Advanced Human Language Technologies

UNIVERSITAT POLITÈCNICA DE CATALUNYA
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Outline

NERC using machine learning

Assignment

The main program parses all XML files in the folder given as argument and recognizes and classifies drug names, calling a sequence-tagging machine learning algorithm.

```
$ python3 ./ml-NER.py data/devel result.out
$ more result.out
DDI-DrugBank.d278.s0|0-9|Enoxaparin|drug
DDI-DrugBank.d278.s0|93-108|pharmacokinetics|group
DDI-DrugBank.d278.s0|113-124|eptifibatide|drug
DDI-MedLine.d88.s0|15-30|chlordiazepoxide|drug
DDI-MedLine.d88.s0|33-43|amphetamine|drug
DDI-MedLine.d88.s0|49-55|cocaine|drug
DDI-MedLine.d88.s1|82-95|benzodiazepine|drug
...
```

Outline

Sequence tagging: the B-I-O approach

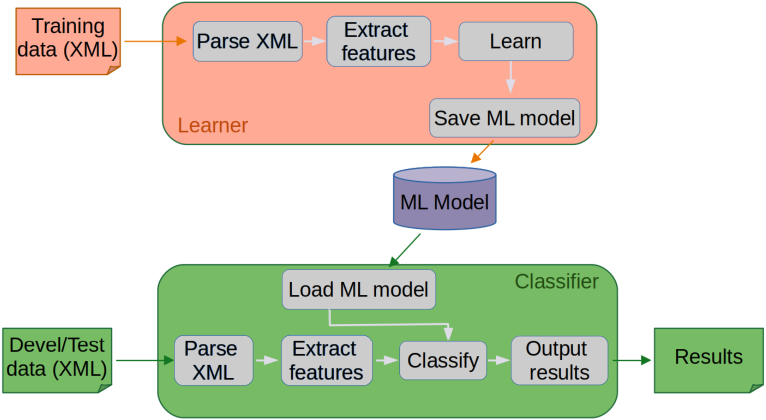
- We want to detect *subsequences* in a sentence (e.g. drug names).
- To approach this as a ML classification problem, we will classify each token.
- The classes predicted by the classifier must allow the later reconstruction of the target subsequences.
- B-I-O schema: mark each token as **B**egin of a subsequence, **I**nside a subsequence, or **O**utside any subsequence.
- If we not only want to recognize the subsequences, but also classify them, we use more informative B-I-O classes:

Ascorbic	**acid**	**,**	**aspirin**	**,**	**and**	**the**	**common**	**cold**	**.**
B-drug	I-drug	O	B-brand	O	O	O	O	O	O

- Different variations of this schema exist: BIO, BIOS, BIOES (aka BILOU)

Outline

General Structure



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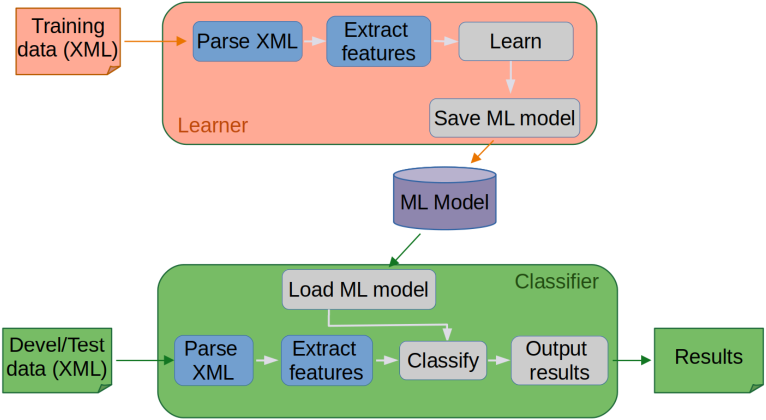
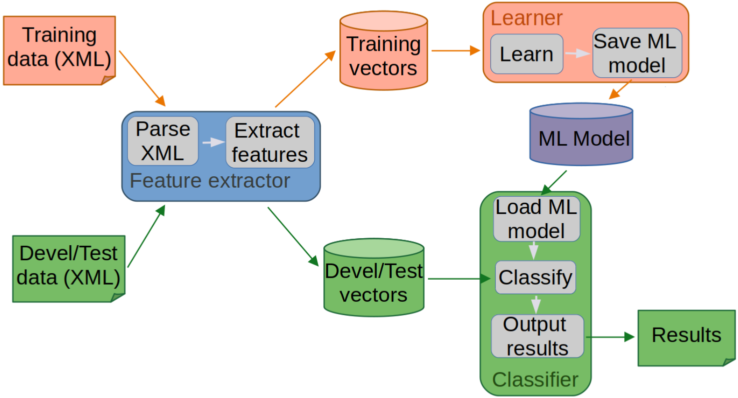


Extracting features is a costly operation, which we do not want to repeat for every possible experiment or algorithm parametrization.

General Structure



Feature extraction process is performed once, out of learning or predicting processes.

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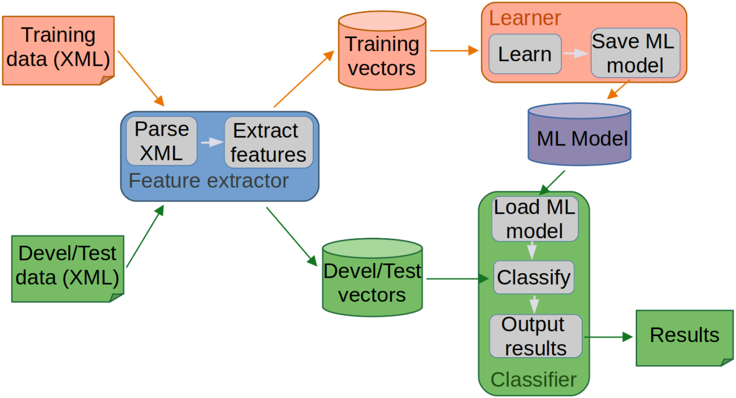

Feature extraction process is performed once, out of learning or predicting processes.
Thus, we need to write not a single program, but three different components: feature extractor, learner, and classifier.

Outline

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Feature Extractor

The feature extractor:

- Independent program, separated from learner and classifier
- Receives as argument the directory with the XML files to encode.
- Prints the feature vectors to `stdout`

```
$ python3 ./extractor_features.py data/devel devel.feat
$ more devel.feat
DDI-DrugBank.d658.s0 When 0 3 O form=When formlower=when suf3=hen
suf4=When isTitle BoS formNext=administered
formlowerNext=administered suf3Next=red suf4Next=ered
DDI-DrugBank.d658.s0 administered 5 16 O form=administered
formlower=administered suf3=red suf4=ered formPrev=When
formlowerPrev=when suf3Prev=hen suf4Prev=When isTitlePrev
formNext=concurrently formlowerNext=concurrently suf3Next=tly
suf4Next=ntly
...
```

Feature Extractor

```
# create analyzer. We don't need the parser now (it's faster without)
nlp = spacy.load("en_core_web_trf", disable=["parser"])
# parse XML file, obtaining a DOM tree
tree = parse(datafile)  # process each sentence in the file
sentences = tree.getElementsByTagName("sentence")
for s in sentences :
  sid = s.attributes["id"].value   # get sentence id
  spans = []
  stext = s.attributes["text"].value   # get sentence text
  entities = s.getElementsByTagName("entity") # get gold standard
 entities
  for e in entities :
     # for discontinuous entities, we only get the first span
     # (will not work, but there are few of them)
     (start,end) = e.attributes["charOffset"].value.split(";")[0].split(
 "-")
     typ =  e.attributes["type"].value
     spans.append((int(start),int(end),typ))
  tokens = nlp(stext)    # convert the sentence to a list of tokens
  features = extract_sentence_features(tokens)  # extract features
  # print features in format expected by CRF/SVM/MEM trainers
  for i,tk in enumerate(tokens) :
     # see if the token is part of an entity
     tks,tke = tk.idx, tk.idx+len(tk.text)
     # get gold standard tag for this token
     tag = get_label(tks, tke, spans)
     # print feature vector for this token
     print (sid, tk.text, tks, tke-1, tag, "\t".join(features[i]), sep='
 \t', file=outf)
  # blank line to separate sentences
  print(file=outf)
```

Feature extraction for NLP

- In most ML applications, the feature space is finite and known (e.g. credit scoring, medical diagnose prediction, churn prevention, fraud detection, etc).
- Also, most of the used features are numerical or categorial (income, age, sex, colestherol level, number of receipts returned, etc.)
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- In most NLP applications, features are related to appearing words, suffixes, prefixes, lemmas, etc. Thus, the feature space is huge.
- Moreover, features are usually binary-valued (a word appears or not, a suffix appears or not, etc).
- Thus, in NLP applications, feature vectors are usually *intensive* lists of strings (i.e. listing the names for features with value `true`, and ommiting all the rest), and are stored as *sparse vectors*.

Sparse vector representation: CSR matrix

- NLP applications usually have feature spaces of hundreds of thousands of dimensions, which can not be stored in a table.
- However, vectors are usually very sparse: Each example (each token in NERC case) has only a reduced number of non-zero columns
- CSR matrix representation consists of storing the coordinates and the value for non-zero elements in the matrix.
- The matrix elements are indexed by their (row,column) coordinates.

$$\begin{pmatrix} 0 & 0 & 3 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 6 \end{pmatrix} \Longrightarrow \begin{pmatrix} \mathit{row} & \mathit{col} & \mathit{val} \\ 0 & 2 & 3 \\ 1 & 0 & 2 \\ 3 & 2 & 1 \\ 3 & 4 & 6 \end{pmatrix}$$

- Each row in the matrix corresponds to a training example (a sentence token, for NERC).
- Each column corresponds to a boolean feature (a distinct string among all those instantiated by the training data).
- A feature index is needed to keep the correspondence between feature names and their column number.

Feature Extractor Functions - Extract features

```
def extract_features(s) :
  '''
  Task:
    Given a tokenized sentence, return a feature vector for each token

  Input:
    s: A tokenized sentence (list of triples (word, offsetFrom, offsetTo) )

  Output:
    A list of feature vectors, one per token.
    Features are binary and vectors are in sparse representation (i.e. only
     active features are listed)

  Example:
    >>> extract_features([("Ascorbic",0,7), ("acid",9,12), (",",13,13),
          ("aspirin",15,21), (",",22,22), ("and",24,26), ("the",28,30),
          ("common",32,37), ("cold",39,42), (".",43,43)])
    [ [ "form=Ascorbic",  "suf4=rbic", "next=acid", "prev=_BoS_", "
     capitalized"  ],
      [ "form=acid",  "suf4=acid", "next=,", "prev=Ascorbic" ],
      [ "form=,",  "suf4=,", "next=aspirin", "prev=acid", "punct" ],
      [ "form=aspirin",  "suf4=irin", "next=,", "prev=," ],
      ...
    ]
  '''
```

Outline

Learner

The B-I-O approach consists of a classifier that assigns a label to each token, so any ML algorithm may be used

- Local classifiers: Each token is classified independently.
  - Maximum Entropy Classifiers (MEM)
  - Support Vector Machines (SVM)
  - ...

  May lead to inconsistencies (e.g `III` sequences without a `B` at the beggining)
- Global Classifiers: The whole sequence is taken into account for a global decision. Features are factorized to get an affordable cost.
  - Maximum Entropy Markov Models (MEMM)
  - Conditional Random Fields (CRF)
  - ...

Learner: MEM (a.k.a. Logistic Regression)

- Install and import `scikit-learn`
  `$ pip install scikit-learn`
- Use provided `train.py` to learn a MEM model.
  `$ python3 run.py train MEM`

  You may modifiy learner parameters (loss function, thresholds, learning rates, etc).
- Check performance on development data.
  `$ python3 run.py predict MEM`
- `scikit-learn` implementation of `LogisticRegression` (MEM), admits sparse matrix representations such as CSR (Compressed Sparse Row) matrix.

Learner: SVM

- Install and import `scikit-learn`
  `$ pip install scikit-learn`
- Use provided `train.py` to learn a SVM model.
  `$ python3 run.py train SVM`
  You may modifiy learner parameters (loss function, thresholds, learning rates, etc).
- Check performance on development data.
  `$ python3 run.py predict SVM`
- `scikit-learn` implementation of `SVC` (SVM), admits sparse matrix representations such as CSR (Compressed Sparse Row) matrix.

Learner: CRF

- Install and import `pycrfsuite`
  `$ pip install python-crfsuite`
- Use provided `train.py` to learn a CRF model.
  `$ python3 run.py train CRF`
  You may modifiy learner parameters (loss function, thresholds, learning rates, etc).
- Check performance on development data.
  `$ python3 run.py predict CRF`
- `python-crfsuite` admits sparse vectors of boolean features represented as lists of names of the columns (i.e. features) that are true for each example.

Learner: Others

- You are welcome to try and compare any other ML algorithm of your choice available in scikit-learn. The chosen algorithm must support sparse vectors of binary features (e.g. scipy `csr_matrix`). DO NOT use neural network approaches, we'll do that later in the course.
- Create a new class similar to `MEM.py`, `SVM.py` or `CRF.py` with:
  - A constructor that allows either loading an exisiting model or initializing one for training
  - A `train` method that receives a dataset and trains a model
  - A `predict` method that receives a classification example and returns its class.
  - Adapt `train.py` and `predict.py` to use the new class depending on the provided file extension
- Use `train.py` to learn your new XYZ model.

```
$ python3 train.py train.feat model.xyz
```

Outline

Classifier - All options

You can apply the learned models to new data:

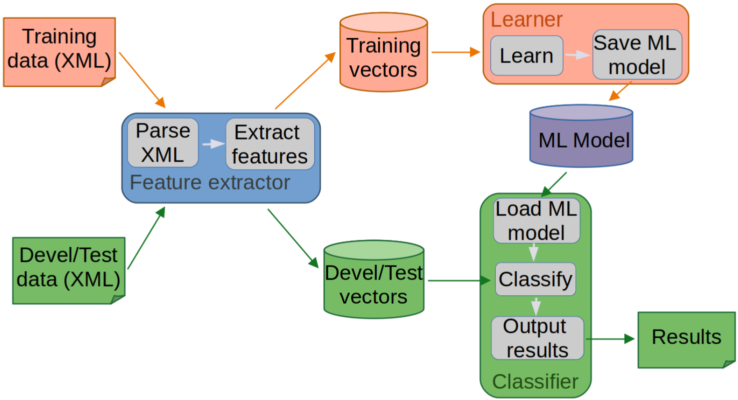
```
$ python3 run.py extract test
$ python3 run.py predict MEM test
$ python3 run.py predict SVM test
$ python3 run.py predict CRF test
```

Once a best learner is selected experimenting with different algorithms and parameters, the best model can be applied to test data to evaluate generalization ability of the model.

Outline

Build a good ML-based drug NERC

Strategy to follow:



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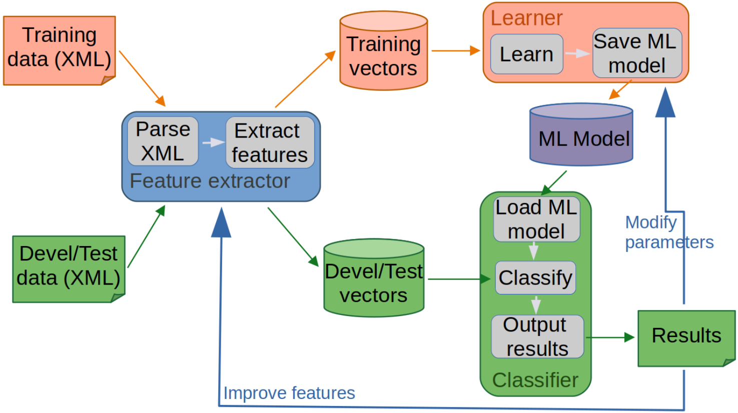

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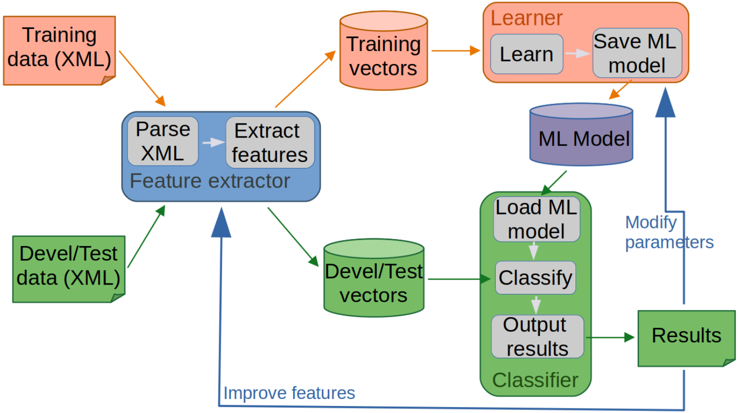

- Repeat training – evaluation cycle on devel dataset to find out which is the best parameterization for the used algorithm.

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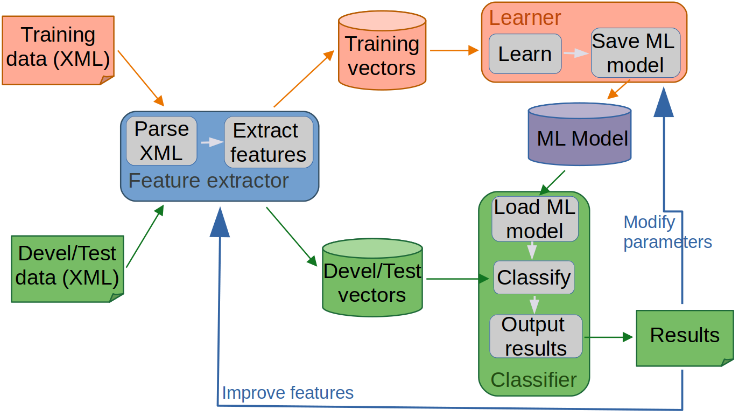

- Repeat training – evaluation cycle on devel dataset to find out which is the best parameterization for the used algorithm.
- Repeat feature extraction – training – evaluation cycle on devel dataset to find out which features are useful.

Choosing useful features

- Used models are *token* classifiers, so there is a feature vector *per token*.
- Features about a token should allow its classification, so they should encode information about *both* the token itself and its context (i.e. nearby words).
- Feature names must be *unambiguous*. E.g., a feature named `sufx=azole` may not be enough if one wants to encode also context word suffixes. In that case, different feature names are needed (e.g.: `sufx=azole` for the focus word, plus e.g. `sufx-2=azole`, `sufx-2=azole`, `sufx+1=azole`, `sufx+2=azole` for nearby words).
- Including features encoding information from external dictionaries will largely improve results.

Choosing useful features

- IMPORTANT: Feature names such as `sufx=azole` are not key-value pairs (i.e. not a `sufx` feature with value `azole`), but just a string naming a binary (true/false) feature.
  The feature name could be any (`sufxisazole`, `wordendsinazole`, ...) as long as it is active (i.e. present in the sparse vector) only when that property holds.
- IMPORTANT: Features are boolean, and only those with value `true` are listed. So, a feature not present in the list is an *existing* column with value `false`.

  Thus, it does not make sense to have e.g. a boolean feature `capitalized:true` and another feature `capitalized:false`, since the absence of the former is equivalent to the presence of the latter and viceversa.

Outline

Exercise Goals

What you should do:

- Work on your feature extractor. It is the component of the process where you have most control.
- Experiment with different algorithms and parameterizations.
- Keep track of tried features and parameter combinations, and results produced by each.

What you should **NOT** do:

- Use neural network learners. We'll do that later on the course.
- Produce an overfitted model: If performance on the test dataset is much lower than on devel dataset, you probably are overfitting your model.

Exercise Goals

Orientative results:

- Provided initial version achieves over 45% macro average F1 on devel with 2 simple feature templates (word form and size-3 suffix).
- A set of 10 feature templates is enough to get a macroaverage F1 over 65%. Used information includes (for current, previous, and next tokens)
  - word forms, original and lowercase
  - suffixes (of different lenghts)
  - capitalization pattern (all upper, title, camelcase,...)
  - presence of numbers, dashes, etc. in the token
  - existence (and class) of the token in external lists
  - ...

Deliverables

After DDI-ML task, you will need to deliver a single report on the work carried out on both (NERC-ML and DDI-ML) tasks.

So, during the development and experimentation on NERC task:

- keep track of tried/discarded features
- keep track of used algorithms and parameterizations.
- Record obtained results in the different experiments, and compile the information you'll later need to elaborate the report.