Multi-target prediction

Outline

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- Intuition and Applications
- Basic Use-Cases
- Multi-target vs. multi-label classification
- Different approaches
- Predictive Clustering Trees
- Measurement of prediction quality
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What is Multi-target prediction?

- Multi-target prediction, multi-output or multi-task learning.
- The goal is to predict multiple dependent variables (targets) simultaneously from a set of input variables (features).
- Particularly relevant in complex real-world scenarios where multiple outcomes are interrelated and can influence each other.

Intuition

- Shared Representation: the targets share some common underlying factors. By learning these shared representations, the model can make more informed predictions for each target.
- Exploiting Correlations: Multi-target models aim to exploit the correlations and interactions between targets. E.g., in a health-related dataset.
- Joint Learning: Where the model learns to optimize the predictions for multiple targets in a coordinated manner. This joint learning approach can help in uncovering insights that may not be apparent when targets are considered in isolation.

Applications

- Complex Interdependencies: Traditional single-target prediction models might ignore interdependencies of targets, potentially leading to suboptimal performance.
- Efficiency: Reducing the need to train separate models for each target. This can lead to more efficient use of computational resources and data.
- Improved Generalization: Multi-target models can potentially improve prediction accuracy by learning shared representations that capture underlying patterns relevant to multiple targets.

i) Basic Use-Cases: Weather Forecast

- Applied to many domains, such as genomics, finance, and recommendation systems, where multiple outcomes or variables are of interest are not independent of each other.
- An illustrative use cases of multi-target prediction: in environmental modeling, specifically in predicting various aspects of weather or climate conditions from a set of input variables.
- Forecast multiple weather parameters, such as temperature, humidity, precipitation, wind speed,
 and air pressure, from historical and current weather data.

ii) Basic Use-Cases: Drug Discovery

- In drug discovery and personalized medicine, it's crucial to understand how different compounds interact with various genetic markers or cellular processes.
- A single drug can have multiple effects, impacting various genes, proteins, or pathways.
- Traditional approaches might involve building separate models to predict the effect of compounds
 on each marker or response, which can be inefficient and may ignore the interdependencies
 between these effects.

Multi-target vs. multi-label prediction

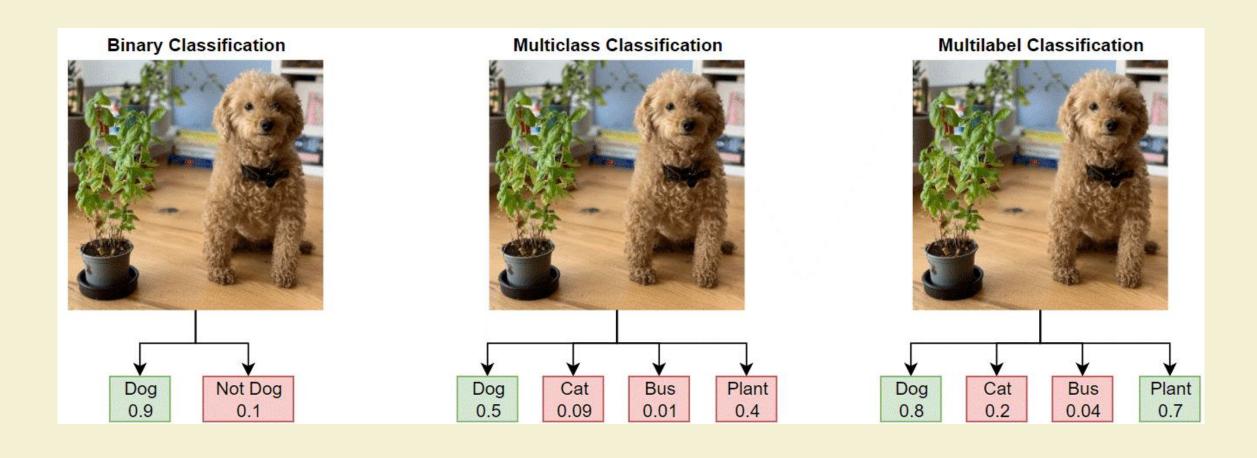
Multi-target:

- Can predict categorical and continous targets as well
- Each instance in the dataset has a fix number of targets
- Target variables usually have some kind of connection
- e.g.: predicting the number of customers and revenue; predicting whether customers take an offer and the number of times they use the service etc.

Multi-label:

- Predicts only categorical labels
- Each instance in the dataset can belong to multiple categories, but it is not fixed, how many categories they belong to
- Target labels usually have some kind of connection
- e.g.: predicting what objects are on a picture, predicting movie genres, predicting whether one has different diseases etc.

Multi-target vs. multi-label prediction



Different approaches

Problem transformation methods

transform the problem into separate prediction problems

one-vs-all OR one-vs-one

- straightforward, but loses information about the relationship of different targets/labels
- e.g.: Binary Relevance, **Classifier Chains**, Conditional Dependency Network, Hierarchy of Multilabel Classifiers (HOMER) etc.

Algorithm adaptation methods

- algorithms are changed in order to take account of label/target correlations
- can be more complex, but does not lose information about target/label relationships
- e.g.: **Predictive Clustering Trees**, different Neural Networks, Twin Multi-Label Support Vector Machine, Multi-label k Nearest Neighbour etc.

Predictive Clustering Trees (PCT)

- Decision tree and random forest modified → TDIDT algorithm
- **Splitting criterion is changed:** Partition data into clusters that are as homogenous as possible in terms of target variables/labels
- Similarity measure: depends on the specific task, for MLC: sum of Gini indicies of the labels
- Prototype and variance function
 - Prototype function: representative summary of a given cluster
 - Variance function: measure of diversity within cluster
- Stopping criteria are the usual suspects: max depth, impurity decrease, max features etc.
- Efficient computation

Measurement of prediction quality

- Output of prediction is more complex than for single-target/binary-label prediction → evaluation is more complex
- But usual scoring methods can be used with some twists
 RMSE, accuracy, precision, F1 score, R², Jaccard index, Hamming loss
- Macro- vs. micro-averaging
 per target/label measures are averaged into a single measure vs. the joint value of a statistic is
 calculated for all targets/labels
 - e.g.: MSE with k targets/labels with n observations

$$\underline{\text{Macro:}} \ \sum_{j}^{k} w_{j} \sum_{i}^{n} \frac{(y_{ji} - \hat{y}_{ji})^{2}}{n} \\ \underline{\text{Micro:}} \ \sum_{j}^{k} \sum_{i}^{n} \frac{(y_{ji} - \hat{y}_{ji})^{2}}{kn}$$

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