A (very short) introductory journey through data science

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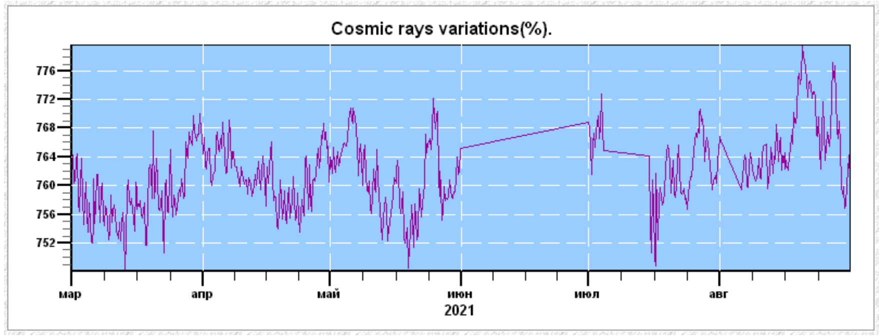
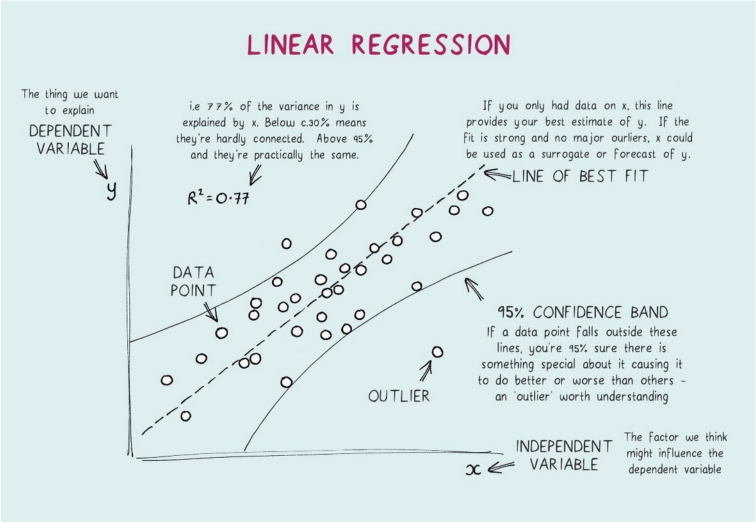
Contents

We are talking about three important topics (or common task) in Data Sciene:

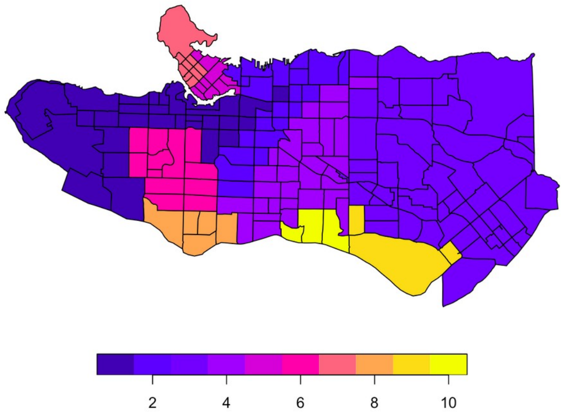
Imputation methods



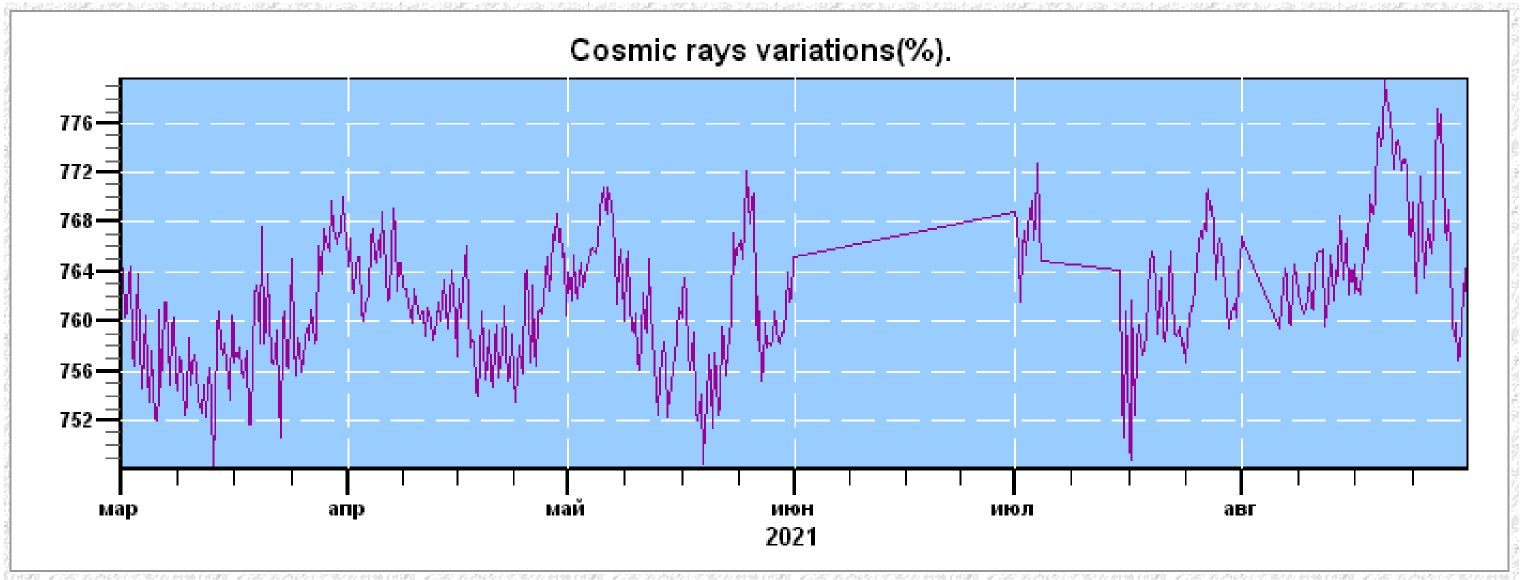
Regression methods



10 cluster example



Clustering methods



Tutorial: Introduction to Missing Data Imputation

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Think fast 1...

131 → 12
241 → 24
162 → 36
343 → 48
146 → **??**

Think fast 2...

111 → 12
231 → 24
324 → 36
453 → 48
542 → **??**

Think fast 1...

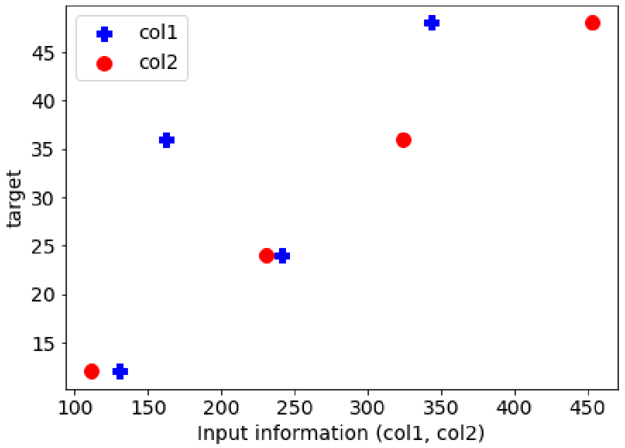
131 → 12
241 → 24
162 → 36
343 → 48
146 → ??

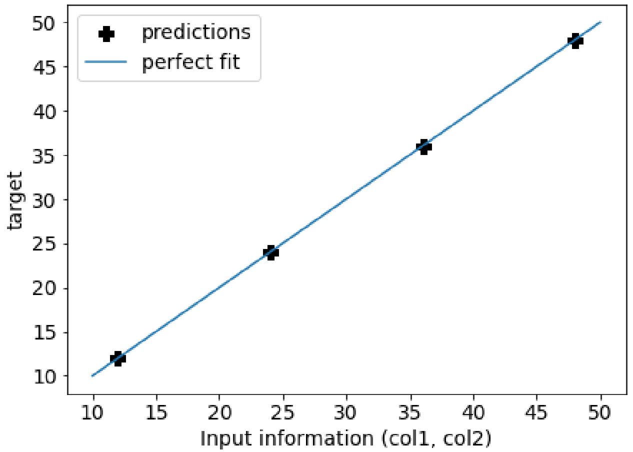
	col1	col2	targ
0	131	111	12
1	241	231	24
2	162	324	36
3	343	453	48
4	146	542	??

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   targ   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 1.319e+05
Date:                Mon, 27 Jun 2022   Prob (F-statistic):            0.00195
Time:                        08:56:49   Log-Likelihood:                 8.9039
No. Observations:                   4   AIC:                            -11.81
Df Residuals:                       1   BIC:                            -13.65
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.2792      0.075     17.113      0.037       0.329       2.229
col1          -0.0160      0.001    -30.284      0.021      -0.023      -0.009
col2           0.1152      0.000    333.744      0.002       0.111       0.120
==============================================================================
```

Think fast 2...

111 → 12
231 → 24
324 → 36
453 → 48
542 → ??



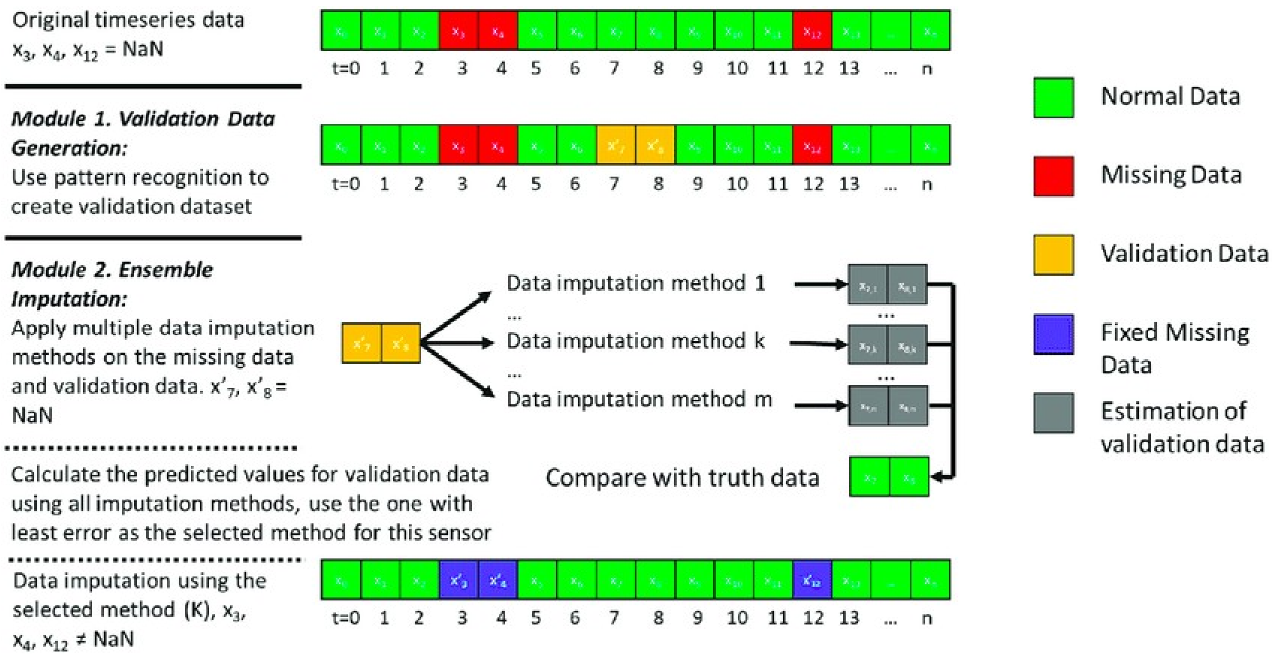


Model: targ ~ col1 + col2, *target(predcition)=**61***

Missing data mechanisms

Missing data is a common problem in practical data analysis. They are simply observations that we intend to make but did not. In datasets, missing values could be represented as ‘?’, ‘nan’, ’N/A’, blank cell, or sometimes ‘-999’, ’inf’, ‘-inf’. The aim of this tutorial is to provide an introduction of missing data and describe some basic methods on how to handle them.

The study of missing data was formalized by Donald Rubin (see [6], [5]) with the concept of missing mechanism in which missing-data indicators are random variables and assigned a distribution. Missing data mechanism describes the underlying mechanism that generates missing data and can be categorized into three types — missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). Informally speaking, MCAR means that the occurrence of missing values is completely at random, not related to any variable. MAR implies that the missingness only relate to the observed data and NMAR refers to the case that the missing values are related to both observed and unobserved variable and the missing mechanism cannot be ignored.



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April 30, 2021

Dataset Open Access

Water-quality data imputation with a high percentage of missing values: a machine learning approach

Rafael Rodríguez; Marcos Pastorini; Lorena Etcheverry; Christian Chreties; Mónica Fossati; Alberto Castro; Angela Gorgoglione

The monitoring of surface-water quality followed by water-quality modeling and analysis is essential for generating effective strategies in water resource management. However, water-quality studies are limited by the lack of complete and reliable data sets on surface-water-quality variables. These deficiencies are particularly noticeable in developing countries.

This work focuses on surface-water-quality data from Santa Lucía Chico river (Uruguay), a mixed lotic and lentic river system. Data collected at six monitoring stations are publicly available at https://www.dinama.gub.uy/oan/datos-abiertos/calidad-agua/. The high temporal and spatial variability that characterizes water-quality variables and the high rate of missing values (between 50% and 70%) raises significant challenges.

To deal with missing values, we applied several statistical and machine-learning imputation methods. The competing algorithms implemented belonged to both univariate and multivariate imputation methods (inverse distance weighting (IDW), Random Forest Regressor (RFR), Ridge (R), Bayesian Ridge (BR), AdaBoost (AB), Huber Regressor (HR), Support Vector Regressor (SVR), and K-nearest neighbors Regressor (KNNR)).

IDW outperformed the others, achieving a very good performance (NSE greater than 0.8) in most cases.

In this dataset, we include the original and imputed values for the following variables:

- Water temperature (*Tw*)
- Dissolved oxygen (*DO*)
- Electrical conductivity (EC)
- pH
- Turbidity (*Turb*)
- Nitrite (*NO2-*)
- Nitrate (*NO3-*)
- Total Nitrogen (*TN*)

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https://www.mdpi.com/2071-1050/13/11/6318

Open Access Article

Water-Quality Data Imputation with a High Percentage of Missing Values: A Machine Learning Approach

by Rafael Rodríguez [1], Marcos Pastorini [2], Lorena Etcheverry [2], Christian Chreties [1], Mónica Fossati [1], Alberto Castro [2] and Angela Gorgoglione [1,*]

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(This article belongs to the Special Issue Water Quality: Current State and Future Trends)

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Abstract

The monitoring of surface-water quality followed by water-quality modeling and analysis are essential for generating effective strategies in surface-water-resource management. However, worldwide, particularly in developing countries, water-quality studies are limited due to the lack of a complete and reliable dataset of surface-water-quality variables. In this context, several statistical and machine-learning models were assessed for imputing water-quality data at six monitoring stations located in the Santa Lucía Chico river (Uruguay), a mixed lotic and lentic river system. The challenge of this study is represented by the high percentage of missing data (between 50% and 70%) and the high temporal and spatial variability that characterizes the water-quality variables. The competing algorithms implement univariate and multivariate imputation methods (inverse distance weighting (IDW), Random Forest Regressor (RFR), Ridge (R), Bayesian Ridge (BR), AdaBoost (AB), Hubber Regressor (HR), Support Vector Regressor (SVR) and K-nearest neighbors Regressor (KNNR)). According to the results, more than 76% of the imputation outcomes are considered "satisfactory" (NSE > 0.45). The imputation performance shows better results at the monitoring stations located inside the reservoir than those positioned along the mainstream. IDW was the model with the best imputation results, followed by RFR, HR and SVR. The approach proposed in this study is expected to aid water-resource researchers and managers in augmenting water-quality datasets and overcoming the missing data issue to increase the number of future studies related to the water-quality matter. View Full-Text

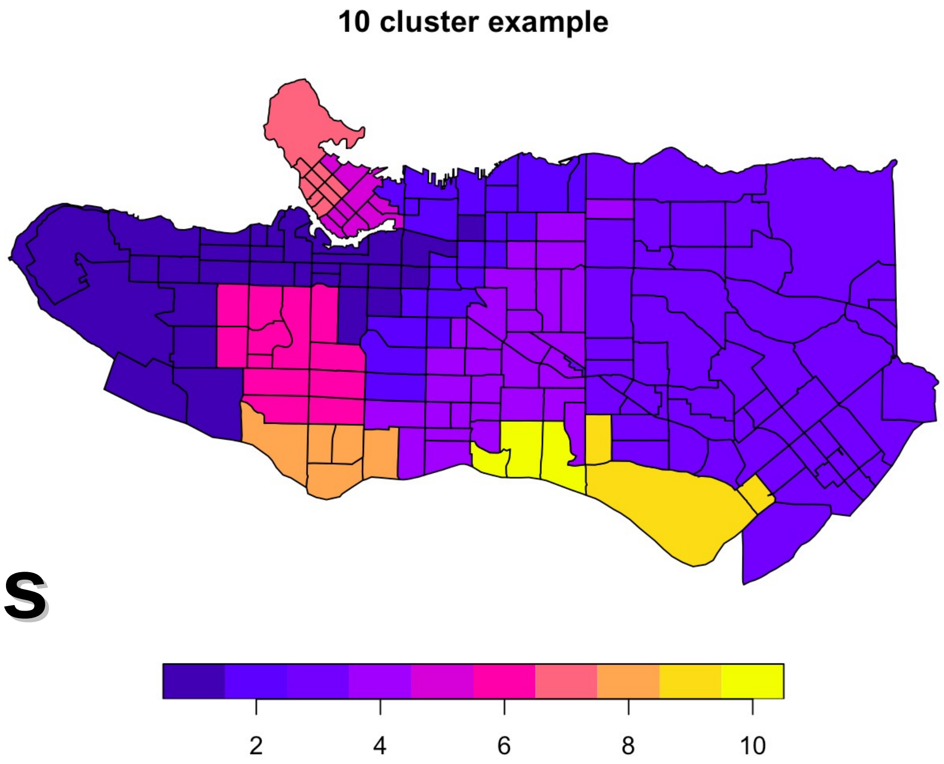
Keywords: data scarcity; water quality; missing data; univariate imputation; multivariate imputation; machine learning; hydroinformatics

▼ Show Figures

...let's get to the data and get to work…

https://github.com/sierraporta/introductory-journey-data-science/blob/main/Notebooks/Inputation.ipynb

A little homework to imputation methods…!



Clustering methods

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A Novel Approach to Predict Popularity Rating Using KNN and SVD

Publisher: IEEE Cite This PDF

N. Kanimozhi ; M.N. Kavitha ; S.S. Saranya ; S Aravinth ; M Kavin Prakash ; D.K Naren **All Authors**

Abstract:
In this hectic world, every one of us wants some peaceful time by doing certain activities like playing our favorite games, watching movies, watching social media platforms, etc..The most popular among them is watching social media platforms. The stress can be reduced by watching different genre of movies like crime, thrillers, love, and emotions. Many social media platforms are available, like Disney + Hot Star, Amazon Prime Video, Netflix, and so on. Finding TRP for these social platforms is essential for the program broadcaster. It was quite challenging task to predict the TRP of each show. In this work, the TRP prediction is done by using the knowledge of machine learning. This paper imposes on finding the television rating point using K-Nearest Neighbors (KNN) and singular value decomposition (SVD) by using Kaggle, an open-source dataset. The KNN is used to find the TRP by calculating the characteristics of each one. Then, the similar one is taken from KNN, and then ranking is done by using SVD. Finally, result is validated with the previous one, which produces high accuracy.

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https://ieeexplore.ieee.org/abstract/document/9742993

Use of KNN for the Netflix Prize

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Abstract

This paper analyzes the performance of various KNNs techniques as applied to the netflix collaborative filtering problem.

1. Introduction

In the Netflix collaborative filtering problem, the goal is that given a set of training data $x = \{(u_i, m_i, t_i, r_i)\}$, consisting of a sample of prior movie ratings r_i (an integer from 1 to 5), associated with user u_i, movie m_i, time t_i to be able to accurately predict the rating that should be associated with a new point (u, m). In this first pass, because we cannot easily ascertain the time associated with the new point we will ignore the time dimension. Furthermore, to simplify the analysis we will not take into consideration any features that could be associated with knowing the actual movie characteristics.

2. KNN

Our main premise is that similar users rate similar movies similarly. With KNN, given a point (u, m) to predict, we compute the K most similar points and average the ratings of those points somehow to obtain our predicted rating $\hat{r}$. Different spaces, similarity metrics and different averaging techniques would affect the performance of KNN.

In the following sections we will consider primarily user similarity, ignoring movie similarity and saving that for future work. In essence, our KNN algorithm becomes: given a point (u, m) to predict, compute the K most similar users and average the ratings of those users gave movie m to obtain our predicted rating $\hat{r}$.

We will consider approximations to KNN to obtain predictions in a reasonable amount of time, and several distance metrics.

3.1 Smaller Data Sets

The training data set provided by Netflix was huge, consisting of 100 million ratings. If we were to run our algorithms on that dataset, we would lose a significant amount of time waiting for the method to train. This would impair our ability to test small changes quickly. Therefore we created training sets that are 1000, 100 and 10 times smaller (meaning they have so many times fewer users), along with their respective testing sets. For each size 5 different datasets were created, by randomly selecting users.

4. Pearson's Correlation Coefficient

If we consider that a given user u_i rates movies with a distribution $R_i \sim (\mu_i, \sigma_i)$ then a natural similarity metric between users u_i and u_j is the correlation coefficient between the two distributions R_i, and R_j: $\rho_{ij} = \dfrac{E[(R_i - \mu_i)(R_j - \mu_j)]}{\sigma_i * \sigma_j}$.

We estimate the covariance and variances by considering the M movies user i and j have in common and

$$E[(R_i - \mu_i)(R_j - \mu_j)] \approx \frac{1}{M}\sum_k (r_{ik} - \mu_i)(r_{jk} - \mu_j),$$

$$\sigma_i \approx \sqrt{\frac{1}{M}\sum_k (r_{ik} - \mu_i)^2}, \quad \sigma_j \approx \sqrt{\frac{1}{M}\sum_k (r_{jk} - \mu_j)^2}$$

But we estimate the means by considering all movies user i/j has rated irrespective of the other users. If a particular user as no ratings, then we consider the user's mean to be 0 (probably should be changed).

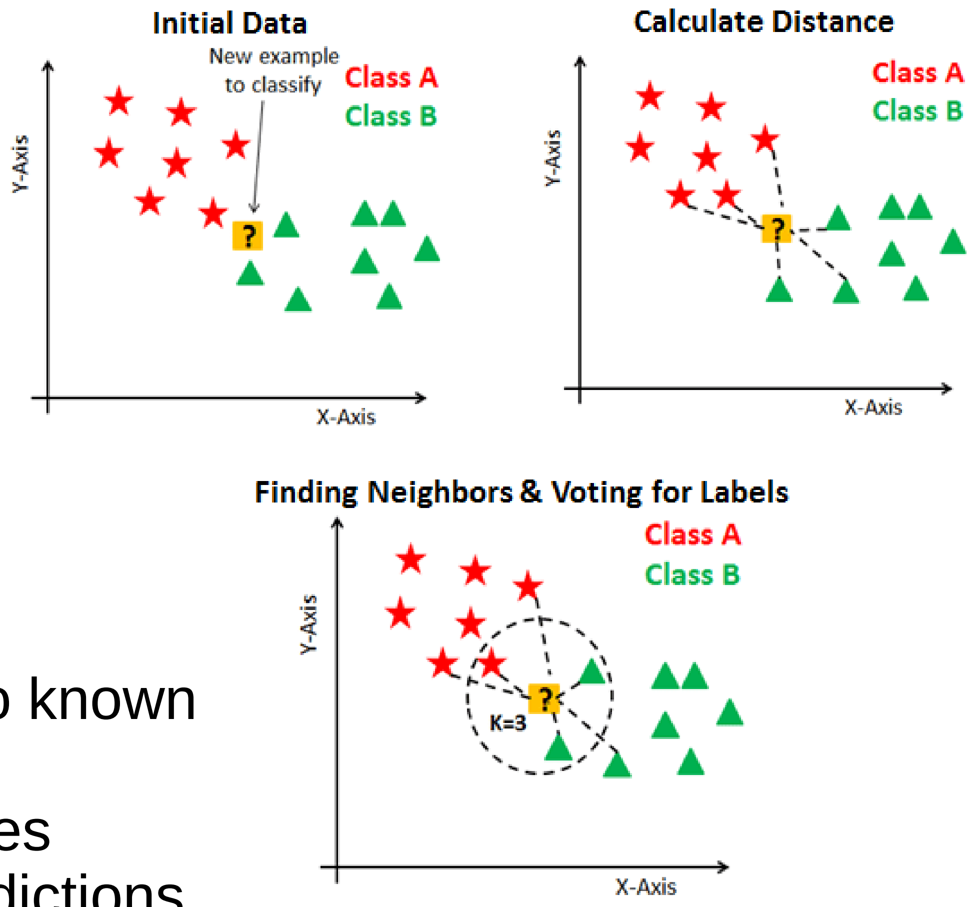
The values of the Pearson Correlation Coefficient lie in the interval [-1, 1]. At KNN the values of the similarity function

http://cs229.stanford.edu/proj2006/HongTsamis-KNNForNetflix.pdf

Algorithm 1 KNN algorithm

Input: $\mathbf{x}, S, d$
Output: class of $\mathbf{x}$
for $(\mathbf{x}', l') \in S$ **do**
  Compute the distance $\mathrm{d}(\mathbf{x}', \mathbf{x})$
end for
Sort the $|S|$ distances by increasing order
Count the number of occurrences of each class l_j among the k nearest neighbors
Assign to $\mathbf{x}$ the most frequent class

k-Nearest Neighbor
Classify $(\mathbf{X}, \mathbf{Y}, x)$ // $\mathbf{X}$: training data, $\mathbf{Y}$: class labels of $\mathbf{X}$, x: unknown sample
for $i = 1$ **to** m **do**
  Compute distance $d(\mathbf{X}_i, x)$
end for
Compute set I containing indices for the k smallest distances $d(\mathbf{X}_i, x)$.
return majority label for $\{\mathbf{Y}_i$ where $i \in I\}$

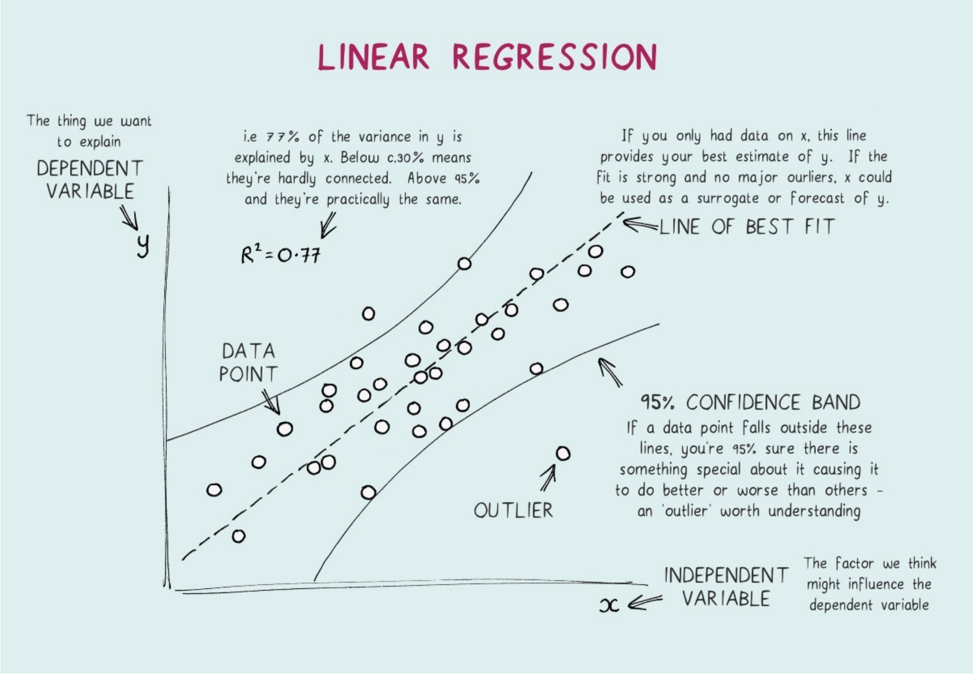


The k-nearest neighbors algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point.

- https://www.analyticsvidhya.com/blog/2015/08/learning-concept-knn-algorithms-programming/
- https://www.kaggle.com/datasets/netflix-inc/netflix-prize-data

...let's get to the data and get to work…

https://github.com/sierraporta/introductory-journey-data-science/blob/main/Notebooks/Clustering_Machine_Learning.ipynb



Regression methods

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