Data Analytics in Cyber Security (CT115-3-M) (Version E)

Data Preprocessing

TOPIC LEARNING OUTCOMES

At the end of this topic, you should be able to:

1. Understand feature selection techniques
2. Understand the importance of Exploratory Data Analysis (EDA)
2. Understand data preparation techniques

Machine Learning Pipeline

What do I have
What do I need
What can I get

- Problem Definition
- Data collection

"Objective" in "objective function"

- Feature extraction
  - Flattening, Labeling
- Data preparation
  - Normalisation by data type
  - Dimensionality reduction

Exploratory Data Analysis (EDA)

Selection of metrics

- Algorithm Selection
  - Train and Test
- Performance Evaluation
  - Visualisation
  - Parameter tuning
- Model Validation

May have special data preparation requirements

Repeat Train and Test

Contents & Structure

- Feature Selection
- Exploratory Data Analysis (EDA)
- Data Preparation

Data Preprocessing

- Data preprocessing is the first step in any machine learning project – **Feature Extraction** and **Data Preparation**.
- Data preprocessing can refer to manipulation or dropping of data before it is used to ensure or enhance performance and is an important step in machine learning process.
- The phrase "garbage in, garbage out" is particularly applicable to machine learning projects. If we use unclean data for machine learning, the result will not be satisfying enough for our end application

Machine Learning Pipeline

- Problem Definition
- Data collection
- Feature extraction
  - Flattening.Labeling
- Data preparation
  - Normalisation by data type
  - Dimensionality reduction
- Algorithm Selection
  - Train and Test
- Performance Evaluation
  - Visualisation
  - Parameter tuning
- Model Validation

Feature Extraction

- **Goal:** Specifying features useful for prediction
- **Methods:** Check distributions, correlation/covariance checks, drop unique identifiers
- **Outcome:** A “flat” (single table) dataset with selected features.

Exploratory Data Analysis (EDA)

- EDA is an important step to first understand the data (identify the trends and patterns within the data, detect outliers or anomalous events, find interesting relations among the variables, points of interest, etc.) before using them for modeling, machine learning, etc.

Checking

1. Feature Distributions
2. Class balance
3. Correlation between input variables and target variable
4. Correlation between input variables (collinearity)

Since the dataset will always be large, <u>visualization</u> is essential

Feature Selection

- The dataset may have many features that may not all be relevant and significant.
  - For certain types of data, like genetics or text, the number of features can be very large compared to the number of data points.
  - Curse of dimensionality: error increases with the increase in the number of features.
- Feature selection is a process of selecting the most relevant variables. The goal is to determine which columns are more predictive of the output.
  - Also called “dimensionality reduction” and “feature engineering”.

Feature Value Variance

- Columns with low variance provide less information for distinguishing one type of thing from another
  - *Remove unique identifiers*

- Columns with high variance have so many unique values that there may be less information for distinguishing one type of thing from another
  - *'bin' values to reduce the number of unique values*

Feature Covariance

- In the worst case, one feature can explain (or already determine) all the other features and makes them obsolete.
- This results in a high redundancy among the features, increasing computational overhead
- The covariance matrix can be used to find redundant features (those that measure the same thing), and make decisions about which can be removed

$$cov_{x,y} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{N-1}$$

$cov_{x,y}$ = covariance between variable x and y

x_i = data value of x

y_i = data value of y

$\bar{x}$ = mean of x

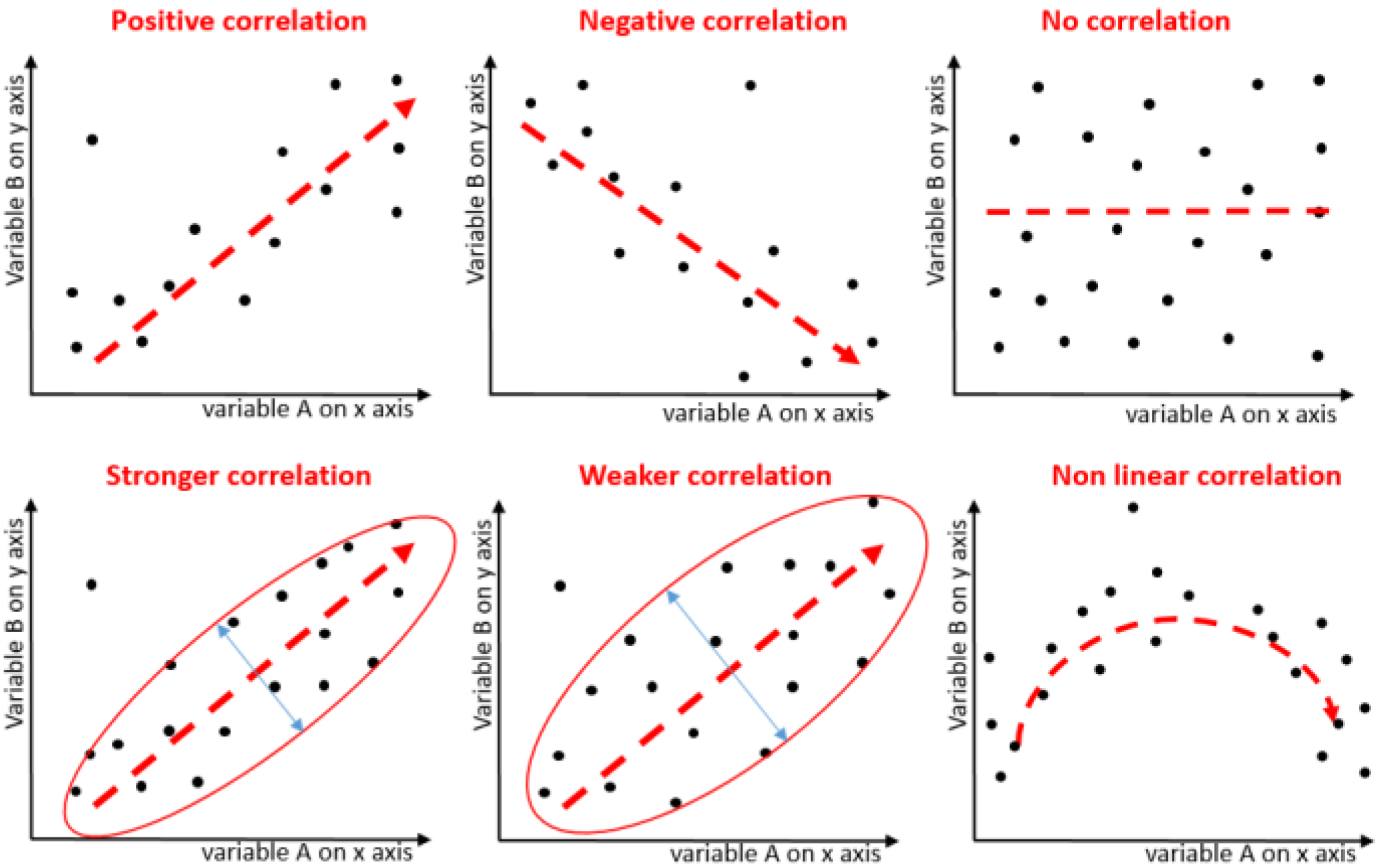
$\bar{y}$ = mean of y

N = number of data values

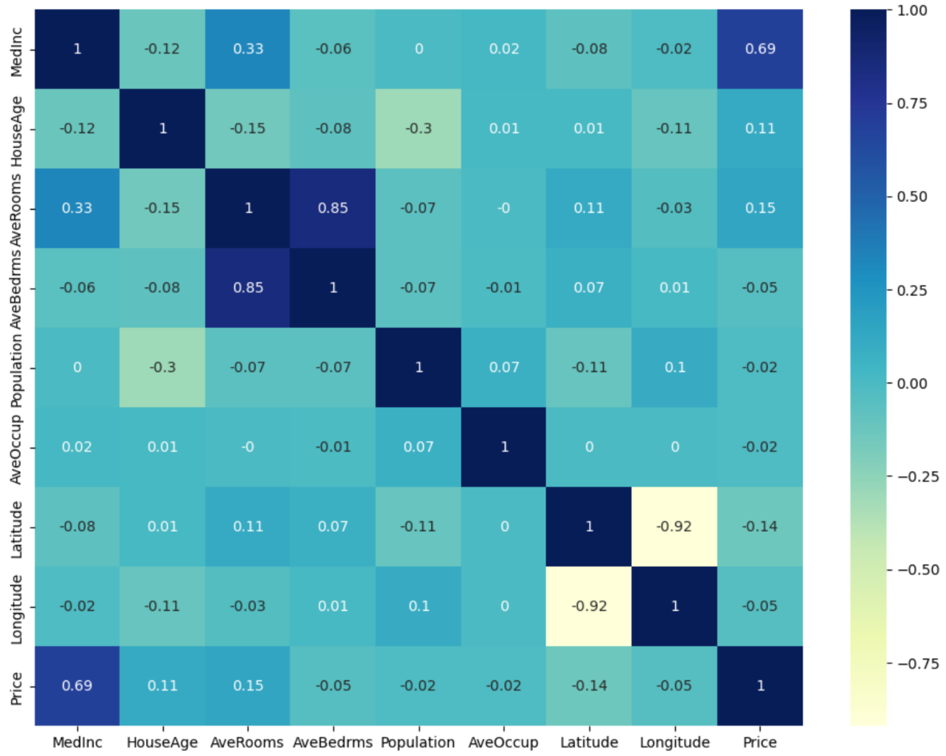
Pearson Correlation

- The Pearson *r* is a standardized covariance, and ranges from -1, indicating a perfect negative linear relationship, and +1,indicating a perfect positive relationship.
- The covariance of two variables divided by the product of their standard deviations gives Pearson's correlation coefficient.
  $\rho\ (X,Y) = \text{cov}\ (X,Y)\ /\ \sigma X.\sigma Y.$
- A value of zero suggests no linear association, but <u>does not mean two variables are independent</u>, an extremely important point to remember.
- **Pearson r is not viable for understanding a great many dependencies**
- **The alternative is Mutual Information Correlation**

Correlation



Correlation Matrix "heatmap"



High Correlations:

Check for greater than 0.7 and less than -0.7

- *Correlations with classification target*

Mutual Information (MI) Correlation

- Mutual Information is based on a measure of **Entropy**
- Entropy is defined as a measure of randomness or disorder of a system
- For example, if all devices connected to the network are iPhones, then *device type* random variable has no uncertainty (zero entropy).
- However, when Android, Chromebook and iPhone devices are all connected to the network, *device type* entropy is non-zero, which captures the uncertainty in predicting what device types are connected to the network.

Good Explanation with graphic
https://thenewstack.io/mutual-information-pearson-correlation-building-blocks-ai/

Mutual Information (MI) Correlation

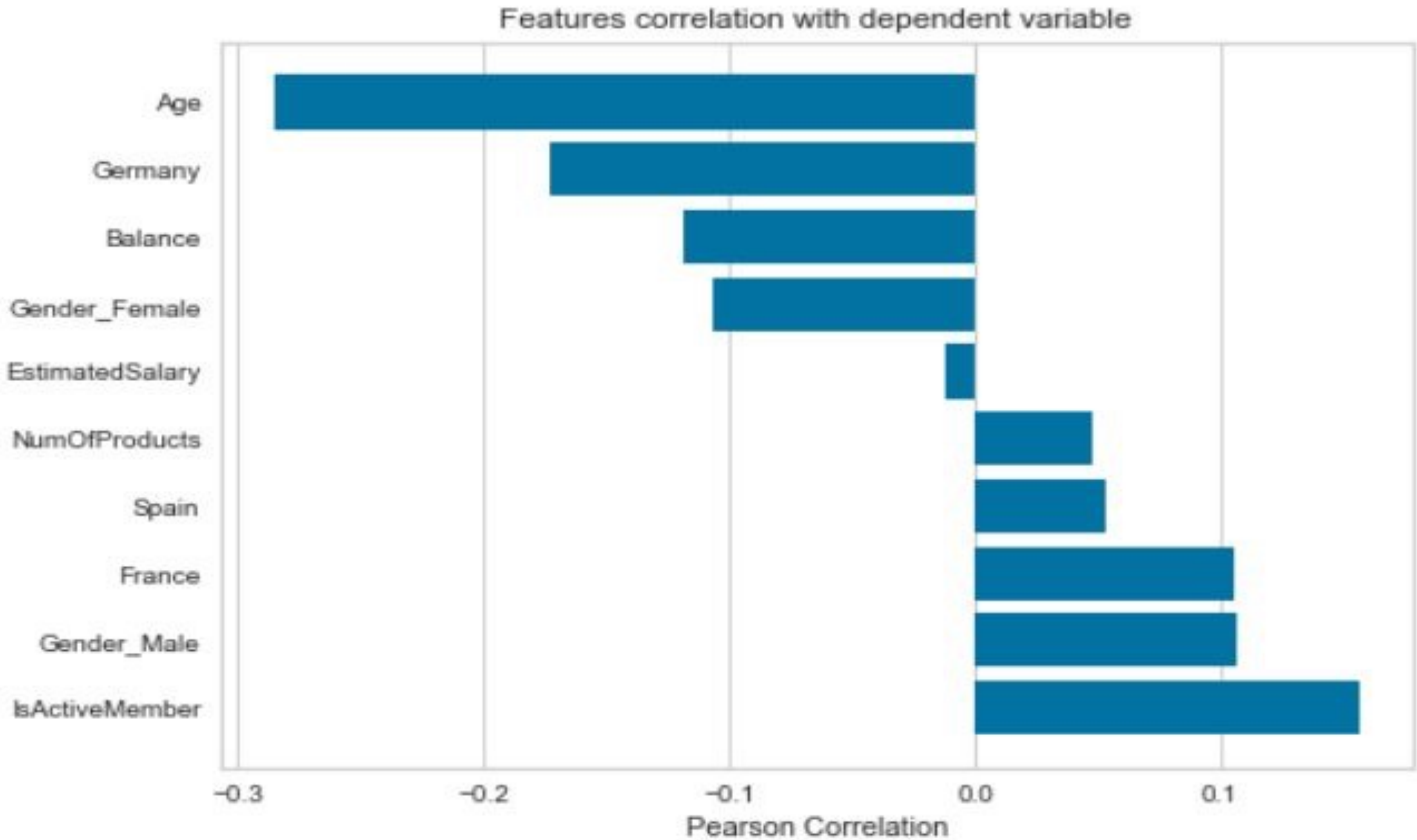
- Mutual Information Correlation is based on a measure of **Entropy**
  - The Pearson correlation coefficient assumes normality and linearity of two random variables; Mutual Information removes these assumptions.

- In essence, mutual information tells us *how useful the feature X is at predicting the random variable Y on a scale of zero to one*, with higher numbers indicating better predictors.
  - Mutual Information Correlation captures many different types of relationships (not just linear) and is considered the best metric.

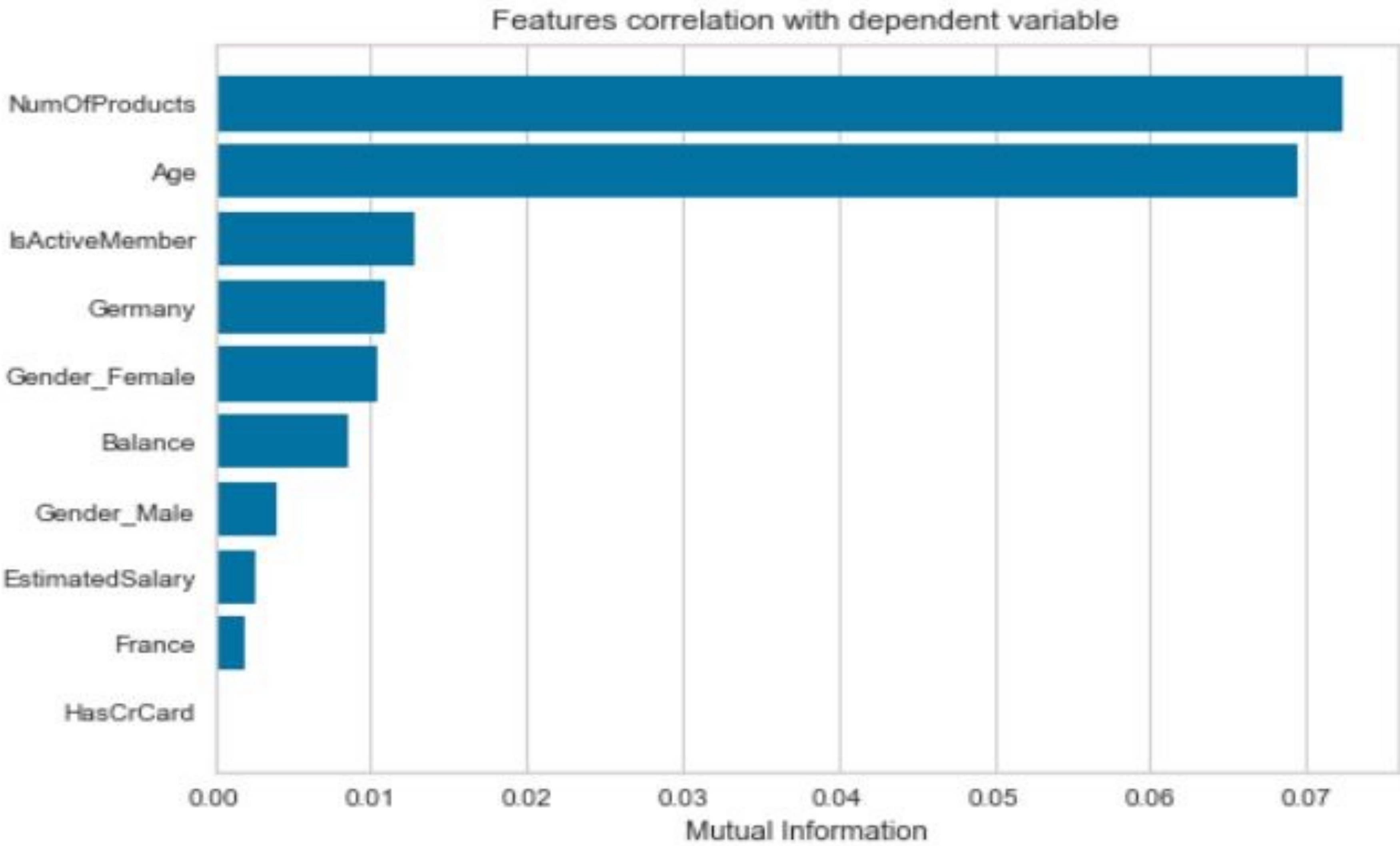
- However, it doesn't tell us if the feature is a predictor of success or failure.

- Mutual Information and Pearson measures are complementary – they do not always move the same way.

Correlation with Target label



Correlation with Target label



Further Reading

- **Exploratory Data Analysis**

https://youtu.be/QiqZliDXCCg

- **Exploratory Data Analysis with Pandas Python 2023**

https://youtu.be/xi0vhXFPegw

Machine Learning Pipeline

- Problem Definition
- Data collection
- Feature extraction
  - Flattening,Labeling
- Data preparation
  - Normalisation by data type
  - Dimensionality reduction
- Algorithm Selection
  - Train and Test
- Performance Evaluation
  - Visualisation
  - Parameter tuning
- Model Validation

Data preparation

- **Goal:** Clean up (normalize, regularize) the data values
- **Methods:** Scaling, dummy variables, interpolating missing values
- **Outcome:** Normalized data in numeric form appropriate for modeling

ML Process: Data Preparation

- Needed for several reasons
  - Some Models have strict data requirements
    - Scale of the data, data point intervals, etc.
  - Some characteristics of the data may have a dramatic impact on the model performance

Time required for data preparation should not be underestimated

- Dealing with missing values
- Transforming text variables
- Scaling numeric variables

Algorithms and Data

3 Types of Features

• Discrete	binary	CPU friendly!
• Continuous	numeric	range
• Categorical	text	convert to numeric

- ***Text must be converted to a numeric representation***
  - An arbitrary sequence (categorical)
  - A set of discrete "dummy variables"

- ***Scaling*** continuous values is required by some algorithms
  - usually considered a good idea

https://scikit-learn.org/stable/modules/preprocessing.html

Missing values

1	COUNTRY	AGE	SALARY	PURCHASED
2	France	44	7200	No
3	Spain	27	48000	Yes
4	Germany	30	54000	No
5	Spain	38	61000	No
6	Germany	40		Yes
7	France	35	50000	Yes
8	Spain		52000	No
9	France	48	79000	Yes
10	Germany	50	83000	No
11	France	37	67000	Yes

Missing values

- There may be many reasons for missing values, but only three ways to handle them: deletion, direct estimation, and imputation
- Deleting all instances (rows) with missing values would delete a lot of potentially useful information; as basic guideline, any feature (column) with more than 30% missing values should be discarded
- Direct estimation requires enough prior knowledge of the dataset to give an accurate estimate for the missing values.
- The most frequently used imputation techniques are filling in the mean or median value for the numeric features and filling in the most frequent value for nominal features.

Categorical Data

2 Categories

	COUNTRY	AGE	SALARY	PURCHASED
2	France	44	7200	No
3	Spain	27	48000	Yes
4	Germany	30	54000	No
5	Spain	38	61000	No
6	Germany	40		Yes
7	France	35	50000	Yes
8	Spain		52000	No
9	France	48	79000	Yes
10	Germany	50	83000	No
11	France	37	67000	Yes

3 Categories

Encoding Categorical Data

- ***Label Encoding*** converts a *categorical* feature into a *continuous* feature by assigning a unique integer based on alphabetical order.
  - there is a very high probability that the model captures the relationship between countries such as China < India < Russia

- ***One-Hot Encoding*** creates additional features based on the number of unique values in the categorical feature. Every unique value in the category will be added as a *discrete* feature.
  - One-Hot Encoding is the process of creating **dummy variables**.
  - This used to be two separate required steps
    - labelEncoder ::> onehotEncoder
  - Not anymore, now we just
    - pandas.getdummies()

One-Hot

dns	imap	smtp	http
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

One-Hot encoding is recommended

The big advantage is that the individual fields show up in the correlation matrix

The number of columns can be a drawback though

LabelEncoder

Protocol	Protocol_val
dns	0
http	1
imap	2
smtp	3

LabelEncoder is most often used (and useful!) for converting target labels from text to numeric values

Required by some SciKit functions

Order does not matter – target labels are only used for matching

One-Hot Encoding

COUNTRY		France	Germany	Spain
France		1	0	0
Spain		0	0	1
Germany		0	1	0
Spain		0	0	1
Germany		0	1	0
France		1	0	0
Spain		0	0	
France		1	0	
Germany		0	1	
France		1	0	

COUNTRY		France	Germany	Spain
France		1	0	0
Spain		0	0	1
Germany		0	1	0
Spain		0	0	1
Germany		0	1	0
France		1	0	0
Spain		0	0	1
France		1	0	0
Germany		0	1	0
France		1	0	0

Encoding Categorical Data

- "dummy variables": In each row, all of the data values are zero except for a single column, following the programming convention "non-zero is True".
- Adding a column for each unique data value means the size of the dataframe grows quickly, requiring more memory and CPU for the analysis.
  - This is known as "the curse of dimensionality"
- Another consideration with a colourful name is "the dummy variable trap", formally known as "multicollinearity",

Encoding Categorical Data

- **Multicollinearity** means the value of one variable can easily be predicted from the values of other variables, which is a serious issue for some **linear forecasting models**
- With linear regression, or generalized linear models estimated by maximum likelihood (ordinary least squares) and no regularization (e.g., ridge, lasso) you need to leave out one column.
  - Often, people will set aside the category which is most populated or one which acts as a natural reference point for the other categories.
  - Excellent explanation: https://towardsdatascience.com/drop-first-can-hurt-your-ols-regression-models-interpretability-4ca529cfb707
- **In every other case, keep all of the new columns**

Scaling Continuous Data

- Reduce values to a predefined range
- Limit absolute magnitude, Preserve relative magnitude

Require data to be scaled:

❖ algorithms like linear regression, logistic regression, neural network, etc. that use *gradient descent* as an optimization technique

❖ algorithms like KNN, K-means, and SVM that exploit distances between data points to determine their similarity

These work better when the values of every feature have a similar range and are close to normally distributed.

Graphical-model based classifiers (e.g.,Fisher LDA, Naive Bayes), Decision trees and Tree-based ensemble methods (RF, XGB) are invariant to feature scaling

When scaling is not strictly required, it usually does not cause complications.

Scaling Continuous Data

Scalers are linear (or more precisely *affine*) transformers and differ from each other in the way they estimate the parameters used to shift and scale each feature.

- StandardScaler standardizes a feature by subtracting the mean and then dividing all the values by the standard deviation. The result is a distribution with mean=0 and standard deviation=1
- MinMaxScaler finds the original minimum and maximum values, then subtracts the minimum and divides by the range for each value. The original distribution is preserved with all values between 0 and 1
- There are several others available, suitable for special purposes

https://scikit-learn.org/stable/modules/preprocessing.html

Data Splitting for ML

100%

DATA

TRAINING SET

70% / 80%

TEST SET

30% / 20%

Scaling Continuous Data

One important special consideration for supervised learning

- If scaling is applied ***before*** the dataset is split into train and test sets, information about the distribution of feature values in the test set "*leaks*" into the train set, which may make the predictions artificially accurate.
- So, the rule is: **fit only on the** train **set**, then transform the values in both the **test** and train sets

ML **Process**: Data Preparation

- scaling and redundant data are an *algorithm problem*, because each algorithm has a different sensitivity to these characteristics of the distribution.
- That means scaler.fit() and feature selection are only applied to the training set, and
- IF we do scaler.transform() on train we also must scaler.transform() on test for compatibility.

Classifying by Features

Possible features in the shapes:

Color: Blue, Green, Orange, Yellow

Size: Large, Small (area)

Geometric shape: Square, Rectangle, Triangle, Circle, …

Curvature: Straight sides only, at least one curved side

Number of edges: 1, 2, 3, 4

“Triangleness”: Yes, No

Thickness?

Material?

Weight?

Floats on water?

Review Questions

1. What are some of the feature selection techniques used in machine learning?
2. What is exploratory data analysis and tasks involved?
3. What are some of data preparation techniques used in machine learning?

Summary / Recap of Main Points

1. Feature selection techniques
2. Importance of exploratory data analysis
3. Data preparation techniques