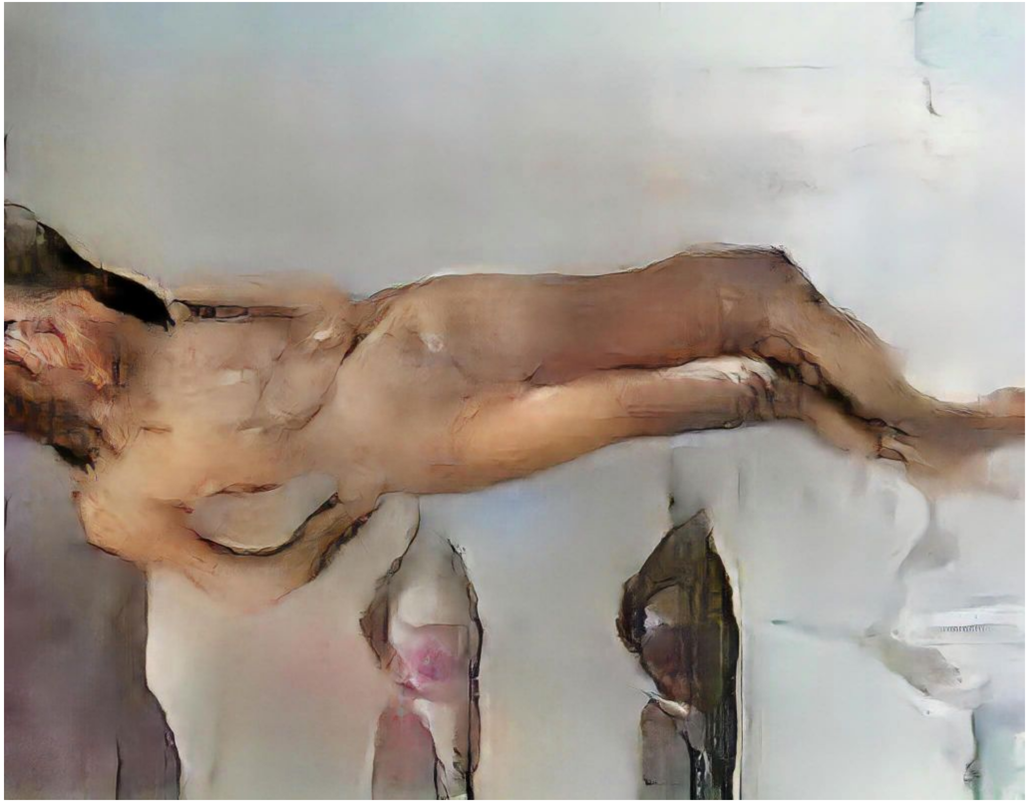
Cluster 2018

Ciencia de Datos en Ingeniería Industrial

clase_02: feature pre-processing

AI & Art: Mario Klingemann



‘My Artificial Muse’
http://quasimondo.com/

agenda_clase_02

- Python: For, IF, functions
- Intro Scikit-Learn
- Categorical Variables: Dummies
- Feature Processing
- EDAs
- Practica en clase

‘for’ loops in python

```
iteraciones = 20
x = np.zeros(iteraciones)
for r in range(0,iteraciones):
    x[r] = np.sqrt(r+1)
```

iterador

‘if’ statements in python

```python
if x > 1 :
    x = pd.concat([data1,data2])

else:
    x = data1
```

‘if’ statements in python

```
if y == "mean":
    mean = np.mean(data.distance)

elif y == "Preproc":
    nans = data.isnull().any()

elif y == "std dev":
    std_dev = np.std(data.distance)
```

functions in python

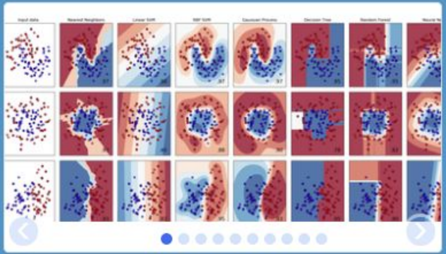
```
def dot_product( x1, x2 ):
    "Esta funcion calcula el producto interno de 2 matrices"
     dotprod = np.dot(x1,x2.T)
     return dotprod

a = dot_prod(x_febrero, x_marzo)
```

Intro scikit-learn

scikits learn

machine learning in Python

Intro scikit-learn



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, ... — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, ... — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

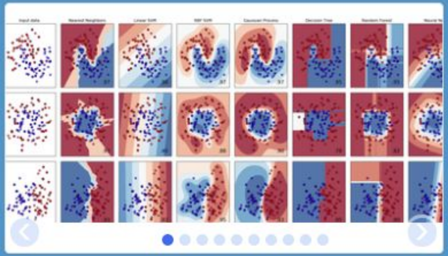
Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples

Intro scikit-learn



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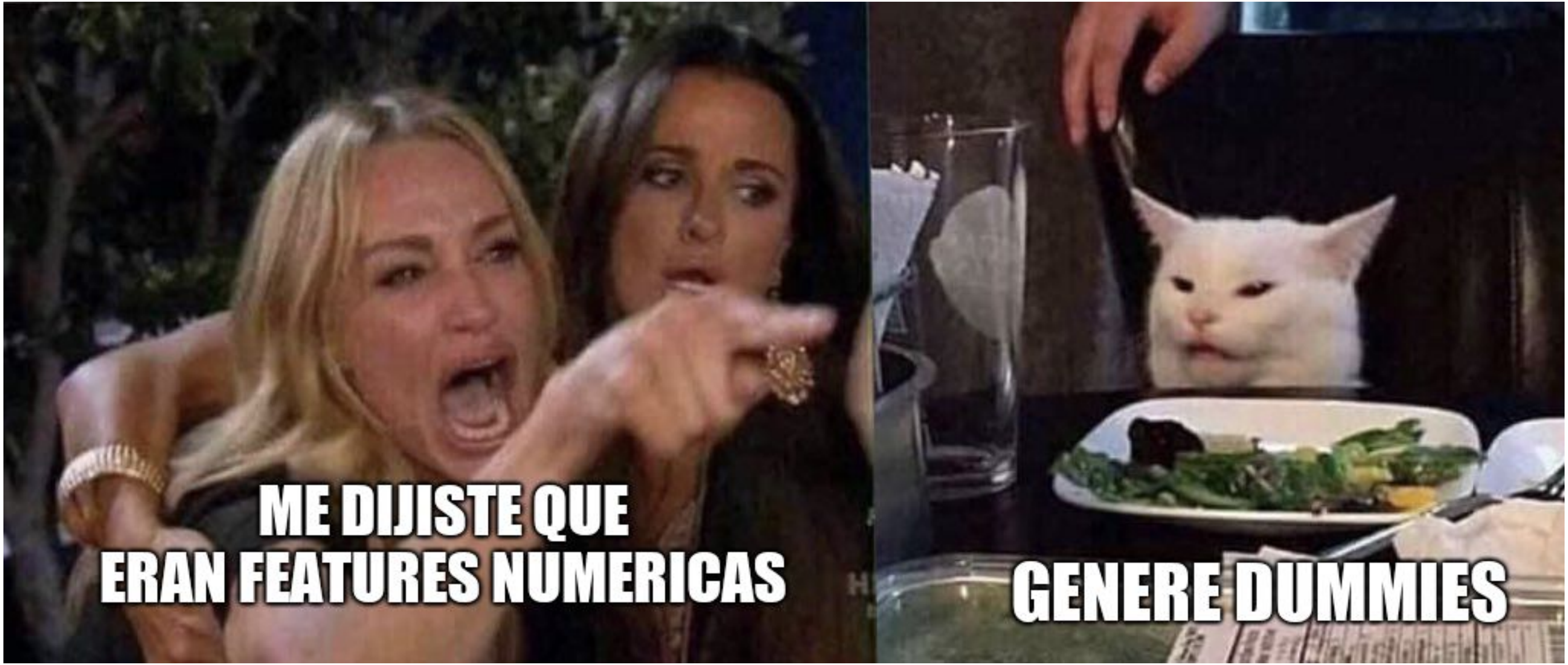
Categorical Variables: Dummies



Feature Engineering: Categorical Variables (Dummies)

Edad	Altura	**Sexo**
18	1.70	Masculino
24	1.60	Femenino
30	1.90	Femenino
28	1.5	Masculino

Edad	Altura	Sexo	**Masculino**	**Femenino**
18	1.70	Masculino	1	0
24	1.60	Femenino	0	1
30	1.90	Femenino	0	1
28	1.5	Masculino	1	0

Feature Engineering:
Categorical Variables (Dummies)

```
# 1 Creamos un dataframe
raw_data = {'edad': [18, 24, 30, 28],
        'altura': [1.7, 1.6, 1.9, 1.5],
        'sexo': ['masculino', 'femenino', 'femenino', 'masculino']}
data = pd.DataFrame(raw_data, columns = ['edad', 'altura', 'sexo'])

# 2 Creamos un dataframe de variables Dummies para columna "Sexo"
df_sexo = pd.get_dummies(data['sexo'])

# 3 Agregamos estas nuevas variables dummies a nuestro dataframe
df_new = pd.concat([df, df_sex], axis=1)
```

Feature scaling & normalization

Feature Engineering: Auto-Scaling & Normalization

En muchas ocasiones las features pueden tener rangos muy distintos. Por ejemplo si utilizamos metros cuadrados y temperatura para caracterizar las condiciones climáticas de un campo la primer variable estará en el rango de decenas de miles y la segunda en decenas, es decir cuando el dominio de las features es distinto. Esto puede generar un problema a la hora de ‘aprender de datos’.

Para eso abordaremos dos estrategias de ingeniería de features:

- Auto-scaling / standarization [1]
- Min-Max normalization [2]

[1] van den Berg, R. A., Hoefsloot, H. C., Westerhuis, J. A., Smilde, A. K., & van der Werf, M. J. (2006). Centering, scaling, and transformations: improving the biological information content of metabolomics data. *BMC genomics*, *7*(1), 142.

[2] Jain, Y. K., & Bhandare, S. K. (2011). Min max normalization based data perturbation method for privacy protection. *International Journal of Computer & Communication Technology*, *2*(8), 45-50.

Feature Engineering: Auto-Scaling

El método de “auto-scaling” o “standarization” o “Z-score normalization” asume que cada feature de manera individual responde a una distribución de probabilidad normal y busca estandarizar los valores afectándolos por la media y el desvío standard.

$$x_i{}' = \frac{(x_i - \mu)}{\sigma}$$

Cada feature después de pre-procesarla quedará con una media = 0 y un desvío standard = 1.

Feature Engineering: Auto-Scaling

```
from sklearn.preprocessing import StandardScaler
data = [[0, 0], [0, 0], [1, 1], [1, 1]]
scaler = StandardScaler()
print(scaler.fit(data))
    "StandardScaler(copy=True, with_mean=True, with_std=True)"
print(scaler.mean_)
    "[0.5 0.5]"
print(scaler.var_)
    "[0.25 0.25]"
print(scaler.transform(data))
    "[[-1. -1.][-1. -1.] [ 1.  1.][ 1.  1.]]"
```

Feature Engineering: Min-Max normalization

El método de "Min-Max normalization" afecta al valor de la feature en cada sample por el mínimo de la feature y lo divide por el rango entre máximo y mínimo.

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

Cada feature después de pre-procesarla quedará un mínimo en 0 y un máximo en 1.

Feature Engineering: Min-Max normalization

```
from sklearn.preprocessing import MinMaxScaler
data = [[-1, 2], [-0.5, 6], [0, 10], [1, 18]]
scaler = MinMaxScaler()
print(scaler.fit(data))
    "MinMaxScaler(copy=True, feature_range=(0, 1))"
print(scaler.data_max_)
    "[ 1. 18.]"
print(scaler.transform(data))
    "[[0. 0.], [0.25 0.25], [0.5  0.5], [1. 1.]]"
print(scaler.transform([[2, 2]]))
    "[[1.5 0.  ]]"
```

Feature Engineering: Min-Max normalization

IMPORTANTE: cuando pre-procesamos las features de un dataset debemos conservar el módulo “scaler” que contiene la información para transformar features. Esto quiere decir que a nuevos datos debemos transformarlos con el scaler ajustado con los datos iniciales y evitar realizar todo el proceso de nuevo con los datos viejos y nuevos.

A agarrar la PyLA