Analyse et manipulation des données

DigitalLab@LaPlataforme_

Descriptive and inferential statistics tools



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- Data transformations: indexing, grouping and aggregation



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- Feature Selection



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- Encoding of categorical variables
- Dimensionality reduction with PCA, LDA
- Explainability with MDS, Isomap, LLE, T-sne



Other Encodings

Scaling

 Standardization: Common requirement for many ML estimators in scikit-learn; they might behave badly if the individual features do not look like standard normally distributed data.

$$z = (x - u) / s$$

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$$x_s = (x - min) / (max - min)$$

 $x_s (R - L) + L$

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MaxAbsScaler: Special case of MinMaxScaler but for [-1, 1].

Given an ordinal categorical r.v N with categories $C_1 < C_2 < \ldots < C_n$ we enumerate them with integers $0 < \ldots < n-1$. This encoding preserves the order.

Given an ordinal categorical r.v X with categories $C_1 < C_2 < ... < C_n$ we enumerate them with integers 0 < ... < n-1. This encoding preserves the order.

Enumeration

Primary	0
Secondary	1
University	2
Doctorate	3
Postdoc	4

Index	Studies Level
0	Primary
1	Postdoc
2	University
3	Doctorate
4	Secondary
5	Primary

Given an ordinal categorical r.v X with categories $C_1 < C_2 < ... < C_n$ we enumerate them with integers 0 < ... < n-1. This encoding preserves the order.

DataFrame to Encode

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	0	0
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Primary

DataFrame to Encode

Studies Level Index 0 0 4 2 Doctorate Secondary 5 Primary

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Index	Studies Level	
0	0	
1	4	
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Primary	0
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Index	Studies Level	
0	0	
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3	3	
4	1	
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DataFrame to Encode

Index	Studies Level
0	0
1	4
2	2
3	3
4	1
5	0

Discretizers

We can take a numerical variable and segment it equally in categories.

For example, if we are dealing with the salary of developers, we can discretize it in three groups, in such a way these groups have more or less the same number of instances.

Polynomial Features

Often it's useful to add complexity to a model by considering nonlinear features of the input data. One possibility is to use polynomial features.

For example, if we have the features of x1 and x2, we can create six features from them by combining through multiplications obtaining:

(1, X1, X2, X1.X1, X1.X2, X2.X2)

Demo notebook 10_pipelines_and_other_encodings. ipynb