Data Mining and Machine Learning

Lecture 3: Data Preprocessing

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Data Preparation-1

Data Preparation= Data Cleansing+ Feature Engineering

Data cleansing converts the raw data into one of good quaity and ready for analysis. It includes the following tasks:

- Select, Filter and removal of duplicates
- Sampling
- Data Partitioning: Creation of the training, the validation and the test sets.
- Data Normalizacion.
- Data Reduction
- Data Integration.
- Discretization (Binning)
- Imputation of missing values

Data Preparation-2

Feature Engineering:
It selects the right attributes to be used in the Machine Learning Algorithm.
It involves

- The use of domain knowledge of the data to select or create attributes.
- Feature selection.
- Validation of how the features work with your model
- Feature Extraction: Principal component Analysis(PCA)

Data Preparation-3

Data Preparation: Data Preprocessing + Data Wrangling (Data Munging)

Data preparation can be classified in two, according to the moment of the analytic process when it is performed:

Data Preprocessing: Preparation of data directly after accessing it from a data source. Typically realized by a data scientist for initial transformations, aggregations and data cleansing. This step is done before the interactive analysis of data begins. It is executed once.

Data Wrangling: Preparation of data during the interactive data analysis and model building. Typically done by a data scientist to change views on a dataset and for features engineering. This step iteratively changes the shape of a dataset until it works well for finding insights or building a good analytic model.

Why Preprocess the Data?

- Data in the Real World Is Dirty: Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, transmission error
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation*=“ ” (missing data)
  - noisy: containing noise, errors, or outliers
    - e.g., *Salary*=“−10” (an error)
  - inconsistent: containing discrepancies in codes or names, e.g.,
    - *Age*=“42”, *Birthday*=“03/07/2010”
    - Was rating “1, 2, 3”, now rating “A, B, C”
    - discrepancy between duplicate records

Why Preprocess the Data?

- Intentional (e.g., *disguised missing* data)
  - Jan. 1 as everyone's birthday?
- It data does not have quality then results Machine Learning algorithms do not have quality! (GIGO Principle)
  - The quality of decisions is based on data quality.
  - A good Data Warehouse is built on integration of data having high quality.

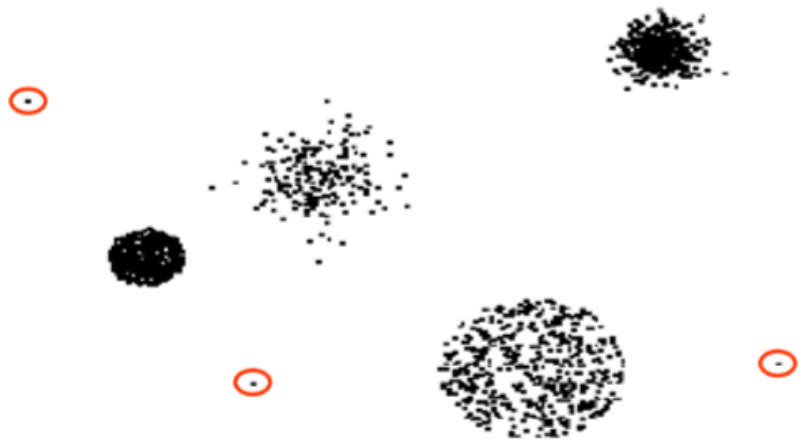
Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values (Noise) may be due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention.

Two Sine Waves **Two Sine Waves + Noise**

Outliers

- Outliers are data objects with characteristics that are considerably different than most of the other data objects in the data set



Major Tasks in Data Preprocessing

- **Data cleaning**
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
  - Integration of multiple databases, data cubes, or files
- **Data reduction**
  - Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results. It includes Dimensionality reduction, Numerosity reduction, Data compression
- **Data transformation**
  - Normalization
- **Data discretization(binning)**

Data Cleaning

- Tasks:
  - Fill in missing values valores.
  - Outlier Detection
  - Smoothing of noisy data.
  - Fixing inconsistences.

Handling of Missing Values

- Data is not always available
  - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
  - equipment malfunction
  - inconsistent with other recorded data and thus deleted
  - data not entered due to misunderstanding
  - certain data may not be considered important at the time of entry
  - not register history or changes of the data
- Missing data may need to be inferred.

Handling of Missing Values (cont)

- Several methods have been proposed in literature to treat missing data. Many of these methods were developed for dealing with missing data in sample surveys.
- Bello (1995), MV in regression
- Troyanskaya et al (2001), MV in unsupervised classification.
- Studies related to supervised classification
  - Chan and Dunn (1972) – Imputation on LDA for two class problems.
  - Dixon (1975) - k-nn imputation technique for dealing with missing values in supervised classification.
  - Tresp (1995)- missing value problem in a supervised learning context for neural networks.

Handling of Missing Values (cont)

- Impact of missing data
  - 1% missing data – trivial
  - 1-5% - manageable.
  - 5-15% - requires sophisticated methods
  - 15% - detrimental interpretation.

Example: The Census dataset

Also it is known as **Adult.**

48842 instances, it contains continuous, ordinals and nominal features (training set =32561 , test set=16281).

Remain 45222 instances after deleting instances containing at least one missing value. (Training set=30162, test=15060).

Size in Bytes=Training set 3.8M, Test set 1.9MB.

Available at: http://archive.ics.uci.edu/ml/

Donors: Ronny Kohavi y Barry Becker (1996).

Features in Census

- 1- age: continuous.
- 2- workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked. Nominal
- 3- fnlwgt (final weight) : Continuous.
- 4- education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool. Ordinal.
- 5- education-num: continous.
- 6- marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse. Nominal
- 7- occupation: Nominal

Features in Census

- 8-relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried. Nominal
- 9-race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black. Nominal
- 10-sex: Female[0], Male[1]. Nominal-Binary.
- 11-capital-gain: continuous.
- 12-capital-loss: continuous.
- 13-hours-per-week: continuous.
- 14-native-country: nominal
- 15 Salary: >50K [2], <=50K [1].

The census dataset

age	employme	education	edun	marital	…	job	relation	race	gender	hour	country	wealth
					…							
39	State_gov	Bachelors	13	Never_mar	…	Adm_cleric	Not_in_fam	White	Male	40	United_Sta	poor
51	Self_emp_	Bachelors	13	Married	…	Exec_man	Husband	White	Male	13	United_Sta	poor
39	Private	HS_grad	9	Divorced	…	Handlers_c	Not_in_fam	White	Male	40	United_Sta	poor
54	Private	11th	7	Married	…	Handlers_c	Husband	Black	Male	40	United_Sta	poor
28	Private	Bachelors	13	Married	…	Prof_speci	Wife	Black	Female	40	Cuba	poor
38	Private	Masters	14	Married	…	Exec_man	Wife	White	Female	40	United_Sta	poor
50	Private	9th	5	Married_sp	…	Other_serv	Not_in_fam	Black	Female	16	Jamaica	poor
52	Self_emp_	HS_grad	9	Married	…	Exec_man	Husband	White	Male	45	United_Sta	rich
31	Private	Masters	14	Never_mar	…	Prof_speci	Not_in_fam	White	Female	50	United_Sta	rich
42	Private	Bachelors	13	Married	…	Exec_man	Husband	White	Male	40	United_Sta	rich
37	Private	Some_coll	10	Married	…	Exec_man	Husband	Black	Male	80	United_Sta	rich
30	State_gov	Bachelors	13	Married	…	Prof_speci	Husband	Asian	Male	40	India	rich
24	Private	Bachelors	13	Never_mar	…	Adm_cleric	Own_child	White	Female	30	United_Sta	poor
33	Private	Assoc_acd	12	Never_mar	…	Sales	Not_in_fam	Black	Male	50	United_Sta	poor
41	Private	Assoc_voc	11	Married	…	Craft_repai	Husband	Asian	Male	40	*MissingVa	rich
34	Private	7th_8th	4	Married	…	Transport_	Husband	Amer_India	Male	45	Mexico	poor
26	Self_emp_	HS_grad	9	Never_mar	…	Farming_fi	Own_child	White	Male	35	United_Sta	poor
33	Private	HS_grad	9	Never_mar	…	Machine_c	Unmarried	White	Male	40	United_Sta	poor
38	Private	11th	7	Married	…	Sales	Husband	White	Male	50	United_Sta	poor
44	Self_emp_	Masters	14	Divorced	…	Exec_man	Unmarried	White	Female	45	United_Sta	rich
41	Private	Doctorate	16	Married	…	Prof_speci	Husband	White	Male	60	United_Sta	rich
:	:	:	:	:	:	:	:	:	:	:	:	:

Reading the data file using Python

```
import pandas as pd
df = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-
databases/adult/adult.data', header=None, sep=',‘,na_values=“ ?”)
df.columns=['v1', 'v2', 'v3', 'v4',v5','v6','v7','v8','v9','v10','v11','v12','v13','v14','class’]
```

Another way:

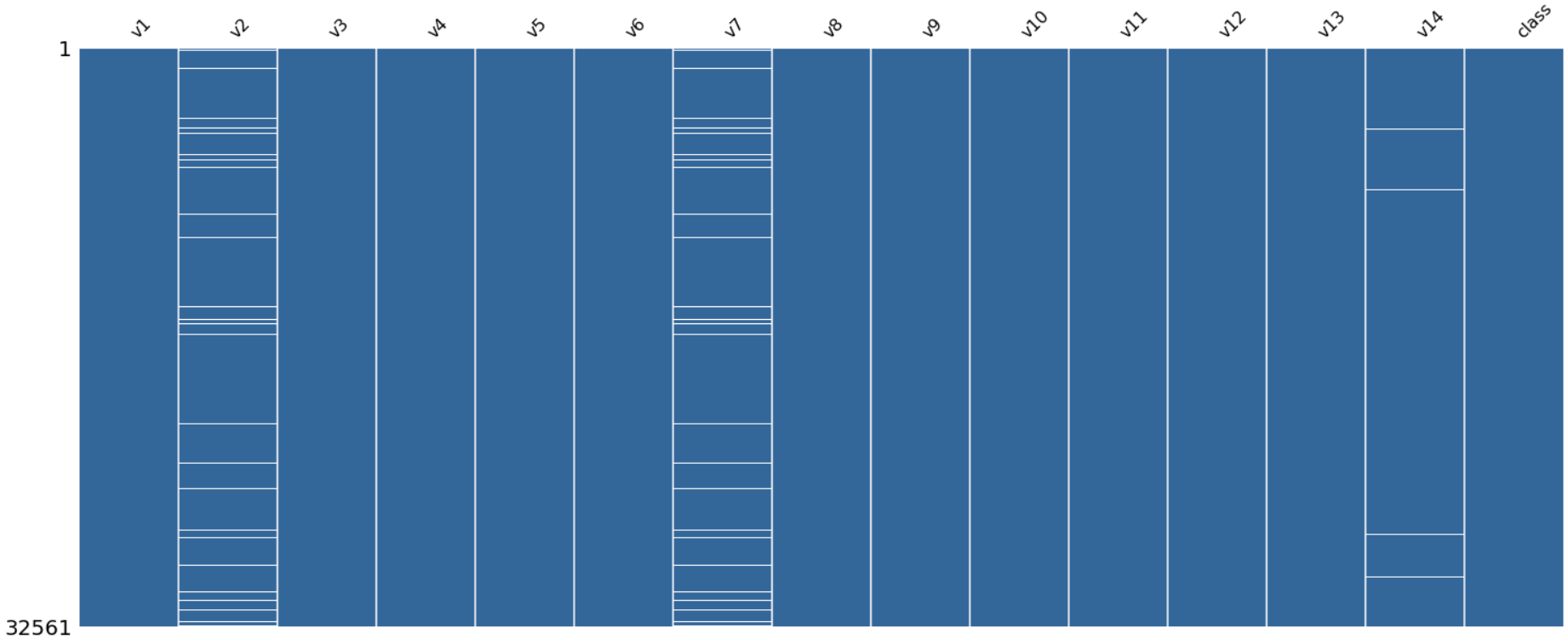
```
 import pandas
names=['v1','v2','v3','v4','v5','v6','v7','v8','v9','v10','v11','v12','v13','v14','clase']
data=pandas.read_csv('c://PW-PR/census.csv',names=names)
print(data.shape)
(32562, 15)
data.describe()
```

Pyhton functions dealing with missing values

Asssuning that df is a Pandas dataframe

- To find out columns containing missing values
  colmiss=df.columns[df.isnull().any()].tolist()
- To find out columns containing missing values
  rowmiss=df.index[df.isnull().T.any()].tolist()
- To find out the percentage of rows with missing values
  df.isnull().T.any().sum()*100/float(len(df))
- To find out the percentage of missing values per column
  df[colmiss].isnull().sum()*100/float(len(df))
- Deleting all the rows conatining missing values
  dfclean=df.dropna()
  print dfclean.shape
  (30162, 15)

Visualizing the missing values



A “clean” function

- Build a function for deleting columns and rows with a large amount of missing values. Something like:

clean(df,tol.col=.5,tol.row=.3)

In here, from the dataframe df we are deleting columns with more than 50 % of missing vaues and rows with more than 30% of missings

Modules in Python to impute missing values

The module scikit-learn has a class named imputer to carry out inputation.

The function fill.na in pandas does imputation.

Also, there are two other module for imputation

Fancyimpute

impyte

Both of them run only in Python 3.

Treating Missing values

- Case/Pairwise Deletion. Ignore the tuple: usually done when class label is missing (assuming the tasks in classification—not effective when the percentage of missing values per attribute varies considerably.
- Parameter estimation, where Maximum likelihood procedures that use variants of the Expectation-Maximization algorithm can handle parameter estimation in the presence of missing data.
- Imputation techniques, where missing values are replaced with estimated ones based on information available in the data set.

Treating Missing Values

- **Mean Imputation (MI)** - Replace the missing data for a given feature (attribute) by the mean of all known values of that attribute in the class to which the instance with missing attribute belongs.
- **Median Imputation (MDI).** Since the mean is affected by the presence of outliers it seems natural to use the median instead just to assure robustness. In this case the missing data for a given feature is replaced by the median of all known values of that attribute in the class to which the instance with missing feature belongs.

Mean Imputation using Pandas:

```
df.fillna(df.mean())
df.apply(lambda x: x.fillna(x.mean()),axis=0)
```

K-Nearest Neighbors Imputation

Divide the data set D into two parts. Let D_m be the set containing the instances in which at least one of the features is missing. The remaining instances with complete feature information form a set called D_c.

For each vector **x** in D_m:

- A) Divide the instance vector into observed and missing parts as $x = [xo; xm]$.
- B) Calculate the distance between the xo and all the instance vectors from the set D_c. Use only those features in the instance vectors from the complete set D_c, which are observed in the vector x.
- C) Use the K closest instances vectors (K-nearest neighbors) and perform a majority voting estimate of the missing values for categorical attributes. For continuous attributes replace the missing value by the mean of the attribute in the k-nearest neighborhood. Also a weighted mean can be used.

K-nn Imputation

A1	A2	A3	A4	Clase
4	5	6	NA	1
5	1	1	4	1
7	9	2	5	1
8	2	8	5	1
6	4	2	6	1

There is a missing value in record 1. We will predict this NA value using knn. Dist(r1,r2)= sqrt[(4-5)^2+(5-1)^2+(6-1)^2]= 6.48, Dist (r1,r3)=6.40, Dist(r1,r4)=5.38, Dist(r1,r5)= 4.58. There is a function distance in the module scipy.spatial. Also numpy.linalg,norm compute the Euclidean distance between to arrays. Using k=1 nearest neighbor, this is record r5, NA would be replaced by 6, using k=3 nearest neighbors: r3,r4 y r5, NA would be replaced by the average value of 5, 5 and 6 that is 5.33

K-nn Imputation (cont)

- The method can not be applied if all the rows have at least a missing value.
- Usually, k is taken equals to 10. The k value is at most equals to the number of complete rows.Usualmente, se toma k igual a 10.
- If the dataset contains numerical and categorical atributes the the euclidean distance can be replaced by the Gower distance.

.

Other imputation methods

- Hot deck and Cold deck. [nces.ed.gov/statprog]
- Prediction model: Linear regresion (continuous attribute), Logistic regresion(Binary attribute), Polychotomous logistic (nominal attributes). The attribute with the missing value is used as the response variable and the remaining attributes are considered predictors. Drawbacks: It can created bias, requires high correlation among predictors. Slow computation.
- Multiple imputation
- The EM algorithm
- Decision trees have their own approach to treat missing values.

Other imputation methods (cont)

- Multiple Imputation. The missing values are imputed several times by choosing randomly from the observed values. The final prediction is obtained by combining the individual predictions.
- The SVD method ($X=U\Sigma V'$). It is iterative. Initially missing values are replaced by the mean of the corresponding column and in each iteration these values are updated until the norm of the matrix converges.

- The above approaches are too expensive.

Effect of the treatment of Missing values

- For datasets with an small amount of missing values, say less than 1 percent, deleting the cases containing missing values does not have much affect on the performance of the machine learning algorithm. However the variability of the estimated error increases.
- There is not much difference between mean imputation and median imputation.
- The effect of the missing values depends on the way that they are distributed on the table and its location with respect to the most important features.
- The percentage of instances containing missing values has more effect than the percentage o table cells containing missing values on the performance of the algorithm.

Preprocessing-Normalization

- Data normalization consists in scaling the attribute values of the data into an small specified range, such as -1 to 1 or 0 to 1.
- Also, it is known as range normalization.
- There is also variance normalization but mostly is used in bioinformatics

Reasons for normalizing

Normalizing the input data will help speed up the learning phase.

Attributes with initially large ranges will outweigh attributes with initially smaller ranges, then dominate the distance measure. For instance, the K-nearest neighbor classifier using a Euclidean distance measure depends on all input dimensions being scaled equally.

Some kind of data normalization also may be necessary to avoid numerical problems such as precision loss from arithmetic overflows.

Z-score normalization

The V values are normalized based on the mean and standard deviation.

$V' = (V - \text{mean}) / \text{std}$

This method works well in cases when you do not know the actual minimum and maximum of your input data or when you have outliers that have great effect on the range of the data.

It can be done with pandas or with the class StandardScaler from scikit-learn

Min-Max normalization

It performs a linear transformation on the original data V into the specified interval [newmin,newmax]

$$V' = (V - min) * (newmax - newmin) / (max - min) + newmin$$

The advantage of this method is that it preserves all relationships of the data values exactly. It does not introduce any potential bias into the data. The disadvantage is that it will encounter an "out of bounds" error if a future input case falls outside of the original data range.

It can be done with Pandas or with the class MinMaxScaler from scikit-learn

Normalization by decimal scaling

It normalizes by moving the decimal point of values. The number of decimal points moved depends on the maximum absolute value.

$V' = V / 10^j$ where j is the smallest integer such that $Max(|V'|) < 1$.

Only useful when attributes values are greater than 1 in absolute value

Sigmoidal normalization

It transforms the input data nonlinearly into the range -1 to 1, using a sigmoid function.

V' = (1 - e^(-a)) / (1 + e^(-a)) where a = (V - mean) / std

Data points within a standard deviation of the mean are mapped to the almost linear region of the sigmoid. Outlier points are compressed along the tails of the sigmoidal function.

Sigmoidal mormalization is especially appropriate when you have outlier data points that you wish to include in the data set. It prevents the most commonly occurring values from being compressed into essentially the same values without losing the ability to represent very large outlier values.

Softmax Normalization

It is so called because it reaches "softly" toward its maximum and minimum value, never quite getting there. The transformation is more or less linear in the middle range, and has a smooth nonlinearity at both ends. The whole output range covered is 0 to 1 and the transformation assures that no present value lies outside this range.

$$V' = 1 / (1 + e^{(-a)})$$

where $a = (V - \text{mean}) / \text{std}$