LECTURER: TAI LE QUY

MACHINE LEARNING

UNSUPERVISED LEARNING AND FEATURE ENGINEERING

TOPIC OUTLINE

UNIT 4

FEATURE ENGINEERING

STUDY GOALS

- Explain the difference between **numerical**, **categorical**, and **text** features.
- **Clean**, **scale**, **encode**, or **transform** these features.
- Generate **new features** by **transforming**, **splitting**, or **grouping** existing features as interaction features.

EXPLAIN SIMPLY

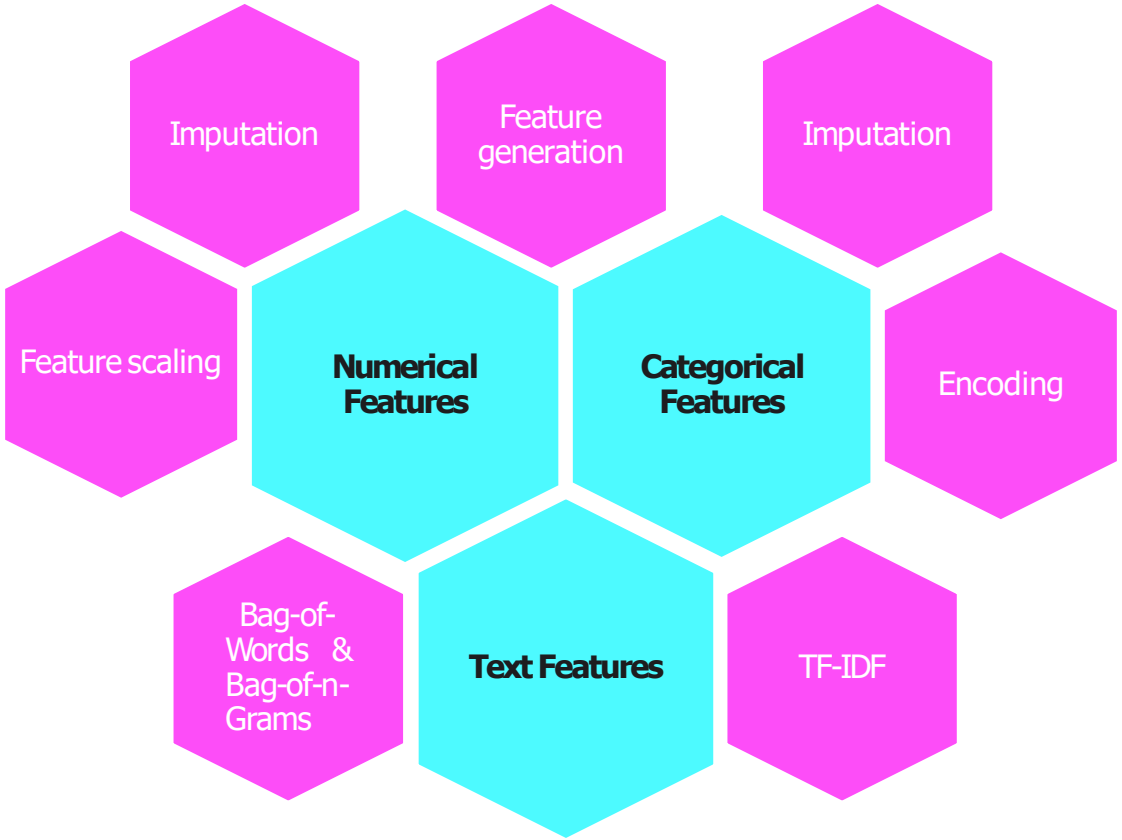
1. Name and explain **three different methods** to deal with **missing values** in a dataset.

2. Explain why, during data preprocessing, **features** are often **scaled**.

3. Name **three methods** that can be applied to **count words** in text data.

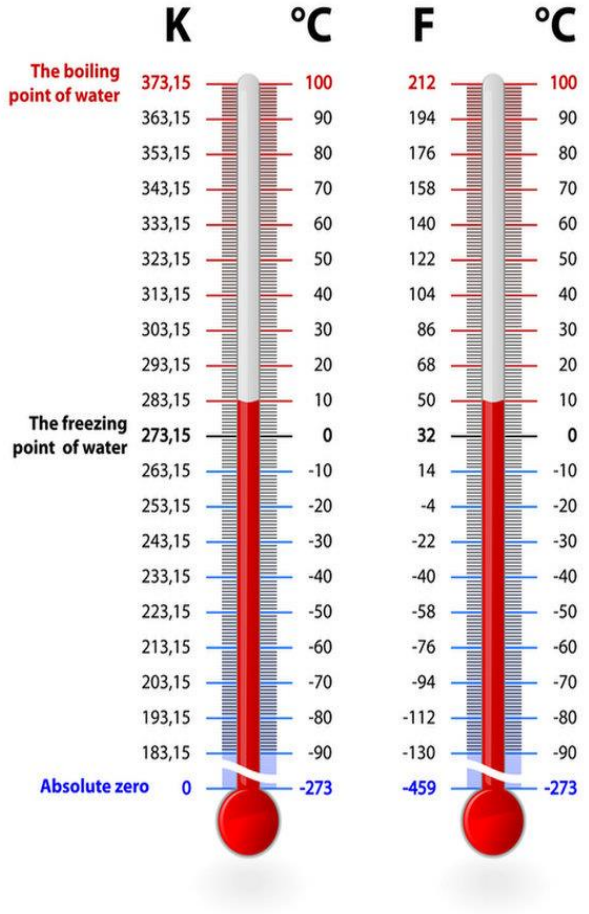
UNIT CONTENT

Image 1: Unit content - Feature engineering



Source of the image: Müller-Kett, 2021.

- Interval scales
  - Differences between values are meaningful
    - The difference between 90° and 100° temperature is the same as the difference between 40° and 50° temperature.
    - Examples: Calendar dates , Temperature in Farenheit or Celsius
    - Ratios till has no meaning
      - A temperature of 2° Celsius is not much different than a temperature of 1° Celsius.
      - The issue is that the 0° point of the Celsius scale is in a physical sense arbitrary and therefore the ratio of two Celsius temperatures is not physically meaningful.
- Ratio scales
  - Both differences and ratios have a meaning
  - E.g., age, weight, length, number of sales
    - A 100 kgs person is twice heavy as a 50 kgs person
    - Temperature in Kelvin: When measured on the Kelvin scale, a temperature of 2° is, in a physical meaningful way, twice that of a 1°. The zero value is absolute 0, represents the complete absence of molecular motion



Types of missing values

- Missing **Completely At Random** (MCAR)
  - The probability of being missing is the same for all cases

- Missing **At Random** (MAR)
  - The probability of being missing is the same only within groups defined by the observed data

- **Not** Missing **At Random** (NMAR)
  - The probability of being missing varies for reasons that are unknown

Source of the text: Badr, 2019.

Types of imputation

- List-wise imputation / complete list
- Mean /median /default substitution
- k-Nearest Neighbors
- Regression
- Multiple imputation
  - Multiple Imputation by Chained Equations (MICE) algorithm

Image 2: Filling the gap

Source of the image: Microsoft Archive.

Min-max scaling /normalization

- Resulting range [0, 1]
- $z = \frac{x_i - min(x)}{max(x) - min(x)}$
- Susceptible to outliers

Image 3: Scaling

Source of the image: Microsoft Archive.

Variance scaling /standardization

- Mean(z) =0, Std(z) =1
- $z = \frac{x - mean(x)}{std(\mathrm{x})}$
- Susceptible to outliers

Image 3: Scaling

Source of the image: Microsoft Archive.

Robust scaling

- Similar to standarization
- $z = \frac{x - median(x)}{IQR(x)}$
- Not susceptible to outliers

Image 3: Scaling

Source of the image: Microsoft Archive.

COMPARISON BETWEEN FEATURE SCALING TECHNIQUES IN THE CASE OF SPARSE DATASET

- Robust scaling has the advantage of being more adapted to scale-sparse data points than min-max scaling and standardization (use of the median and IQR of data points)
- Min-max scaling and standardization compress most of the data points to a narrow range, while robust scaling does much better at keeping the spread of the data points.

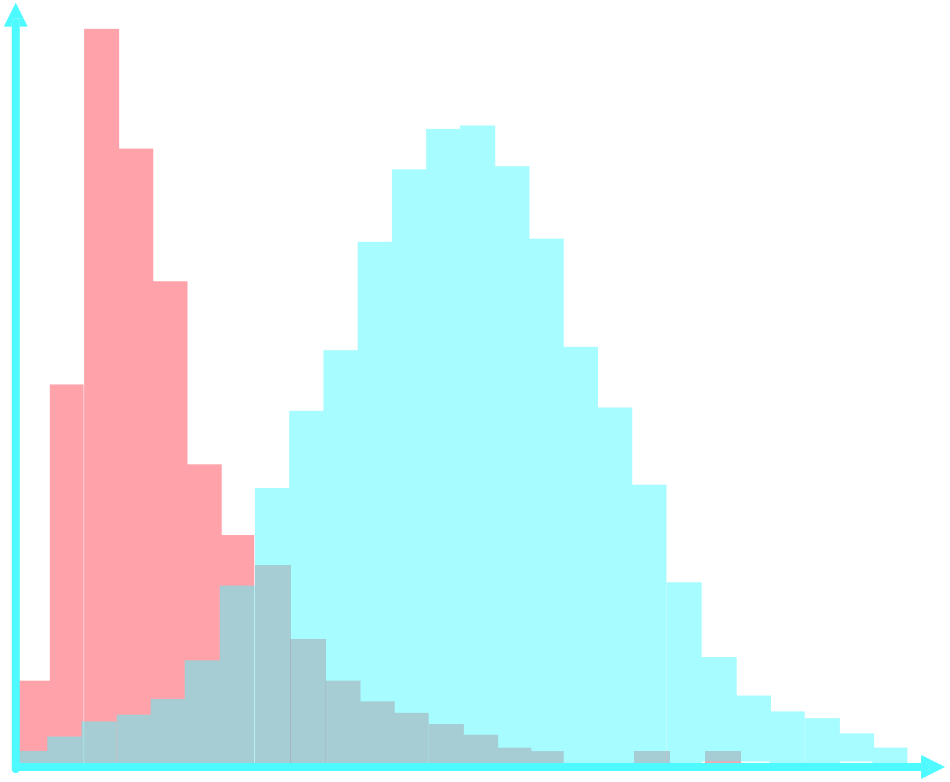
C-ID	Consumption	Min-max scaling of consumption	Standardization of consumption	Robust scaling of consumption
1	70	0.004	−0.50	0
2	140	0.015	−0.47	0.93
3	65	0.003	−0.50	−0.06
4	40	0.000	−0.51	−0.4
5	**6500**	**1**	**2**	**85.73**

New features can be generated as a transformation or combination of existing features

Transformation

- Better interpretability
- Meet statistical assumptions

Image 4: Feature transformation



Source of the image: Müller-Kett, 2023.

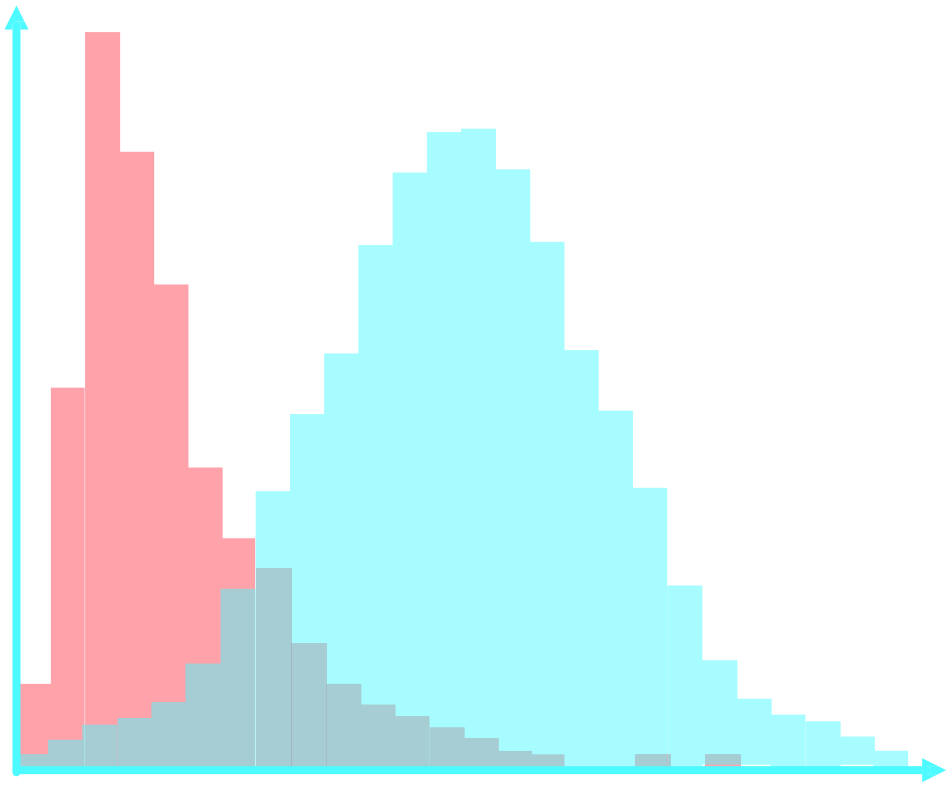
Transformation types

- Square transformation
- Exponential transformation
- Reciprocal transformation
  Eg. population density → area per person
- Log transformation
  Make a nonlinear relationship more linear (e.g., Log(x2) = 2Log(x))

Transform skewed data points to approximately conform to normal distribution

- Others: min, max, variance, mean, median, sum, count

Image 4: Feature transformation



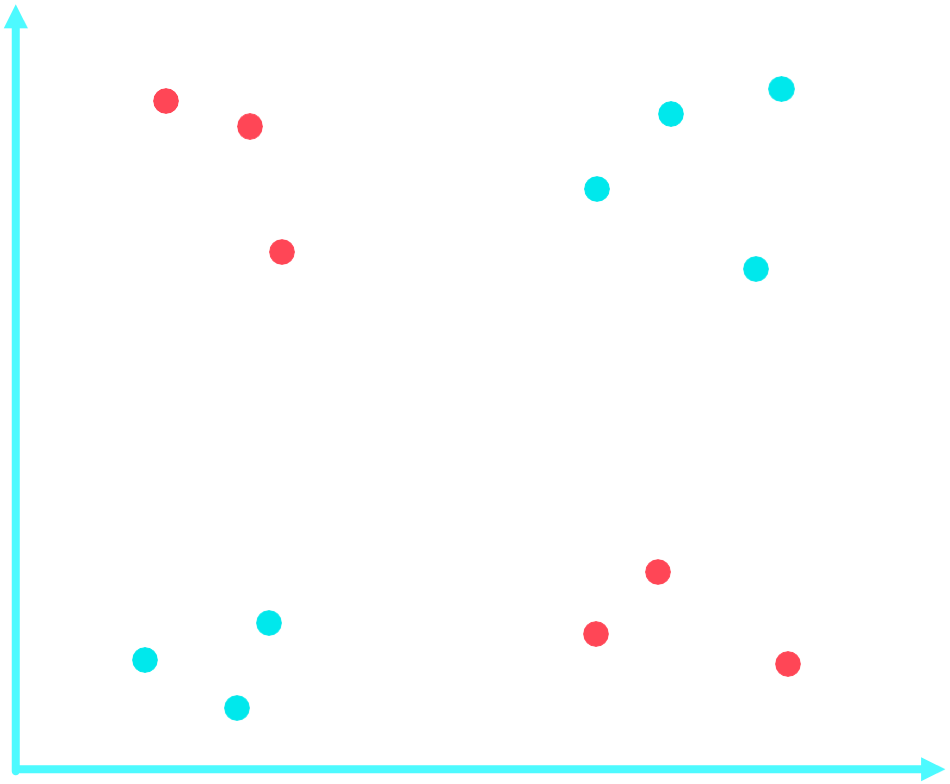
The choice depends on the available dataset and domain application

Source of the image: Müller-Kett, 2023.

Interaction features

- Combining information from two or more features
- Polynomial combinations
- Boolean operators

Image 5: Interaction features

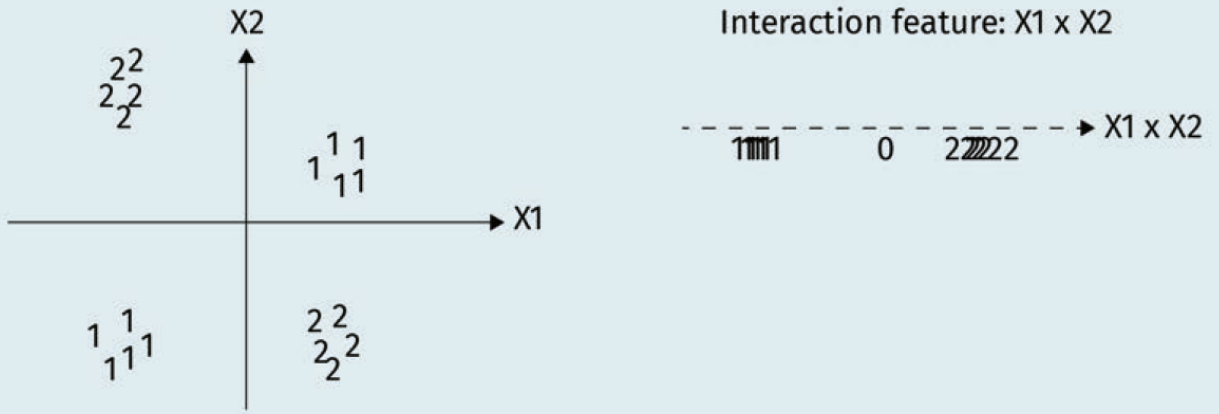


Source of the image: Müller-Kett, 2023.

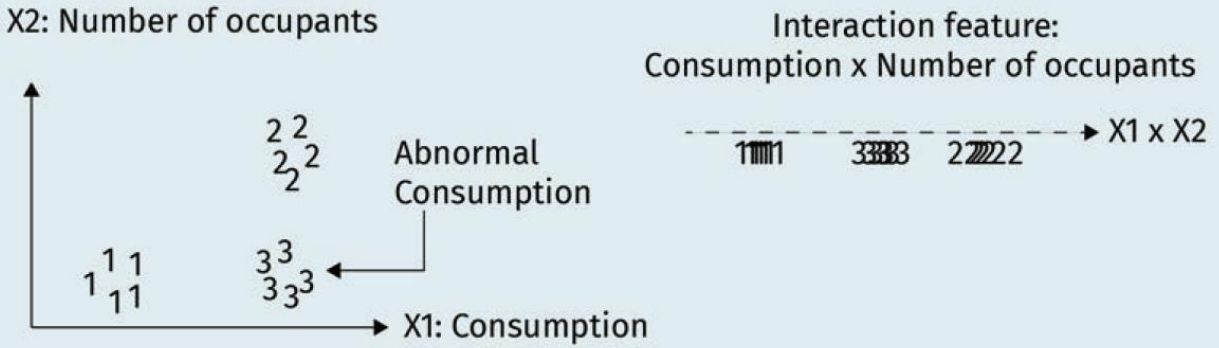
Interaction features

Motivation to Use Cross Product Features for Energy Consumption Example		
2	70	140
4	**140**	**560**
2	65	130
1	40	40
2	65	130

Use of an Interaction Feature to Discriminate Two Different Clusters



Interest of the Use of Interaction Features to Discriminate The Abnormal Consumption Cluster



Source of the image: Müller-Kett, 2023.

Feature Cleaning (Imputing Missing Values)

- Missing values can be replaced with the maximum occurred value in the corresponding column (feature)

Imputing a Missing Value in the Gender Feature of the Energy Consumption Example		
C-ID	Gender before imputing	Gender after imputing by replacing by the maximum occurred value
1	M	M
2	NA	M
3	M	M
4	F	F
5	F	F

Source of the image: Müller-Kett, 2023.

FEATURE ENCODING

- **Translate** each category to a numeric value
- **One-hot encoding**
  - One column for each unique category
  - 1 for applicable
  - 0 for non-applicable

Image 7: Zeros and ones

One-Hot Encoding for Gender and Work-types Features of a Table				
Gender-M	Gender-F	Work-type-1	Work-type-2	Work-type-3
1	0	1	0	0
0	1	0	1	0

Source of the image: Microsoft Archive, Müller-Kett, 2023.

Types of imputation

- List-wise imputation / complete list
- Mode /default substitution
- k-Nearest Neighbors
- Classification
- Multiple imputation
  - Multiple Imputation by Chained Equations (MICE)

Image 2: Filling the gap

Source of the image: Microsoft Archive.

FEATURE GENERATION

- **Splitting /spreading**
- Extract useful features from raw and irrelevant features
- **Grouping**
- **Date extraction**
  - Year, month, quarter, day of the week
  - Elapsed time
  - Weekdays, holidays

Image 6: Information in columns

Source of the image: Microsoft Archive.

Cross products features (interaction features)

Certain features grouped together can generate useful information

Example Showing Whether the Gender Affects the Status of Receiving a Grant	
Gender	Scientific-Grant
M	Y
F	N
M	Y
F	N
F	Y
M	N
F	N
M	N

Source of the image: Müller-Kett, 2023.

BAG-OF-WORDS (BOW)

- **Tokenizer /naïve scoring**
- **Word counts**
  - Each unique word in a text or document represents one dimension or feature
- **Stop words** must be removed
  - "a," "an," "the," "they," "where," "etc.," punctuation, white spaces, and so on
- Does not preserve **semantics** or **categorical hierarchies**
  - "dog toy" and "toy dog" have different semantics while sharing the same BoW

Image 8: Text data

"Martin is not bad person. Kevin, Martin's brother, is bad person."
The text feature is ['bad', 'brother', 'is', 'Kevin', 'Martin', 'not', 'person']
BoW = [[1 0 1 0 1 1 1] [1 1 1 1 1 0 1]].

Source of the image: Microsoft Archive.

BAG-OF-N-GRAMS

- Counts **n successive words**
  - one word is 1-gram or unigram, two successive words is 2-grams or bigram
- **Stop words** must be removed
- **Punctuation** is regarded words
- Aims to preserve **semantics** to some extent
  - The higher the number of successive words to consider n, the better the conserved information or semantic
  - A feature text of p individual words, there are p^2 bigrams

Image 8: Text data

"Martin is not bad person. Kevin, Martin's brother, is bad person."
Bag-of-2-Grams feature text ['Kevin Martin', 'Martin brother',
'Martin is', 'bad person', 'brother is', 'is bad', 'is not', 'not bad']
BoW vector [[0 0 1 1 0 0 1 1] [1 1 0 1 1 1 0 0]].

Source of the image: Microsoft Archive.

TERM FREQUENCY-INVERSE DOCUMENT FREQUENCY (TF-IDF)

- Counts the words **per document**
  - weights the words by their occurrence frequency in the text.
- **Term Frequency (TF)**
  - Number of word occurrences in a document
- **Inverse Document Frequency (IDF)**
  - Number of documents and number of overall word occurrences
  - Often logarithmized
- **Often normalized** by all TF-IDF values

Image 8: Text data

Source of the image: Microsoft Archive.

TERM FREQUENCY-INVERSE DOCUMENT FREQUENCY (TF-IDF)

$$TF - IDF = BoW(w,d) \,.\, \frac{N}{n_w} = TF \,.\, IDF$$

- BoW(w,d) be the number of times that the word w appeared in a document d (the frequency term (TF) of word w in document d.
- Inverse Document Frequency (IDF) is the number of documents N in the dataset divided by the number n_w that the word w occurred in the documents contained in the dataset

Example:

1. The first document d_1 is "Martin is good person"
2. The second document d_2 is "Kevin is bad person"

Feature vector: ['Kevin', 'Martin', 'bad', 'good', 'is', 'person'].

TF (Kevin,d_1) =0, TF (Martin,d_1) =1, TF (bad,d_1) =0, TF (good,d_1) =1, TF (person,d_1) =1 TF (Kevin,d_2) =1, TF (Martin,d_2) =0, TF (bad,d_2) =1, TF (good,d_2) =0, TF (person,d_2) =1

IDF(Kevin,d_1) =(N=2/n_w=1)=2, IDF(Martin,d_1) = (2/1)=2, IDF(bad,d1) =(2/1)=2, IDF(good,d_1) =(2/1)=2, IDF(person,d_1) =(2/2)=1, IDF(Kevin,d_2) =(2/1)=2, IDF(Martin,d_2) = (2/1)=2, IDF(bad,d_2) = (2/1)=2, IDF(good,d_2) = (2/1)=2, IDF(person,d_2) = (2/2)=1

TERM FREQUENCY-INVERSE DOCUMENT FREQUENCY (TF-IDF)

Often, we take the log of IDF instead of the raw IDF

$$TF - IDF = TF \,.\, IDF = BoW(w, d) \,.\, \log_2\left(\frac{N+1}{n_w+1} + 1\right)$$

TF(Kevin,d_1) = 0, IDF(Kevin,d_1) = $\log_2((2+1)/(2+1))+1$ = 1, therefore, TF-IDF = 1

TF(good,d_1) = 1, IDF(good,d_1) = $\log_2((2+1)/(1+1))+1$ = 1.4, TF-IDF = 1.4

TF-IDF for a Simple Dataset of Two Simple Documents

Word	TF		IDF	TF-IDF	
	d_1 (0)	d_2 c		d_1 (0)	d_2 (1)
Kevin (0)	0	1	$\text{Log}_2(3/2)+1$	0	1.4
Martin (1)	1	0	$\text{Log}_2(3/2)+1$	1.4	0
bad (2)	0	1	$\text{Log}_2(3/2)+1$	0	1.4
good (3)	1	0	$\text{Log}_2(3/2)+1$	1.4	0
is (4)	1	1	$\text{Log}_2(3/3)+1$	1	1
person (5)	1	1	$\text{Log}_2(3/3)+1$	1	1

d_1: "Martin is good person"
d_2: "Kevin is bad person"

Source of the image: Müller-Kett, 2023.

TERM FREQUENCY-INVERSE DOCUMENT FREQUENCY (TF-IDF)

- The computed TF-IDF is not scaled or normalized
- It is very useful to scale the TF-IDF to obtain unbiased TF-IDF with respect to the document length
- There are several norms used to normalize TF-IDF. One of the most used norms is l2 norm.

$$(TF-IDF(w_i,d))_{l2} = TF-IDF\left(w_i,d\right) / \sqrt{\sum_{w_k \in d} (TF-IDF(w_k,d))^2}$$

Normalized TF-IDF According to l2 Norm for a Simple Dataset of Two Simple Documents

	Kevin (0)	Martin (1)	bad (2)	good (3)	is (4)	person (5)
d1 (0)	0	0.57	0	0.57	0.40	0.40
d2 (1)	0.57	0	0.57	0	0.40	0.40

Source of the image: Müller-Kett, 2023.

REVIEW STUDY GOALS

- Explain the difference between **numerical**, **categorical**, and **text** features.
- **Clean**, **scale**, **encode**, or **transform** these features.
- Generate **new features** by **transforming**, **splitting**, or **grouping** existing features as interaction features.

SESSION 4

TRANSFER TASK

TRANSFER TASKS

A start-up that sells **sustainable products in smaller stores worldwide** has been very successful in recent years. As a Data Scientist, you and your team are **tasked with tidying up the data** stored in the company's databases. During a quick scan, you noticed the following issues:

- There are **gaps** in the data. Consulting the ones who collected the data, you learn that some gaps are the result of a longer **power shortage** and others were not filled out, as this information is **evident from other columns**
- The columns contain values with highly **different ranges**, some with values between 0.1 and 1 and others between 100 and 1000
- There seem to be some **extreme values** that are **not outliers** to be removed but correct values
- Some columns are **hard to interpret**. For example, there is a column containing the persons per squared sales for some reason
- The **stores are encoded as integers** (1 for the first store, 2 for the next store, …)
- The **product names** and **IDs** are stored in **one column**
- You are also assigned the task of **sorting the products into categories**. You noticed a **textual description** for each product that might be for this.

Describe how you would approach these tasks.

TRANSFER TASK
PRESENTATION OF THE RESULTS

Please present your results.

The results will be discussed in plenary.

1. Which of the following scale levels is a person’s age?
   a) an interval scale
   b) a ratio scale
   c) a nominal scale
   d) an ordinal scale

2. Which of the following scale levels is customer satisfaction (low, medium, high)?
   a) an ordinal scale
   b) a ratio scale
   c) an interval scale
   d) a ratio scale

3. Which of the following scale levels are car brands?
   a) an ordinal scale
   b) a ratio scale
   c) a nominal scale
   d) an interval scale

LIST OF SOURCES

Text

Badr, W. (2019). 6 Different Ways to Compensate for Missing Values In a Dataset (Data Imputation with examples). Popular strategies to statistically impute missing values in a dataset, Towards Data Science, https://towardsdatascience.com/6-different-ways-to-compensate-for-missing-values-data-imputation-with-examples-6022d9ca0779

Images

Müller-Kett, 2021.
Müller-Kett, 2023.
Microsoft Archive.