

k-Nearest_neighbors

k-Nearest neighbors (KNN)¶

- No paramétrico, significa que no hace suposiciones explícitas sobre la forma funcional de los datos, evitando modelar mal la distribución subyacente de los datos.
- Memoriza las instancias de formación que posteriormente se utilizan como "conocimiento" para la fase de predicción.
- La fase de formación mínima de KNN se realiza tanto a un coste de memoria, ya que debemos almacenar un conjunto de datos potencialmente enorme, como un coste computacional durante el tiempo de prueba, ya que la clasificación de una observación determinada requiere un agotamiento de todo el conjunto de datos.

Find nearest similar points¶

Se encuentra la distancia entre puntos, utilizando alguna de las medidas de distancia:

- Distancia euclidiana:

$$\sqrt{\sum_{i=1}^k (\mathbf{x}_i - \mathbf{y}_i)^2}$$

- Distancia Manhattan: $\sum_{i=1}^k |\mathbf{x}_i - \mathbf{y}_i|$
- Distancia Minkowski $[\sum_{i=1}^k (|\mathbf{x}_i - \mathbf{y}_i|)^4]^{1/4}$

1. Calcular la distancia
2. Encontrar sus vecinos más cercanos
3. Votar por las etiquetas

Definir el valor de K¶

- El número de vecinos (K) es un hiperparámetro que se debe elegir en el momento de la construcción del modelo.
- No existe un número óptimo de vecinos que se adapte a todo tipo de conjuntos de datos, cada conjunto de datos tiene sus propios requisitos.

- ## Implementación¶

[illegible]

```

1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
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1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
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1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1]), 'frame': None, 'target_name': 'breast_cancer',
'mean smoothness', 'mean compactness', 'mean concavity',
'mean concave points', 'mean symmetry', 'mean fractal dimension',
'radius error', 'texture error', 'perimeter error', 'area error',
'smoothness error', 'compactness error', 'concavity error',
'concave points error', 'symmetry error',
'fractal dimension error', 'worst radius', 'worst texture',
'worst perimeter', 'worst area', 'worst smoothness',
'worst compactness', 'worst concavity', 'worst concave points',
'worst symmetry', 'worst fractal dimension'], dtype='<U23'), 'filename': 'breast_cancer.csv')

```

visualizar las características del dataset

In [35]:

```
print(dataset.DESCR)
```

```
.. _breast_cancer_dataset:
```

```
Breast cancer wisconsin (diagnostic) dataset
```

```
**Data Set Characteristics:**
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```
:Number of Instances: 569
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```
:Number of Attributes: 30 numeric, predictive attributes and the class
```

```
:Attribute Information:
```

- radius (mean of distances from center to points on the perimeter)
- texture (standard deviation of gray-scale values)
- perimeter
- area
- smoothness (local variation in radius lengths)
- compactness (perimeter² / area - 1.0)
- concavity (severity of concave portions of the contour)
- concave points (number of concave portions of the contour)

- symmetry
- fractal dimension ("coastline approximation" - 1)

The mean, standard error, and "worst" or largest (mean of the three worst/largest values) of these features were computed for each image, resulting in 30 features. For instance, field 0 is Mean Radius, field 10 is Radius SE, field 20 is Worst Radius.

- class:
 - WDBC-Malignant
 - WDBC-Benign

:Summary Statistics:

	Min	Max
radius (mean):	6.981	28.11
texture (mean):	9.71	39.28
perimeter (mean):	43.79	188.5
area (mean):	143.5	2501.0
smoothness (mean):	0.053	0.163
compactness (mean):	0.019	0.345
concavity (mean):	0.0	0.427
concave points (mean):	0.0	0.201
symmetry (mean):	0.106	0.304
fractal dimension (mean):	0.05	0.097
radius (standard error):	0.112	2.873
texture (standard error):	0.36	4.885
perimeter (standard error):	0.757	21.98
area (standard error):	6.802	542.2
smoothness (standard error):	0.002	0.031
compactness (standard error):	0.002	0.135
concavity (standard error):	0.0	0.396
concave points (standard error):	0.0	0.053
symmetry (standard error):	0.008	0.079
fractal dimension (standard error):	0.001	0.03
radius (worst):	7.93	36.04
texture (worst):	12.02	49.54
perimeter (worst):	50.41	251.2
area (worst):	185.2	4254.0
smoothness (worst):	0.071	0.223
compactness (worst):	0.027	1.058
concavity (worst):	0.0	1.252
concave points (worst):	0.0	0.291
symmetry (worst):	0.156	0.664

fractal dimension (worst): 0.055 0.208
===== ===== =====

:Missing Attribute Values: None

:Class Distribution: 212 - Malignant, 357 - Benign

:Creator: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian

:Donor: Nick Street

:Date: November, 1995

This is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) datasets.
<https://goo.gl/U2Uwz2>

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

Separating plane described above was obtained using Multisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree Construction Via Linear Programming." Proceedings of the 4th Midwest Artificial Intelligence and Cognitive Science Society, pp. 97-101, 1992], a classification method which uses linear programming to construct a decision tree. Relevant features were selected using an exhaustive search in the space of 1-4 features and 1-3 separating planes.

The actual linear program used to obtain the separating plane in the 3-dimensional space is that described in:
[K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34].

This database is also available through the UW CS ftp server:

ftp ftp.cs.wisc.edu
cd math-prog/cpo-dataset/machine-learn/WDBC/

|details-start|

References

|details-split|

- W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear feature extraction for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on

- Electronic Imaging: Science and Technology, volume 1905, pages 861-870, San Jose, CA, 1993.
- O.L. Mangasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and prognosis via linear programming. Operations Research, 43(4), pages 570-577, July-August 1995.
 - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learning techniques to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994) 163-171.

|details-end|

In [36]:

```
X = dataset.data
y = dataset.target
```

separar los datos en test y train

In [37]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

train

In [38]:

```
algorithm = KNeighborsClassifier(n_neighbors=5, metric= 'minkowski', p=2)
```

```
algorithm.fit(X_train, y_train)
y_pred = algorithm.predict(X_test)
```

matriz de confusion

In [39]:

```
matrix = confusion_matrix(y_test,y_pred)
```

```
print(matrix)
```

```
[[37  7]
 [ 1 69]]
```

precision del modelo

In [40]:

```
precision = precision_score(y_test, y_pred)
print(precision)
```

0.9078947368421053

In []: