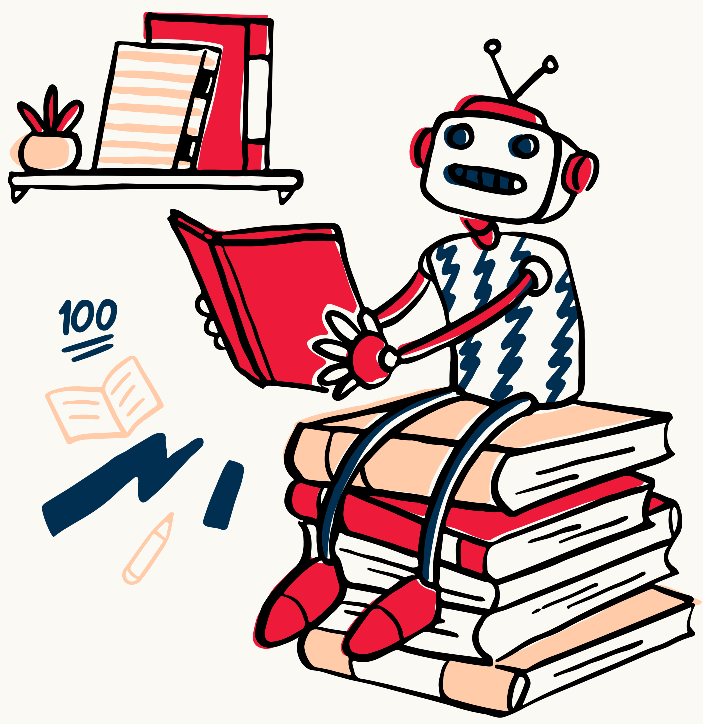
APPLIED DATA SCIENCE PROJECT

# Patient Preference Studies Classification System




UNIVERSITÀ DI TORINO

Cesar Augusto Seminario Yrigoyen
Francesco Giuseppe Gillio

Politecnico di Torino

# The **Picture**

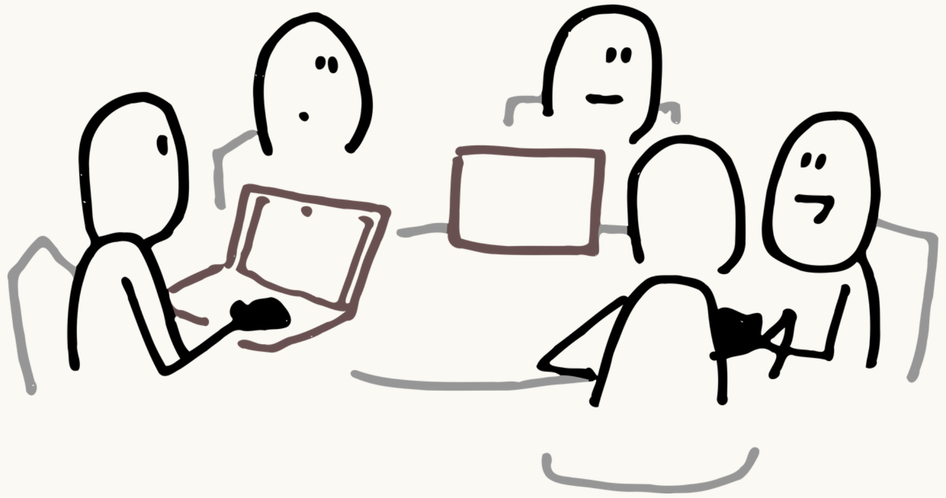
European
Commission

"The **urgent demand for tools** that support efficient access, integration, and analysis of health data **to derive actionable insights from patient-reported outcomes** and real-world evidence"

- European Commission

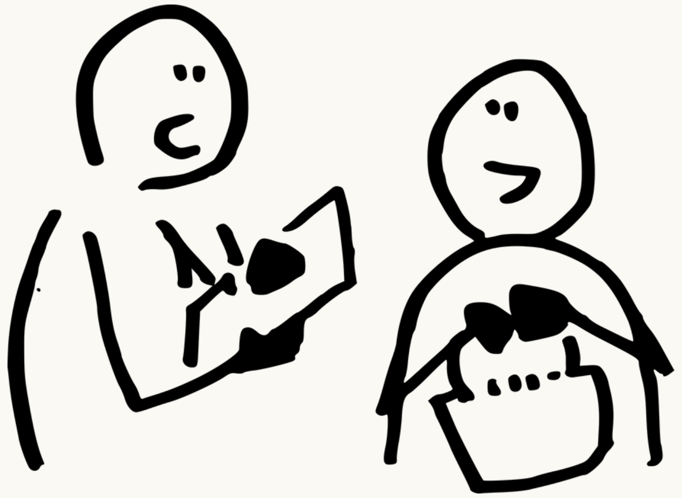
**Medical Researchers**

actionable insights to



**Healthcare Ecosystem**

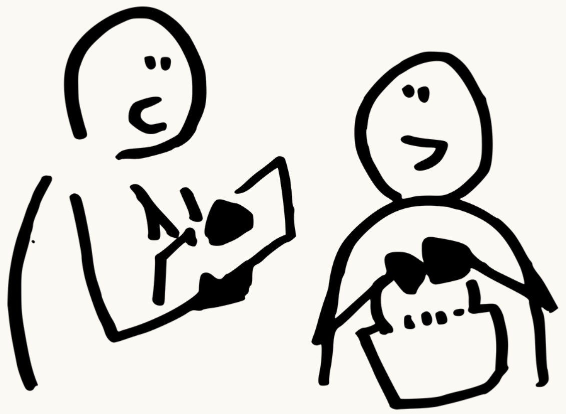
valuable services to

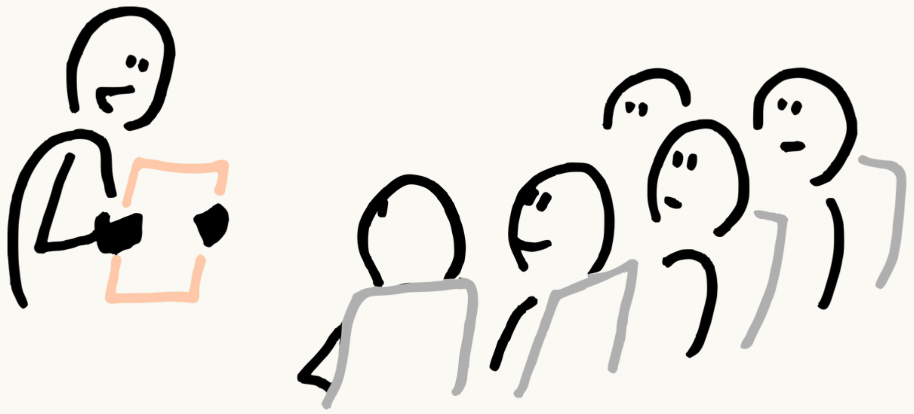


**Patient Communities**

## The **Values**

**United Nations**
**Sustainable Development Goals**
2030





3 GOOD HEALTH AND WELL-BEING

Support the advancement of
**patient care systems and processes**

4 QUALITY EDUCATION

Support the advancement of
**information retrieval in medical research**

## The User Journey

# Data Collectors

Medical **Researchers**

UNIVERSITÀ DI TORINO

# Data Source


**PubMed**
links queries to records through keywords matching, term mapping, and indexed vocabulary

# Textual Data

**The head-to-head comparison of diabetic patient preferences for glucose-monitoring devices.**

**Abstract**

A comparison of discrete choice experiment (DCE) and swing-weighting (SW) methods assesses diabetic **patient preferences** for glucose-monitoring devices. The analysis highlights critical attributes such as ease of use, accuracy, and cost, revealing differences in attribute prioritization and trade-offs. Insights from this evaluation inform the selection of preference-elicitation techniques in patient-centered healthcare research.

Politecnico di Torino

## The **Problem**

**The head-to-head comparison of diabetic patient preferences for glucose-monitoring devices.**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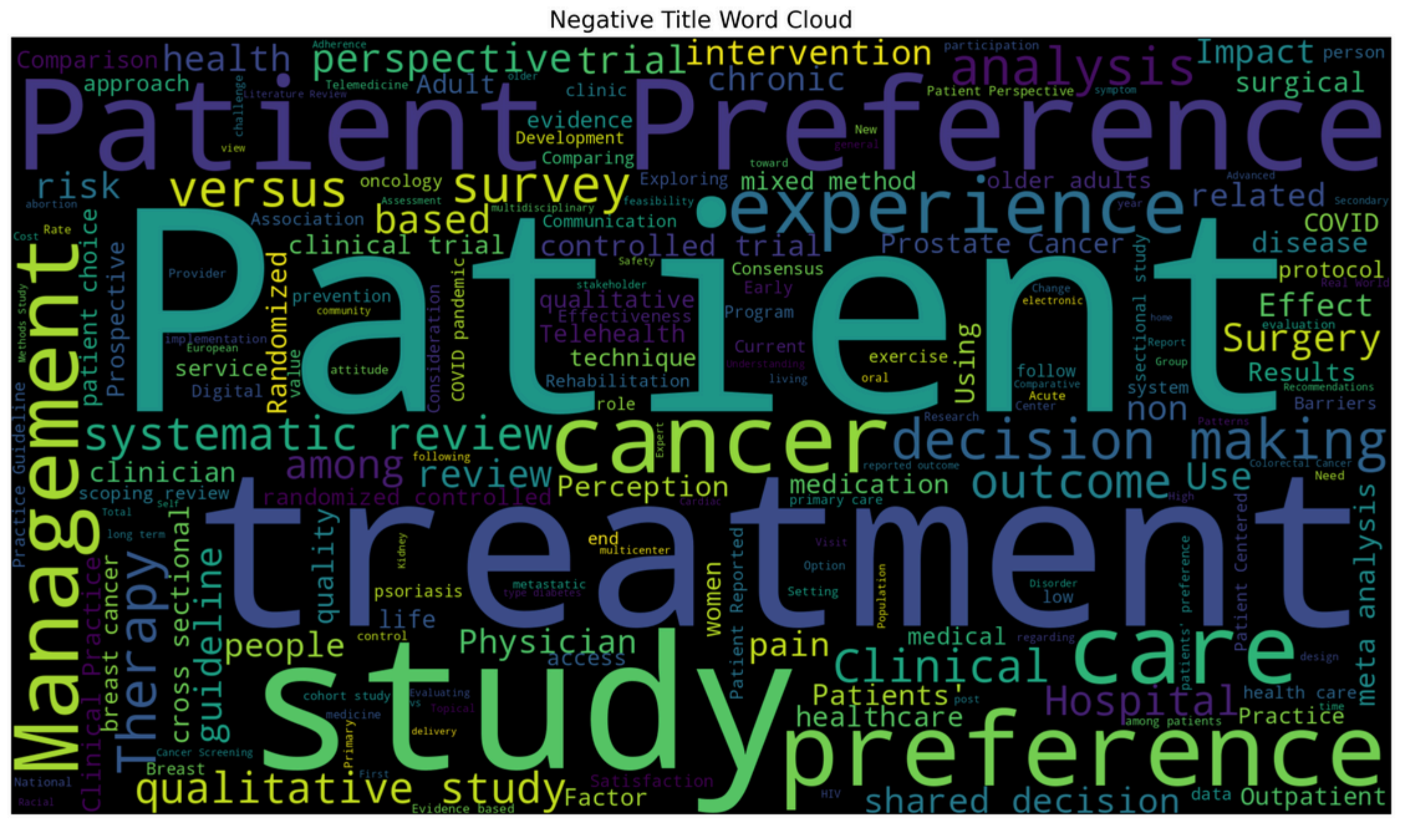
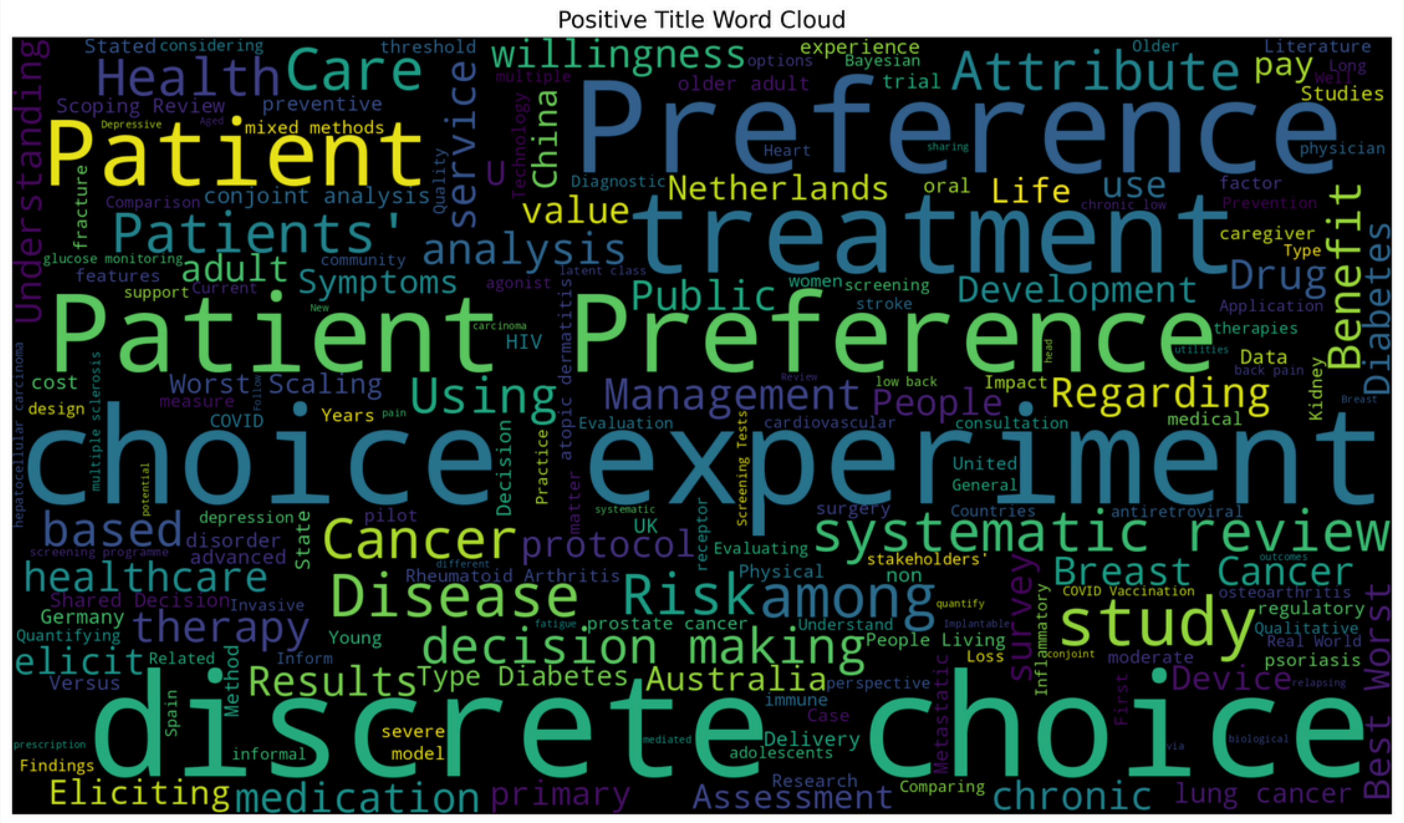
## **Patient Preference Study** or **Not**?

## What about the **Clinical Area**?

### **Non Patient Preference Study**



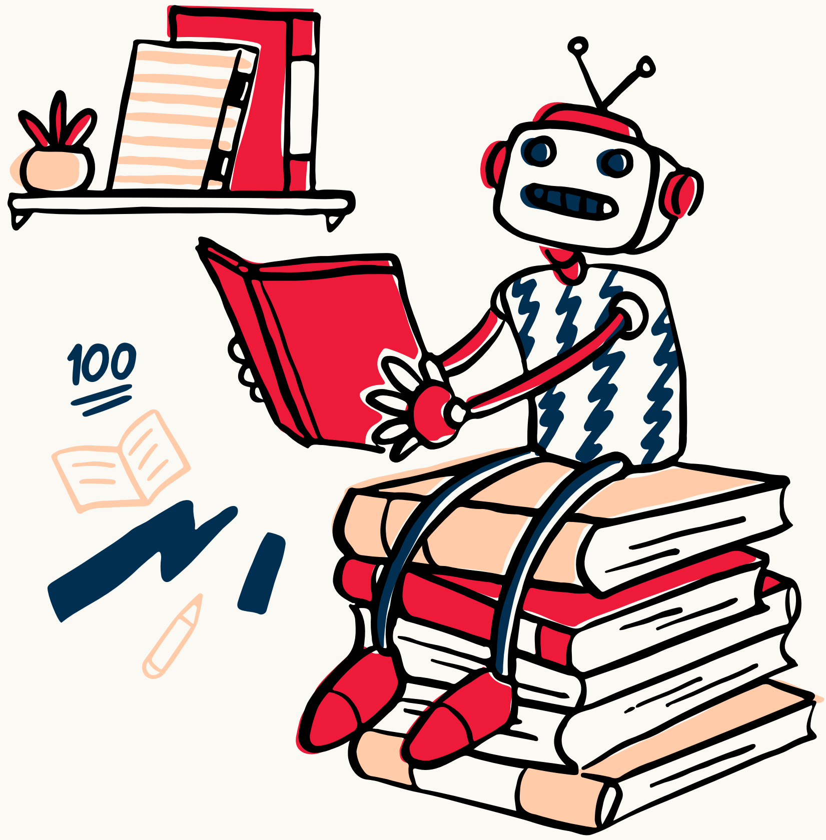

### **Patient Preference Study**



The **Solution**

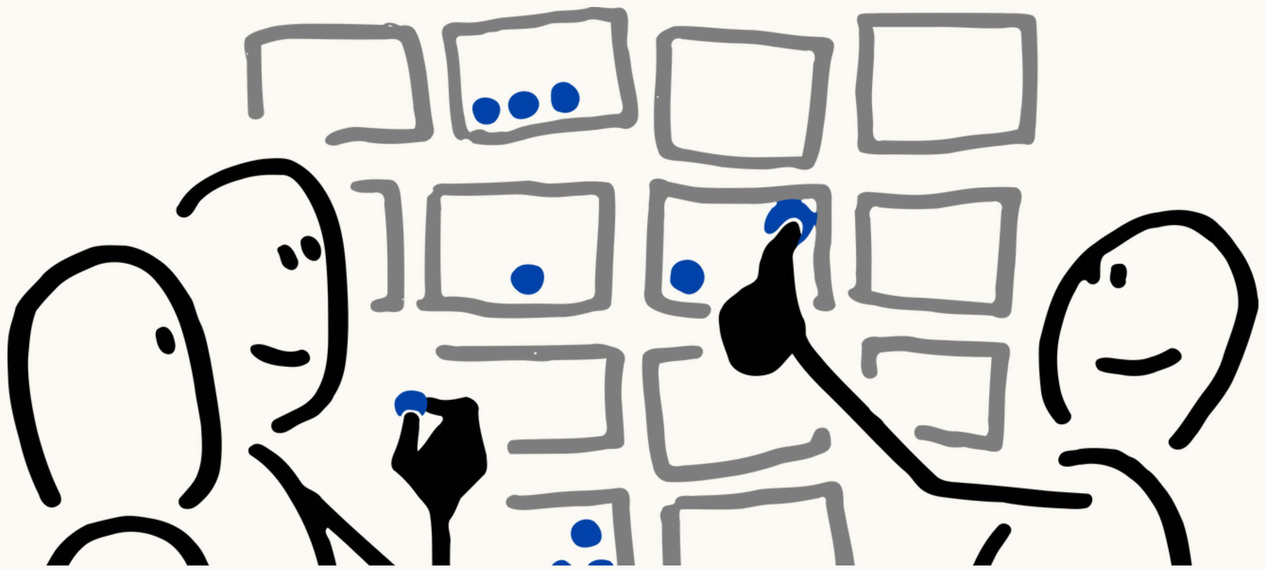
# **Text** Classification

The **non**-solution:
**read** to **know**




The solution:
**teach** to **read**

The **Objective**



# Classifier Model for **Medical Research Papers**

- Papers classification by relevance to Patient Preference Studies (PPS)
- Papers classification by relevance to Clinical Areas

The **Task**

# Two-Stage
# Text Classification

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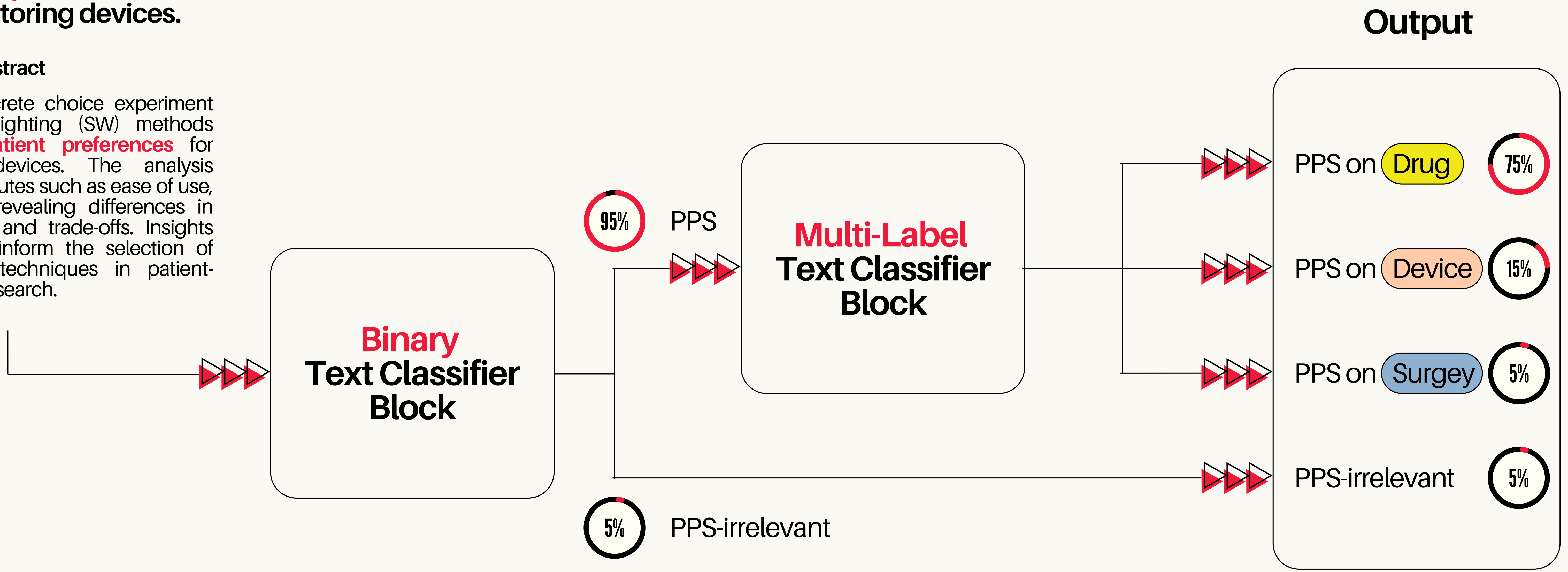

# The **Binary** Text Classifier

## Classification by relevance to Patient Preference Studies

### The head-to-head comparison of diabetic patient preferences for glucose-monitoring devices.

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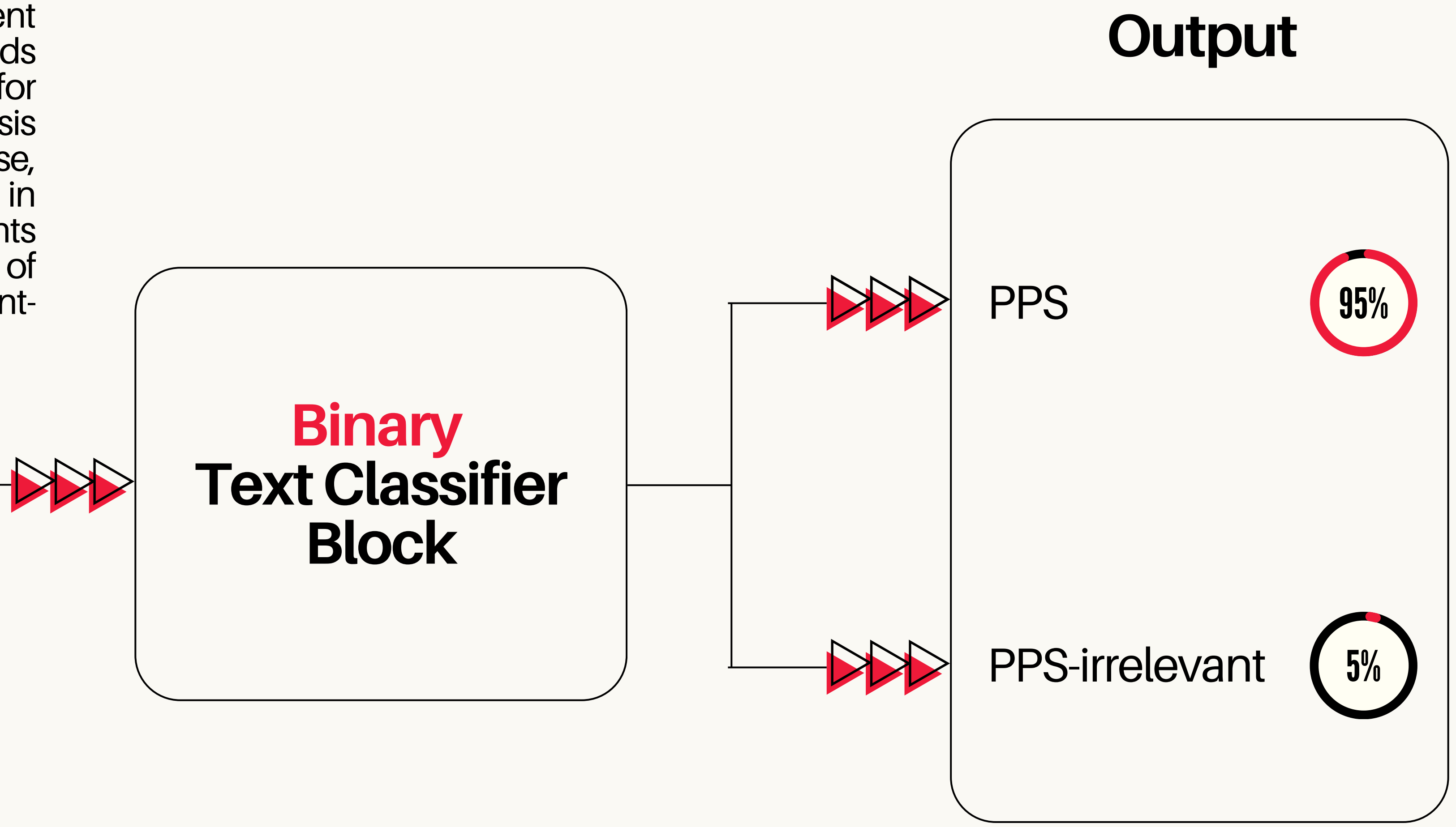

# **What** to **evaluate?**

The worst outcome:
**researchers lose papers on PPS**

## True Positive Rate (TPR)

$$\frac{TP}{TP+FN}$$ for Class 1 (PPS)

The probability that an actual positive tests positive

The target outcome:
**researchers retrieve papers on PPS alone**

▶▶▶ remove noise

## Positive Predictive Value (PPV)

$$\frac{TP}{TP + FP}$$ for Class 1 (PPS)

The probability that a positive test matches an actual positive

# Inside The Box

## The head-to-head comparison of diabetic patient preferences for glucose-monitoring devices.

### Abstract

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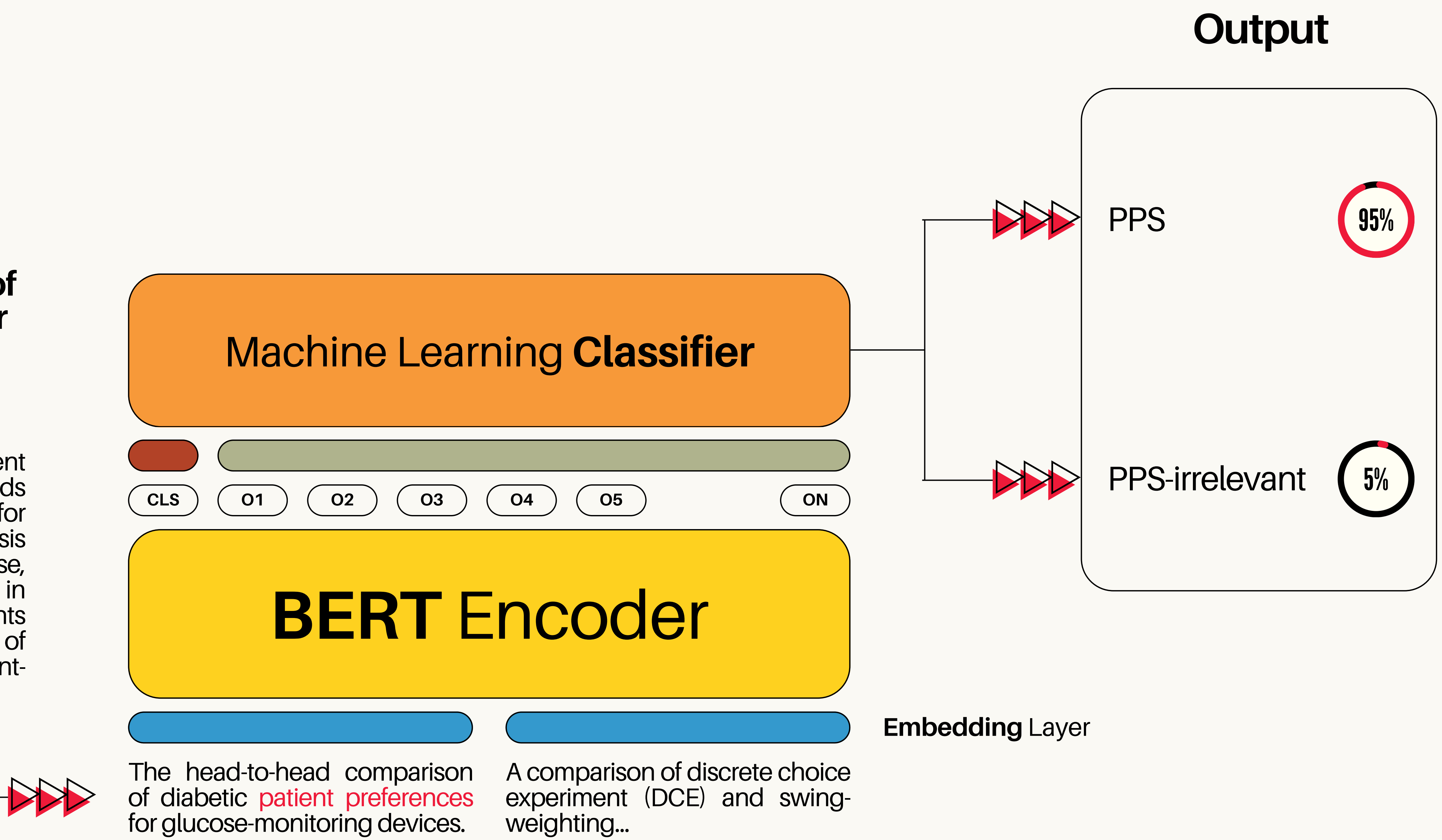

# The **Experimental** Setup

**The head-to-head comparison of diabetic patient preferences for glucose-monitoring devices.**


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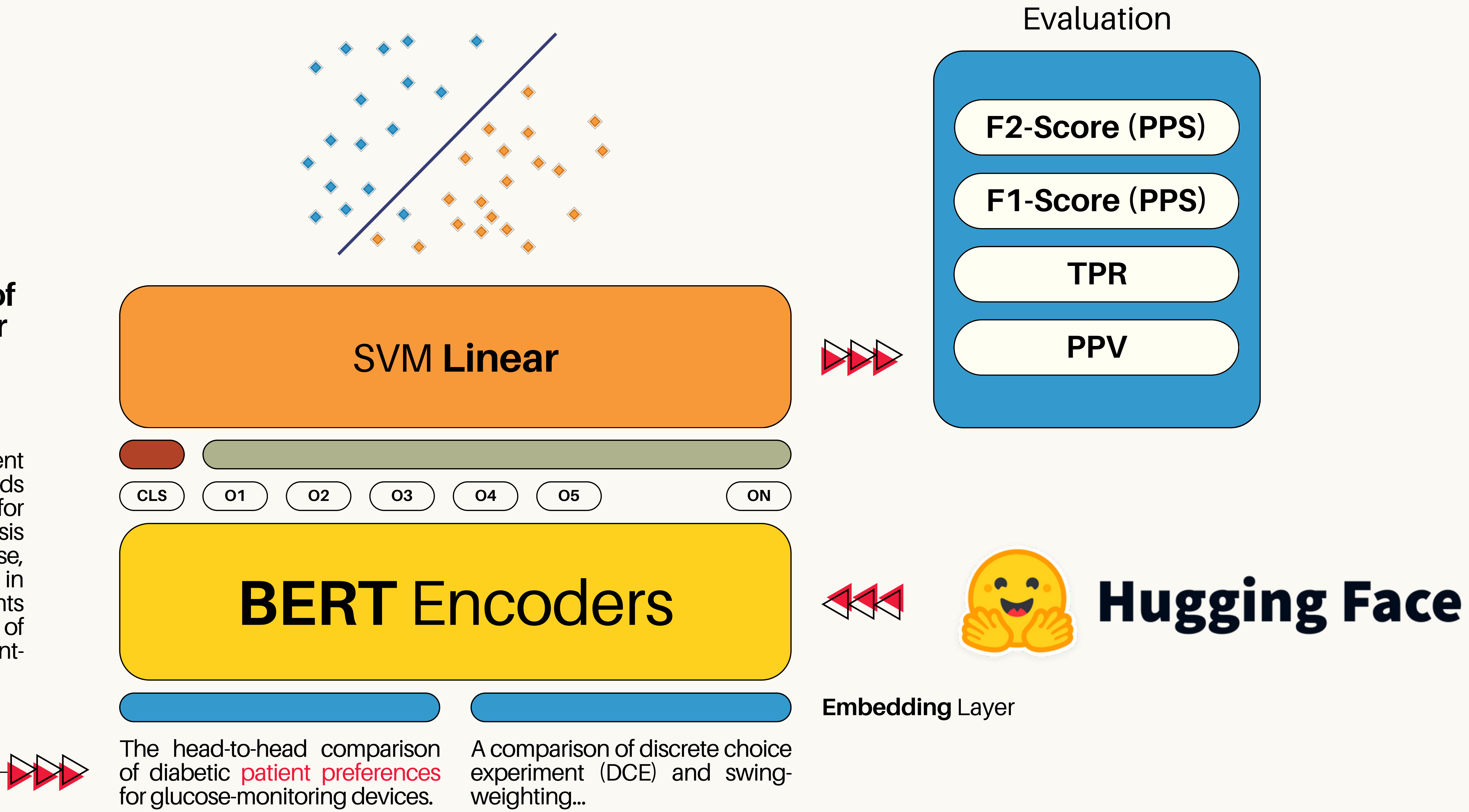

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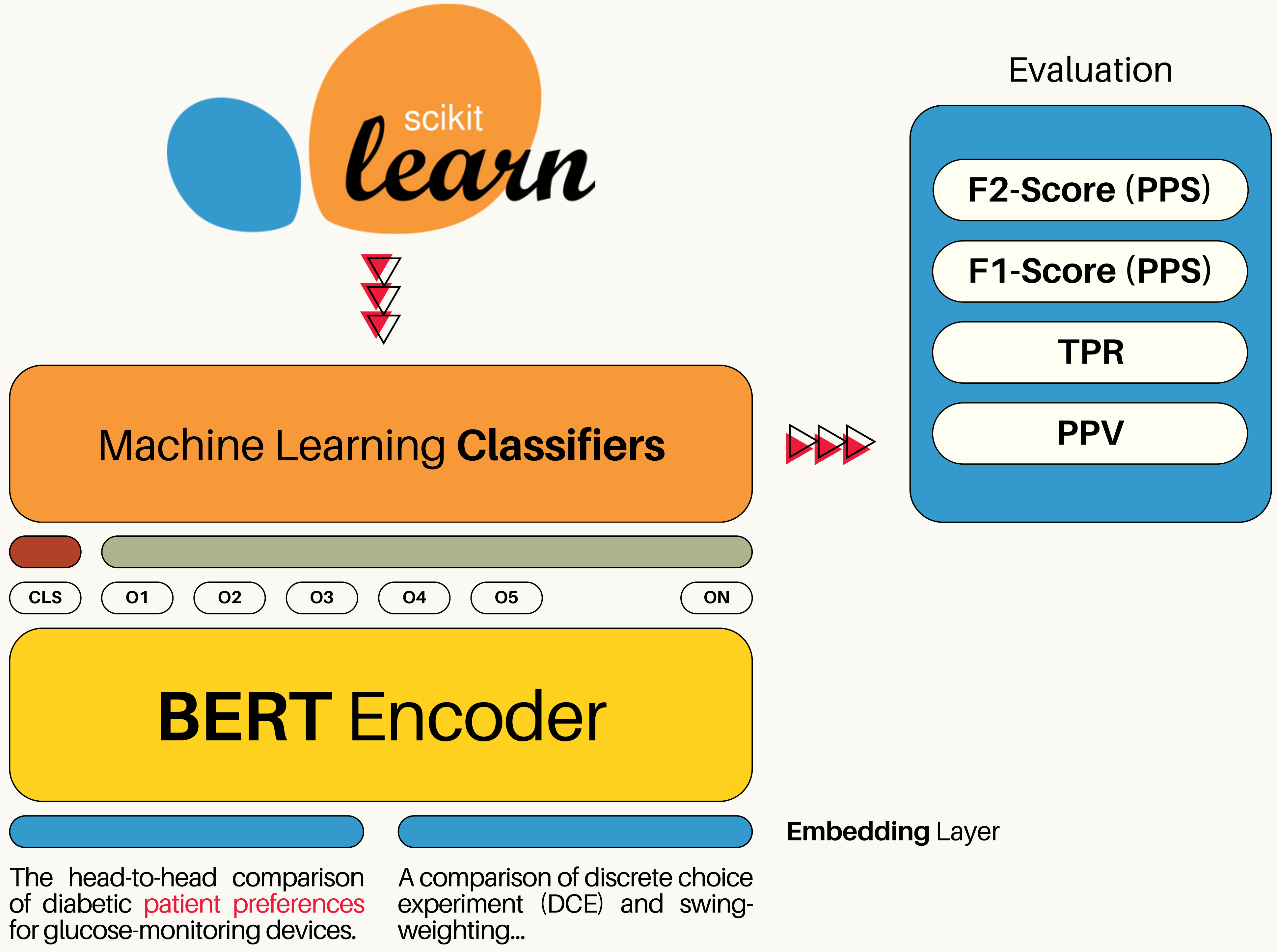


# The Top Three

Hugging Face

## BERT Models

| BERT-Base Model | F2-PPS | F1-PPS | TPR | PPV |
|---|---|---|---|---|
| pubmedbert-base-embeddings | **0.833** | 0.836 | 0.831 | 0.844 |
| BiomedNLP-BiomedBERT-base-uncased-abstract | **0.821** | 0.821 | 0.822 | 0.825 |
| S-PubMedBert-MS-MARCO | 0.816 | 0.81 | 0.819 | 0.803 |

scikit learn

### pubmedbert-base-embeddings

| Classifier Model | F2-PPS | F1-PPS | TPR | PPV |
|---|---|---|---|---|
| k-Nearest Neighbors | **0.895** | 0.82 | **0.953** | 0.719 |
| Deep Neural Network | 0.893 | 0.892 | 0.894 | 0.882 |
| Logistic Regression | 0.891 | 0.891 | 0.889 | 0.884 |

### BiomedNLP-BiomedBERT-base-uncased-abstract

| Classifier Model | F2-PPS | F1-PPS | TPR | PPV |
|---|---|---|---|---|
| SVM (RBF Kernel) | **0.906** | 0.91 | 0.903 | **0.918** |
| Neural Network | 0.9 | 0.906 | 0.896 | 0.914 |
| Logistic Regression | 0.899 | 0.9 | 0.898 | 0.899 |

# The **Top** Parameters

## k-Nearest Neighbours

| **Parameters** | **Values** |
|---|---|
| **K** (**neighbours**) | 3, 5, 8, 13, 21 |
| **Metric** | euclidean, manhattan, minkowski |

for **pubmedbert-base-embeddings**

### **High Recall** Model

| **K-Nearest Neighbors Parameters** | **F2-PPS** | **F1-PPS** | **TPR** | **PPV** |
|---|---|---|---|---|
| **K** = 5, **Metric** = euclidean | 0.897 | 0.823 | **0.953** | 0.724 |

## Support Vector Machine

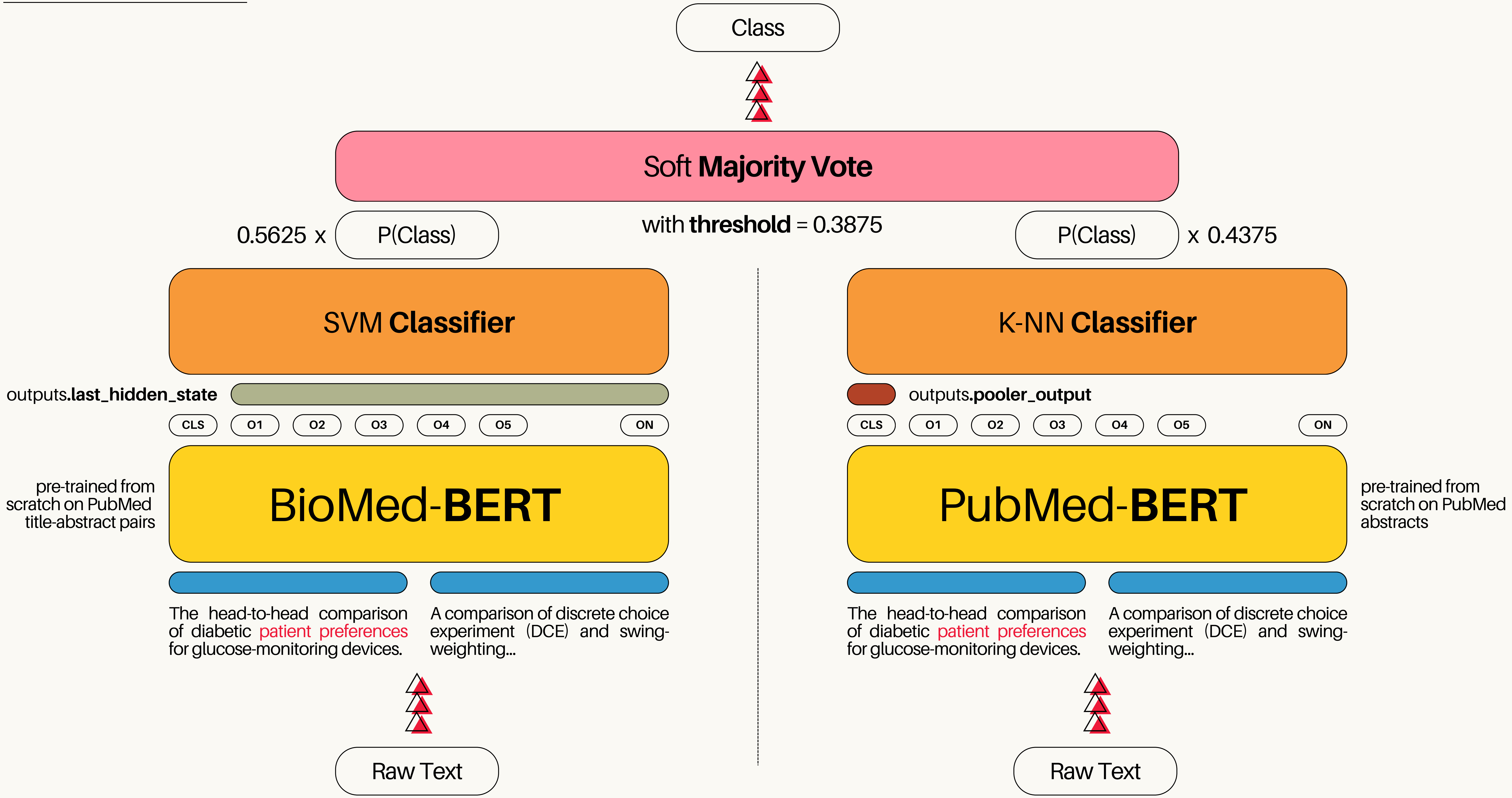
| **Parameters** | **Values** |
|---|---|
| **C** (**penalty parameter**) | 1e0, 1e1, 1e2 |
| **Gamma** (**kernel coefficient**) | 1e-5, 1e-4, 1e-3, auto, scale |

for **BiomedNLP-BiomedBERT-base-uncased-abstract**

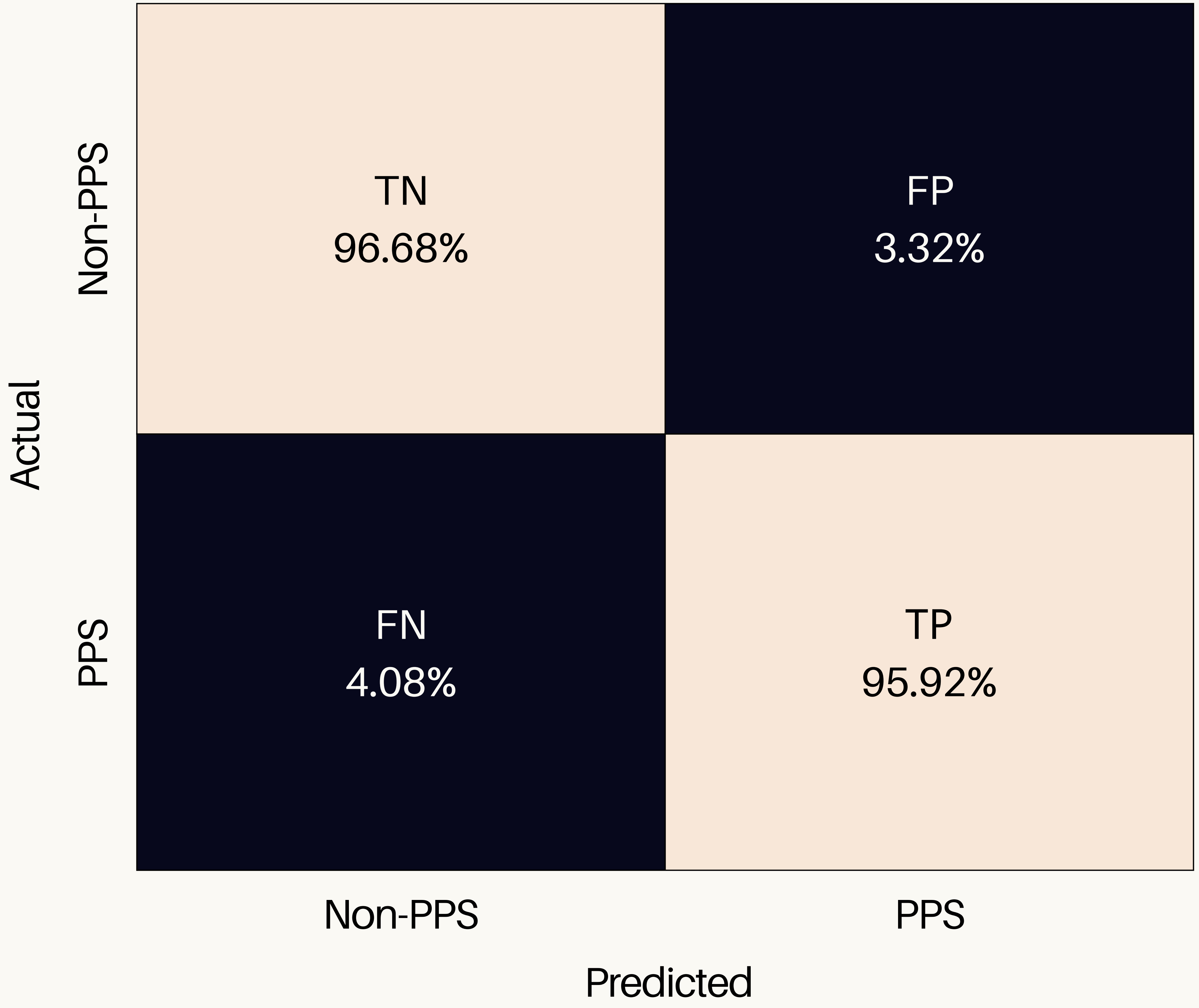
### **High Precision** Model

| **Support Vector Parameters** | **F2-PPS** | **F1-PPS** | **TPR** | **PPV** |
|---|---|---|---|---|
| **C** = 1e1, **Gamma** = auto | 0.901 | 0.921 | 0.888 | **0.957** |

# The **Target** Model



## The **Result**




The binary classifier model loses 5 **Patient Preference Studies** out of 100 papers, but removes more than **95%** of the noise

# The **Multi-Label** Text Classifier

## Classification by relevance to Clinical Areas

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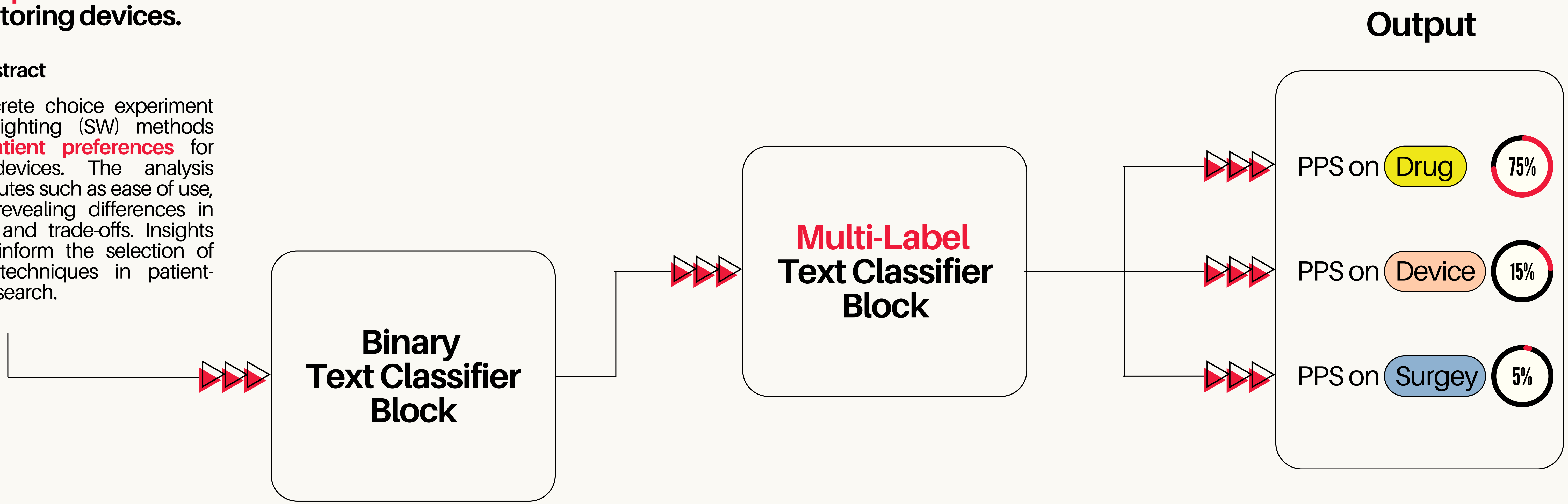
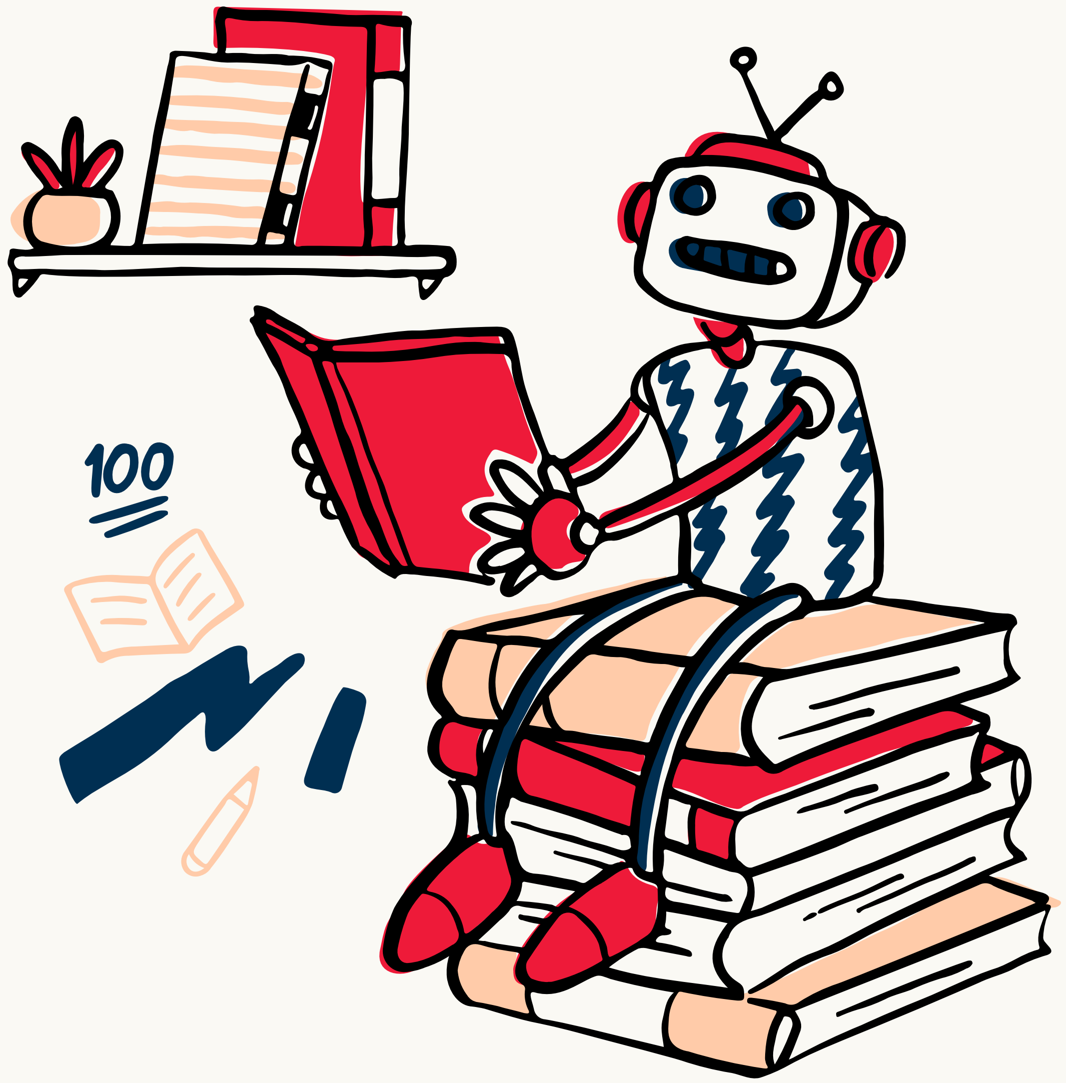


# The **Multi-Label** Classifier Methods



## 1. **ML Dataset and Imbalance Analysis**

- Mean imbalance ratio
- Coefficient of variation of IR
- Scumble index

## 2. **Data-driven approach for model selection: comparison of most used MLC**

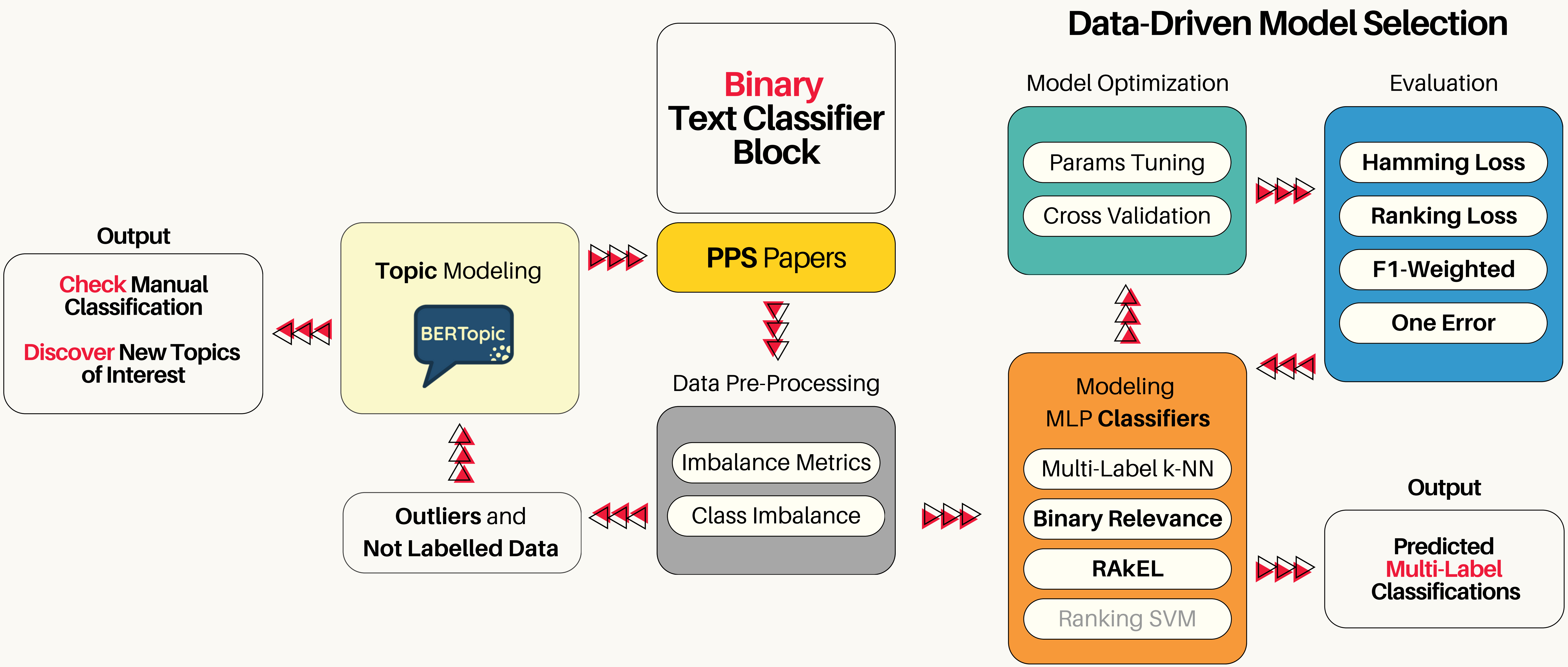
- Problem transformation (Binary relevance, RAkEL)
- Algorithm adaptation (multilabel kNN, VW ML kNN, ranking SVM)
- Ensemble models
- Cost sensitive (RAkEL)

## 3. **Metrics for model comparison**

- Hamming loss
- Ranking loss
- F1-score (micro, weighted)
- Coverage error
- One error

## 4. **Best model selection**

# The Experimental Setup



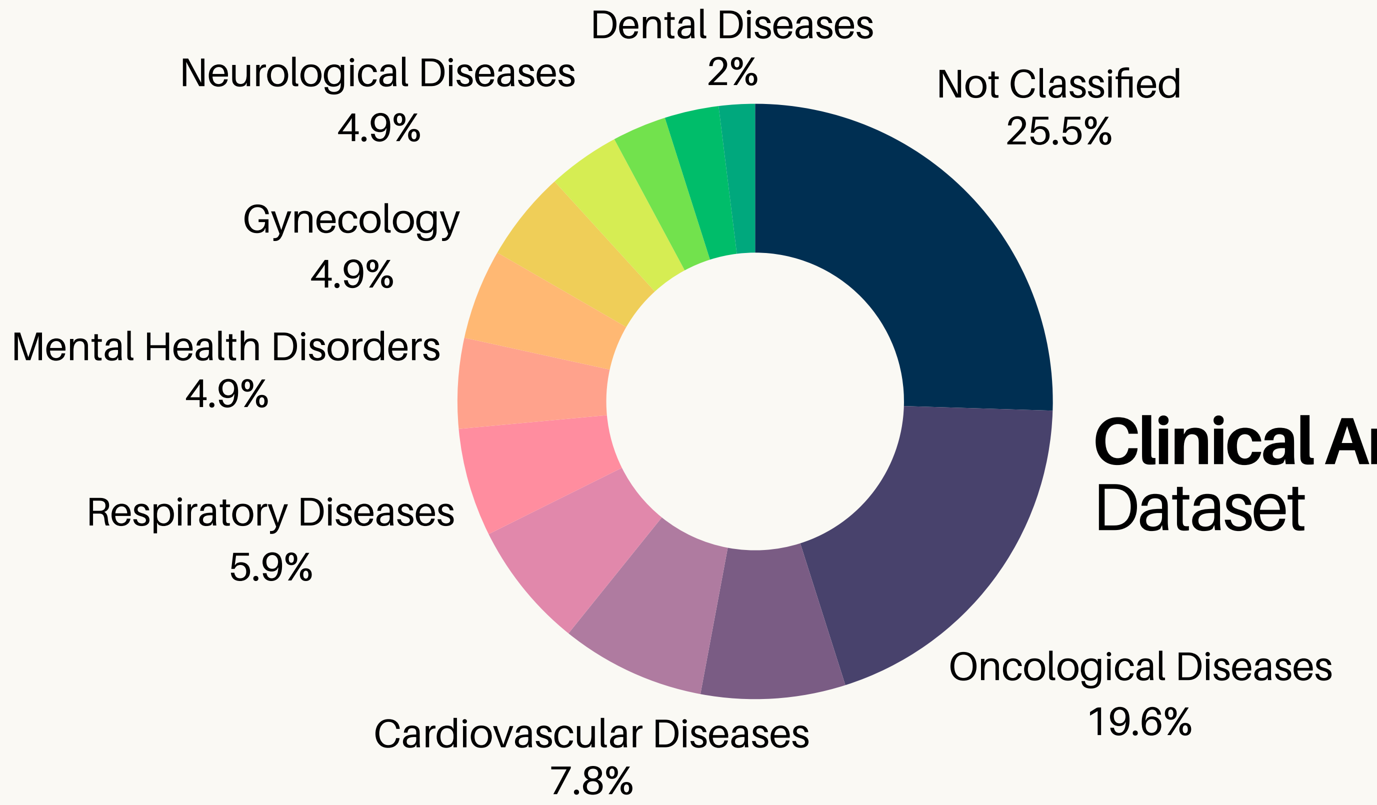
# Dataset **Imbalance** Metrics

## Dataset Imbalance

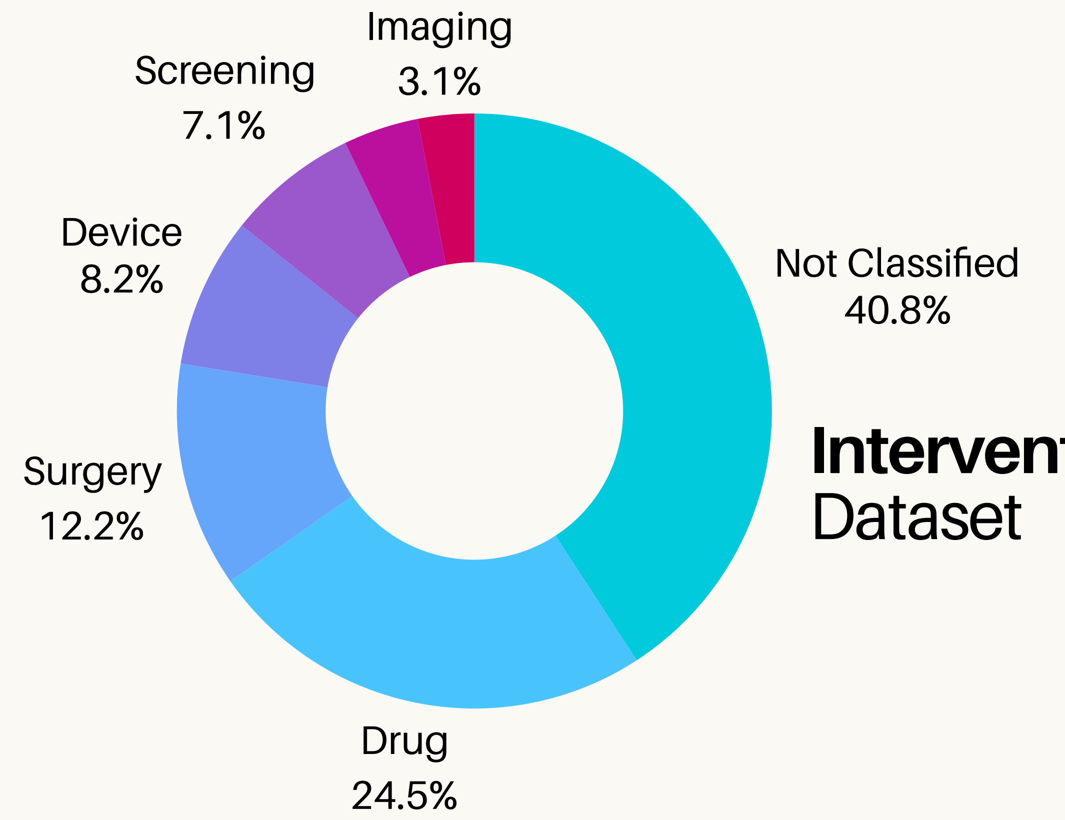
| ML Dataset | Mean IR | Max IR | CVIR | Scumble |
|---|---|---|---|---|
| **Clinical Areas** | 4,53 | 12,20 | 1,91 | 0,63 |
| **Interventions** | 4,63 | 8,82 | 2,37 | 0,44 |

## Dataset Description

| ML Dataset | # samples | Labels | Class Sets | Card | Dens | TCS |
|---|---|---|---|---|---|---|
| **Clinical Areas** | 2192 | 12 | 88 | 0,87 | 0,07 | 13,19 |
| **interventions** | 2192 | 6 | 23 | 0,63 | 0,11 | 11,12 |




**Clinical Areas** Dataset




**Interventions** Dataset

# The **Experiments**

## Multi-Label k-Nearest Neighbours

| Parameter | Values |
|---|---|
| K (neighbours) | 3, 5, 7, 11 |
| S (smooth) | 10, 50, 100, 200 |

| Dataset | K | s |
|---|---|---|
| Clinical Areas | 11 | 1 |
| Interventions | 11 | 1 |

## Value-Weighted Multi-Label k-Nearest Neighbours

| Parameters | Values |
|---|---|
| K (neighbours) | 1, 3, 5, 7, 11 |
| a | 0.3, 0.5, 0.7 |
| b | 0.3, 0.5, 0.7 |

| Dataset | K | a | b |
|---|---|---|---|
| Clinical Areas | 1 | 0.5 | 0.5 |
| Interventions | 1 | 0.3 | 0.3 |

# The Experiments

## RAkEL - Labelset: [2, 3, 4, 5, 6, 7]

| Model | Parameter | Values |
|---|---|---|
| **Gaussian NB** | Smoothing | 1e-9, 1e-8, 1e-7, 1e-6 |
| **Random Forest** | N (estimators) | 10, 50, 100, 200 |

| Dataset | Labelset | s |
|---|---|---|
| **Clinical Areas** | 6 | 1e-9 |
| **Interventions** | 3 | 1e-7 |

| Dataset | Labelset | N |
|---|---|---|
| **Clinical Areas** | 6 | 50 |
| **Interventions** | 7 | 200 |

## Binary Relevance

| Model | Parameter | Values |
|---|---|---|
| **kNN** | K (neighbours) | 1, 3, 5, 7, 11 |
| **Multinomial NB** | Alpha | 0.3, 0.5, 0.7 |
| **SVC** | Kernel | linear, rbf, sigmoid |
| | Penalty Parameter | 1e-2, 1e-1, 1e0, 1e1, 1e2 |

| Dataset | K |
|---|---|
| **Clinical Areas** | 5 |
| **Interventions** | 11 |

| Dataset | Alpha |
|---|---|
| **Clinical Areas** | 0.3 |
| **Interventions** | 0.3 |

| Dataset | Kernel | C |
|---|---|---|
| **Clinical Areas** | Linear | 1e-2 |
| **Interventions** | Linear | 1e-2 |

# The **Multi-Label Classifier** Results

## Clinical Areas

| Model | F1-Micro | F1-Weighted | Hamming Loss | Ranking Loss | Coverage Error | One Error |
|---|---|---|---|---|---|---|
| **ML kNN** | 0,757 | 0,748 | 0,030 | 0,076 | 1,714 | 0,614 |
| **VW MLkNN** | 0,750 | 0,747 | 0,034 | 0,171 | 2,877 | 0,470 |
| **BR (kNN)** | 0,778 | 0,771 | 0,027 | 0,200 | 3,216 | 0,479 |
| **BR (MultinomialNB)** | 0,704 | 0,720 | 0,047 | **0,032** | **1,242** | **0,409** |
| **BR (SVC)** | **0,823** | **0,815** | **0,022** | 0,158 | 2,735 | 0,437 |
| **RAkEL (Gaussian NB)** | 0,757 | 0,759 | 0,034 | 0,147 | 2,698 | 0,458 |
| **RAkEL (Random Forest)** | 0,426 | 0,361 | 0,050 | 0,510 | 6,660 | 0,742 |

## Interventions

| Model | F1-Micro | F1-Weighted | Hamming Loss | Ranking Loss | Coverage Error | One Error |
|---|---|---|---|---|---|---|
| **ML kNN** | 0,644 | 0,633 | 0,065 | 0,071 | 0,984 | 0,625 |
| **VW MLkNN** | 0,602 | 0,599 | 0,083 | 0,211 | 1,709 | 0,643 |
| **BR (kNN)** | 0,648 | 0,633 | 0,062 | 0,228 | 1,787 | 0,652 |
| **BR (MultinomialNB)** | 0,630 | 0,655 | 0,095 | **0,049** | **0,874** | **0,572** |
| **BR (SVC)** | **0,710** | **0,694** | **0,053** | 0,194 | 1,648 | 0,622 |
| **RAkEL (Gaussian NB)** | 0,661 | 0,675 | 0,080 | 0,145 | 1,396 | 0,606 |
| **RAkEL (Random Forest)** | 0,571 | 0,519 | 0,066 | 0,298 | 2,121 | 0,707 |

# The **BERTopic** Results

## Final **BERTopic** Configuration

| | |
|---|---|
| Representation Tuning | KeyBERT, LLama |
| Weighted Scheme | C-TF-IDF |
| Tokenizer | CountVect |
| Clustering | HDBSCAN |
| Dimensionality Reduction | UMAP |
| Embeddings | SBERT (Pubmedbert) |

## Applied on **"Not Labelled Data"**

| | Topic | Count | Name | Representation | KeyBERT | MMR | POS | Representative_Docs |
|---|---|---|---|---|---|---|---|---|
| 0 | -1 | 290 | -1_service_medical_used_data | [service, medical, used, data, time, research,... | [respondent, utility, measure, attribute, cost... | [service, medical, used, data, time, research,... | [service, medical, data, time, research, attri... | [latent class model heterogeneity latent class... |
| 1 | 0 | 148 | 0_family_endoflife_home_caregiver | [family, endoflife, home, caregiver, advance, ... | [nursing home, end life, advance planning, eld... | [family, endoflife, home, caregiver, advance, ... | [family, endoflife, home, caregiver, advance, ... | [unpacking impact adult home death family care... |
| 2 | 1 | 123 | 1_cancer_breast_information_breast cancer | [cancer, breast, information, breast cancer, o... | [breast cancer, cancer survivor, lung cancer, ... | [cancer, breast, information, breast cancer, o... | [cancer, breast, information, oncology, role, ... | [understanding value regarding early stage lun... |
| 3 | 2 | 85 | 2_attribute_method_dce_healthcare | [attribute, method, dce, healthcare, data, exp... | [experiment dces, dces, technology assessment,... | [attribute, method, dce, healthcare, data, exp... | [attribute, method, healthcare, data, experime... | [novel design process selection attribute incl... |
| 4 | 3 | 63 | 3_colleague_lesson_routine practice_say | [colleague, lesson, routine practice, say, nh,... | [, , , , , , , , , ] | [colleague, lesson, routine practice, say, nh,... | [lesson, routine practice, right, shift, progr... | [ , , implementing nh lesson magic programme ... |
| 5 | 4 | 51 | 4_sdm_clinician_practice_physician | [sdm, clinician, practice, physician, option, ... | [sdm, practice, clinician, physician, provider... | [sdm, clinician, practice, physician, option, ... | [sdm, clinician, practice, physician, option, ... | [assessing option gridxae practicability feasi... |
| 6 | 5 | 47 | 5_woman_pregnancy_contraceptive_attribute | [woman, pregnancy, contraceptive, attribute, m... | [pregnancy, woman, mother, fertility, pregnant... | [woman, pregnancy, contraceptive, attribute, m... | [woman, pregnancy, contraceptive, attribute, m... | [woman attribute firsttrimester miscarriage ma... |
| 7 | 6 | 45 | 6_tto_state_utility_value | [tto, state, utility, value, time, tradeoff, v... | [state valuation, utility value, valuation, st... | [tto, state, utility, value, time, tradeoff, v... | [tto, state, utility, value, time, tradeoff, v... | [correcting value influence importance correct... |
| 8 | 7 | 43 | 7_mental_depression_service_sdm | [mental, depression, service, sdm, consumer, s... | [mental, schizophrenia, depression, sdm, psych... | [mental, depression, service, sdm, consumer, s... | [mental, depression, service, sdm, consumer, u... | [family involvement consumer serious mental il... |
| 9 | 8 | 34 | 8_prostate_prostate cancer_cancer_men | [prostate, prostate cancer, cancer, men, decis... | [prostate cancer, prostate, localized prostate... | [prostate, prostate cancer, cancer, men, decis... | [prostate, cancer, men, decisional, da, decisi... | [voice methodology novel mixedmethods approach... |
| 10 | 9 | 30 | 9_pain_exercise_low_effect | [pain, exercise, low, effect, participation, d... | [pain, level, effectiveness, musculoskeletal, ... | [pain, exercise, low, effect, participation, d... | [pain, exercise, low, effect, participation, d... | [people considering exercise prevent low back ... |
| 11 | 10 | 26 | 10_diabetes_type diabetes_type_utility | [diabetes, type diabetes, type, utility, le, s... | [diabetes, type diabetes, diagnosis diabetes, ... | [diabetes, type diabetes, type, utility, le, s... | [diabetes, type, utility, state, program, beha... | [young adult type diabetes clinic approach att... |
| 12 | 11 | 21 | 11_dental_wtp_oral_dentist | [dental, wtp, oral, dentist, role, preferred | [dental, dentist, teeth, willingnesstopay, pay | [dental, wtp, oral, dentist, role, preferred | [dental, wtp, oral, dentist, role, preferred | [preferred perceived control dental increasing... |

# The **Conclusions**

- The **Binary Classifier** performs the first task (PPS identification): built on 2 models (SVC and KNN) on top of two bert embeddings; a majority voting system drives the class prediction. The model runs with a TPR of 96% and a PPV of 97%.

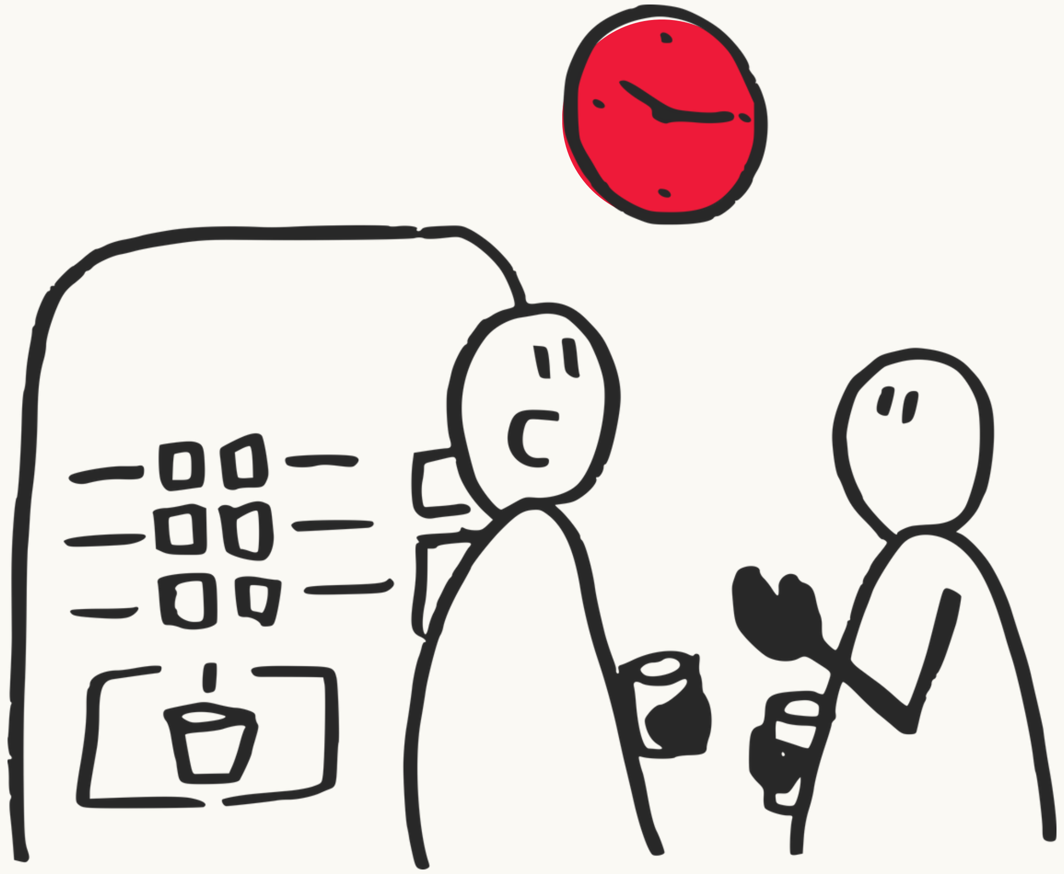
- The **Multi-Label Classifier** classifies papers of relevance (from the binary classifier) into different categories through a multi-label classification process.

- The investigation explores various multilabel classificators, identifying Binary Relevance with SVC as a classifier, ML kNN, and RAkEL with GaussianNB classifier as effective approaches. Data augmentation serves as the next step to enhance results and address low-frequency label-sets.

- The Bertopic study identifies a new label, diabetes, within the clinical areas category and proposes additional topics for further categorization.

APPLIED DATA SCIENCE PROJECT

# Thank You



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