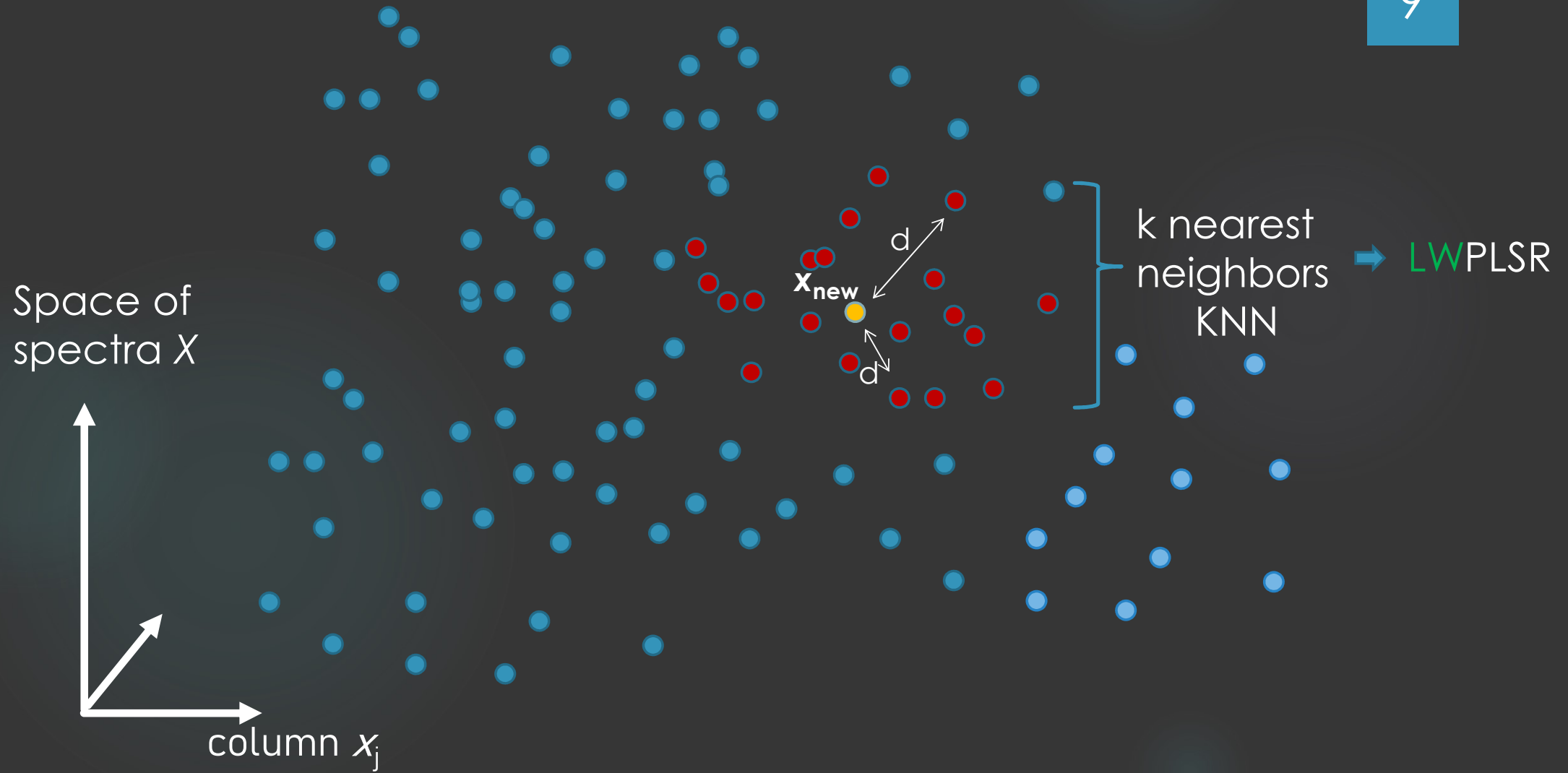






- Usual PLSR  $\max_{\mathbf{t}} \text{Cov}(\mathbf{t}, \mathbf{y})^2 = \sum_{i=1}^n \left( \frac{1}{n} t_i y_i \right)^2$
- Weighted PLSR  $\max_{\mathbf{t}} \text{Cov}_w(\mathbf{t}, \mathbf{y})^2 = \sum_{i=1}^n (w_i t_i y_i)^2$





## Weight function used by Jchemo.lwplsr

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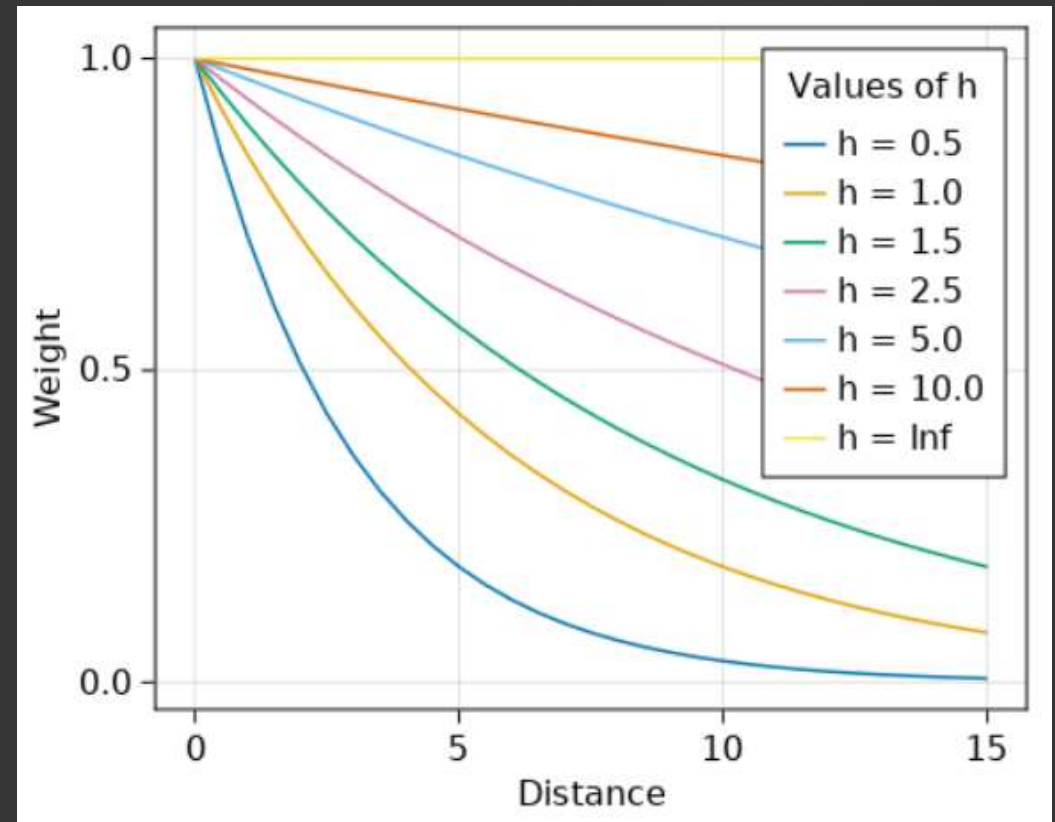
Adaptation from

Kim S, Kano M, Nakagawa H, Hasebe S. Estimation of active pharmaceutical ingredients content using locally weighted partial least squares and statistical wavelength selection. *Int J Pharm.* 2011;421(2):269-274. <https://doi.org/10.1016/j.ijpharm.2011.10.007>

$j = 1, \dots, k$  neighbors

$$w_j = \exp \frac{-d_j}{h \times \max\{d_1, \dots, d_k\}}$$

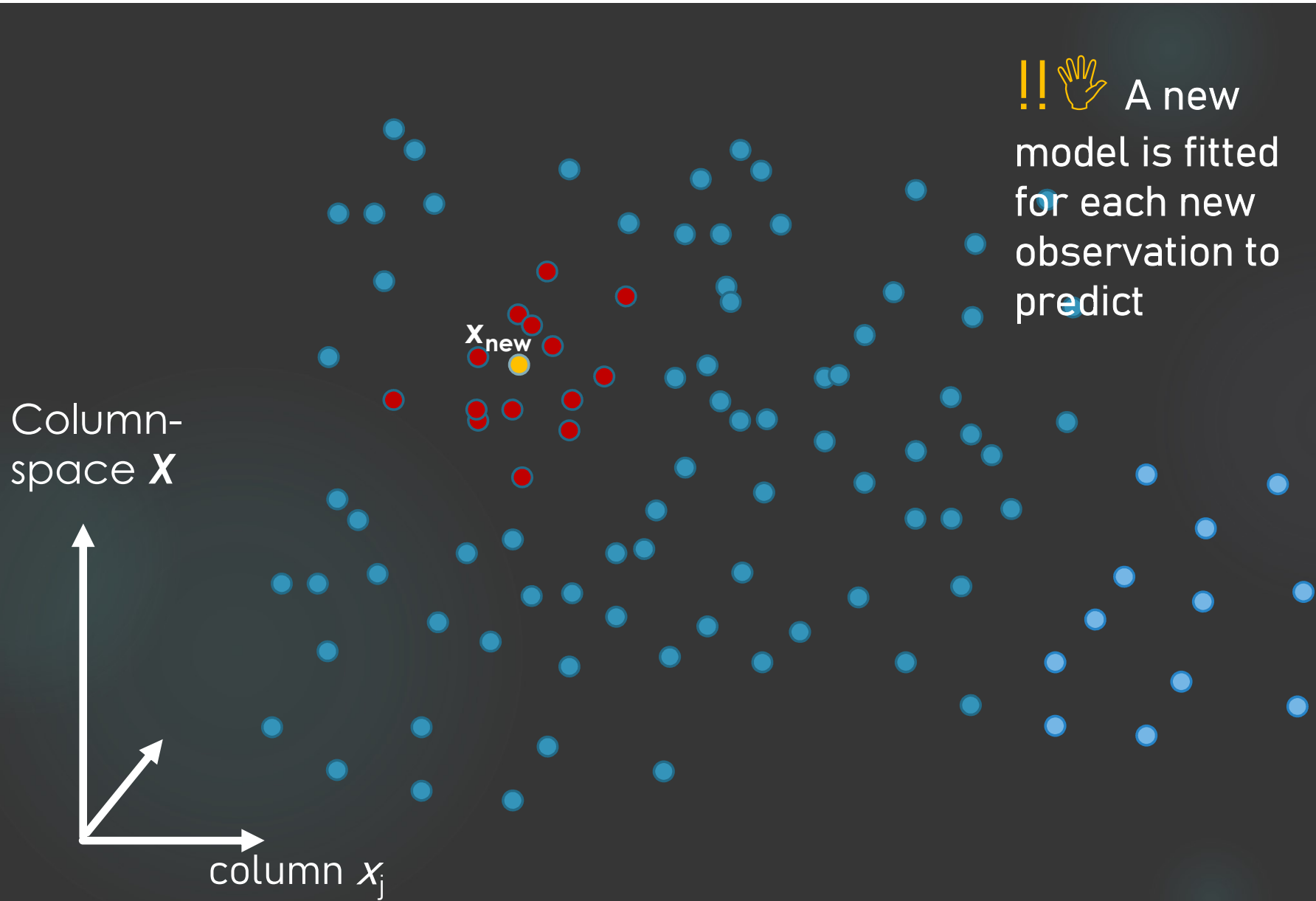
$$w_j = w_j / \max\{w_1, \dots, w_k\}$$



!! 🖐️ A new model is fitted for each new observation to predict

Column-space  $X$

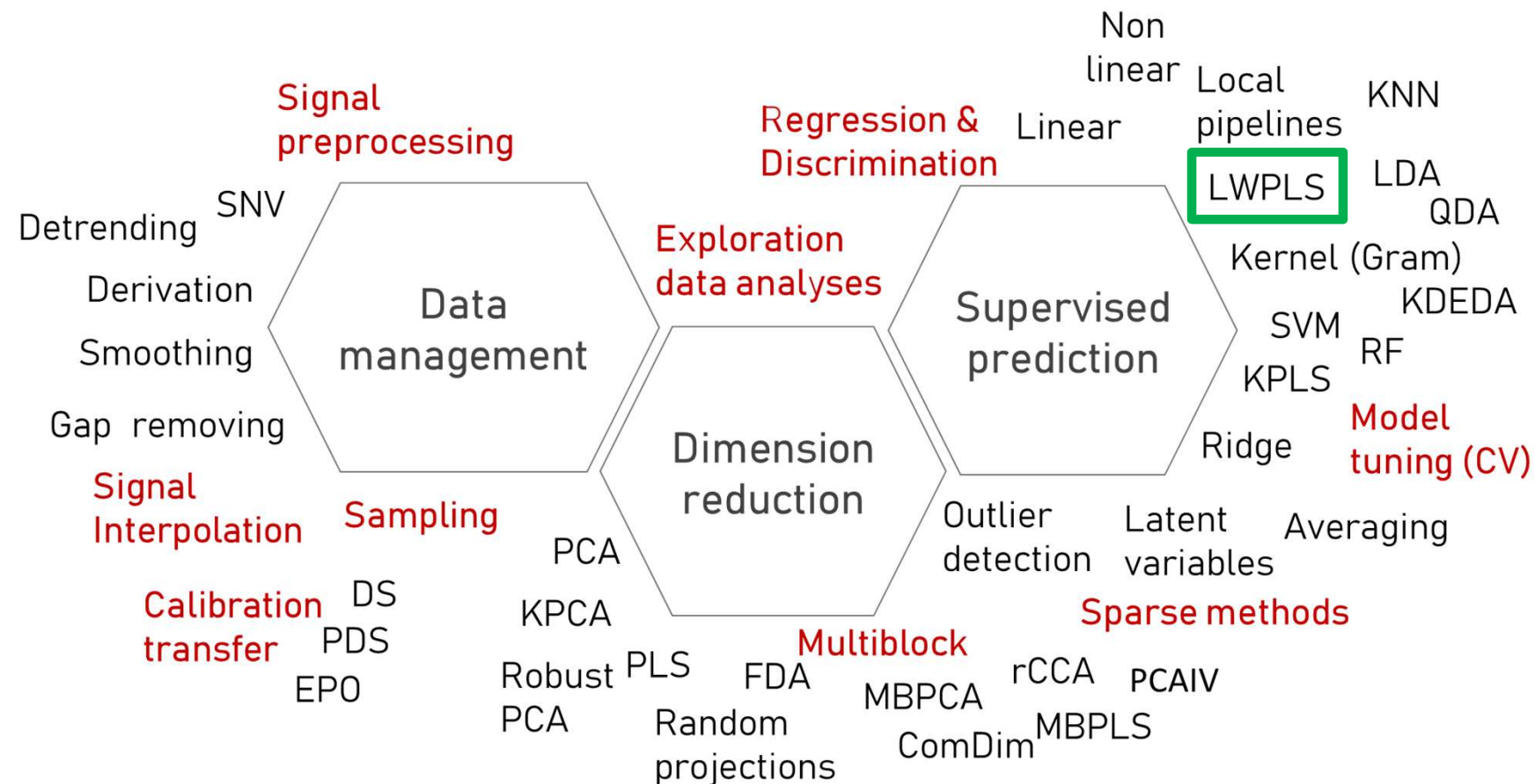
column  $x_j$



# Package Jchemo.jl



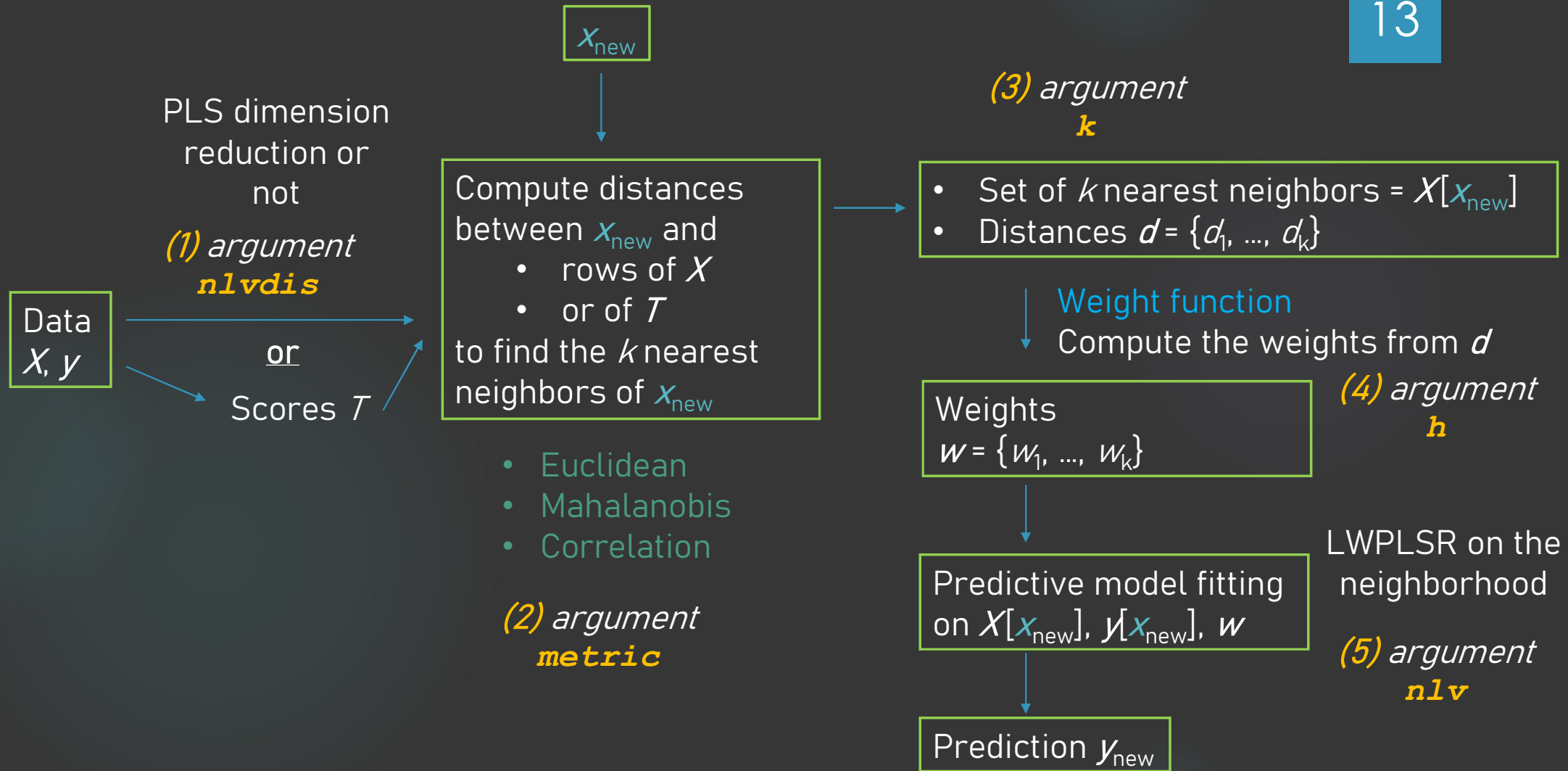
12



<https://mlesnoff.github.io/Jchemo.jl/dev/domains>

# Pipeline of function `lwplsr`

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```
## function lwplsr
```

```
nlvdis = 20 ; metric = :mah  
h = 1 ; k = 500 ; nlv = 15
```

5 main  
arguments

```
mod = model(lwplsr;  
            nlvdis, metric, h, k, nlv)  
fit!(mod, X, y)
```

```
res = predict(mod, Xnew)
```

#### Keyword arguments:

- `nlvdis` : Number of latent variables (LVs) to consider in the global PLS used for the dimension reduction before computing the dissimilarities. If `nlvdis = 0`, there is no dimension reduction.
- `metric` : Type of dissimilarity used to select the neighbors and to compute the weights. Possible values are: `:eucl` (Euclidean distance), `:mah` (Mahalanobis distance).
- `h` : A scalar defining the shape of the weight function computed by function `wdist`. Lower is `h`, sharper is the function. See function `wdist` for details (keyword arguments `criw` and `squared` of `wdist` can also be specified here).
- `k` : The number of nearest neighbors to select for each observation to predict.
- `tolw` : For stabilization when very close neighbors.
- `nlv` : Nb. latent variables (LVs) for the local (i.e. inside each neighborhood) models.
- `scal` : Boolean. If `true`, each column of `X` and `Y` is scaled by its uncorrected standard deviation for the global dimension reduction and the local models.