Reflected Text Analysis beyond Linguistics

DGfS-CL fall school

Nils Reiter,
nils.reiter@ims.uni-stuttgart.de

Sept. 9-13, 2019

Outline

Shared Tasks

Data and Annotations

Hackatorial Setup

- Concrete steps

Shared Tasks

- Established framework in NLP
- Driver of innovation in the past decade (e.g., machine translation)
- Competitive, winners are highly respected

Shared Tasks

- Established framework in NLP
- Driver of innovation in the past decade (e.g., machine translation)
- Competitive, winners are highly respected
- Past STs
  - Chunking Sang and Buchholz (2000)
  - Clause identification Sang and Déjean (2001)
  - Language-independent named entity recognition Tjong Kim Sang and De Meulder (2003)
  - Syntactic parsing either multilingually or for specific languages Buchholz and Marsi (2006), Kübler (2008), and Nivre et al. (2007)
  - semantic representation/role labeling Bos (2008), Carreras and Màrquez (2004), and Carreras and Màrquez (2005)
  - …

Shared Tasks

Workflow

- Organizers define a task and provide a data set with annotations
- Participants develop (automatic) systems to solve the task
- $t-2$: Previously unknown test data is published (without annotations), participants apply their systems to this data set
- $t-1$: Participants upload/send the results of their systems to the organizers
- t: Organizers evaluate each system's results against a (secret) gold standard, results are published
- $t+1$: Gold standard is published, papers written, workshops held

Section 2

Data and Annotations

Corpus

Title	Language	Description
Werther	German	Goethe's *Sorrows of the Young Werther*; pistolary novel, published 1774/1787
Bundestags-debatten	German	Debates from the German federal parliament; stenographic minutes
Parzival	Middle High German	Arthurian Romance; written 12th/13th century CE; verse
Grimm	English	Grimm's folk tales, annotated with coreferences in phrase detectives online game (not in Stuttgart)

Table: Corpus overview

- Heterogeneous with respect to content and form
- German/Middle High German/English

Background: Research interests

- Werther (Modern German Literature)
  - Successful novel, a large number of adaptations have been published
  - What makes a Werther adaptation ('Wertheriade') recognizable as an adaptation (e.g., Wertherness?)
    - Three characters in a triadic relationship (Werther, Lotte, Albert)
    - Importance of nature (e.g., certain lakes or forest clearings)

Background: Research interests

- Werther (Modern German Literature)
  - Successful novel, a large number of adaptations have been published
  - What makes a Werther adaptation ('Wertheriade') recognizable as an adaptation (e.g., Wertherness?)
    - Three characters in a triadic relationship (Werther, Lotte, Albert)
    - Importance of nature (e.g., certain lakes or forest clearings)
- Parliamentary debates (Social Sciences)
  - Relation of armed conflicts and identity building
  - Who mentions which institution in what context?

Background: Research interests

- Werther (Modern German Literature)
  - Successful novel, a large number of adaptations have been published
  - What makes a Werther adaptation (‘Wertheriade’) recognizable as an adaptation (e.g., Wertherness?)
    - Three characters in a triadic relationship (Werther, Lotte, Albert)
    - Importance of nature (e.g., certain lakes or forest clearings)
- Parliamentary debates (Social Sciences)
  - Relation of armed conflicts and identity building
  - Who mentions which institution in what context?
- Parzival
  - 16 volumes, many characters and places
  - Social relations between characters and/or places

Background: Research Interests

Common interest

CRETA works on methods/concepts/workflows that are relevant for multiple disciplines/research questions
In this case: Entities!

- Werther: Characters and locations
- Parliamentary debates: Persons, organizations, locations, dates
- Parzival: Characters and locations

Annotations

Conceptual Overview

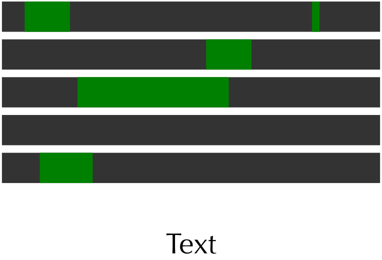


Figure: Entity references and entities

Annotations

Conceptual Overview

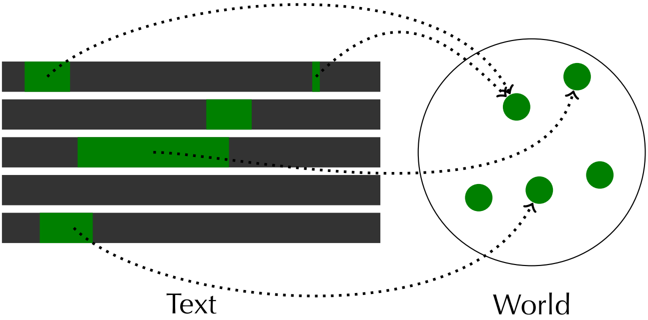


Figure: Entity references and entities

Annotations

Conceptual Overview

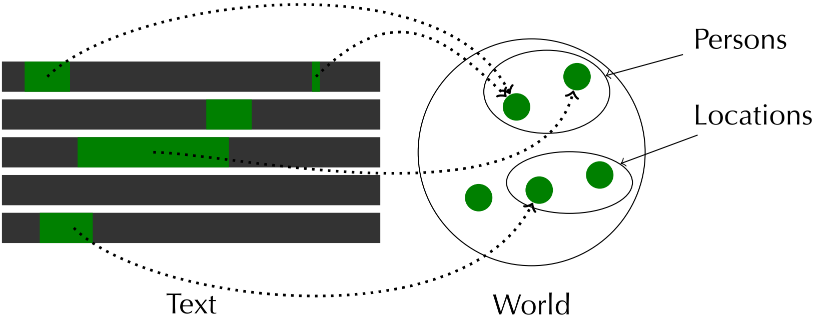


Figure: Entity references and entities

Annotations

Guidelines

Entity references

- ✓ Proper names (‘Werther’)
- ✓ Appellative noun phrases (‘the knight’) – if they refer
  - ✓ Groups: ‘the two knights’
  - ✓ Addresses: ‘My dear friend’
  - × Generic expressions: ‘the chancellor is elected by the parliament’
- × Pronouns are *not annotated*

Annotations

Guidelines

How did we annotate?

- Maximal noun phrases, including
  - relative clauses: ‘the chancellor, who has in Berlin at this time’
  - appositions: ‘Wilhelm, my friend’
- If determiner and preposition are contracted, the contracted form is included
  - ‘in [dem Land]’, ‘[im Land]’
- Embedded phrases are annotated
  - ‘[Wolfram von [Eschenbach]$_{\text{LOC}}$]$_{\text{PER}}$’
    - ST data: Only the longest annotation matters
- Entity type is annotated in context
  - ‘I always wanted to go to [Europe]$_{\text{LOC}}$.’
  - ‘[Europe]$_{\text{ORG}}$ is forcing Greece to take a hard austerity course.’

Annotations

Examples

Text	Classes	Examples
Werther	Person	Werther, liebster Wilhelm, die Kinder aus dem Dorfe
	Location	Die Schweiz, dem Dorfe
	Work	Emilia Galotti
Bundestagsdebatten	Person	Angela Merkel, die Abgeordneten
	Location	Großbritannien, das Land, Europa
	Organization	SPD, die Union, Europa
Parzival	Person	Parzival, der ritter, die tafelrunde
	Location	Nantes, der wald Brazilian, der palas

Annotations

Text-specific properties

- Werther
  - 1878: old language
  - Epistolary novel: First-person narrator
  - Emotional style: Long sentences, interjections, …
- Bundestagsdebatten
  - Non-narrative text, logged direct speech
  - Contemporary text: Style and content
- Parzival
  - Middle High German
  - Proper nouns are upper cased
  - Almost all other words are lower cased
  - Segmentation in 30 verses: Each first row upper case

Annotations and Data

Summary

- Three text types with different properties
- Annotated entity references (according to guidelines)
- Files are split into training and test set

Annotations and Data

Summary

- Three text types with different properties
- Annotated entity references (according to guidelines)
- Files are split into training and test set

BIO scheme

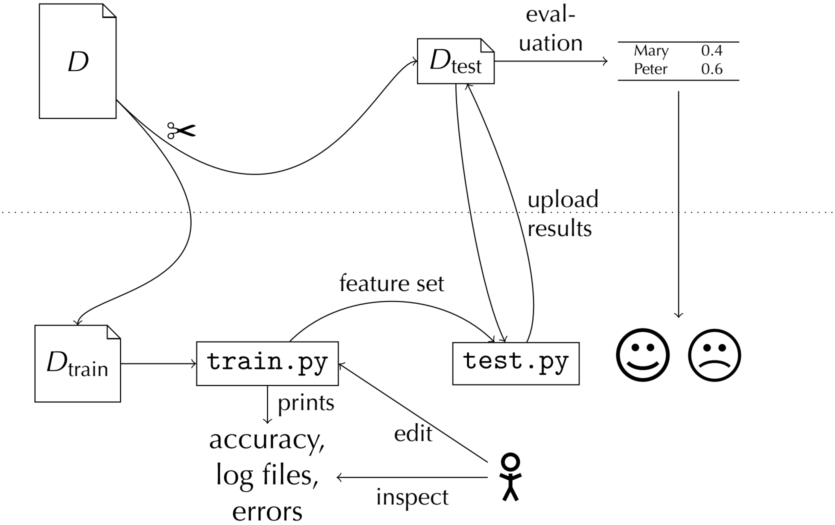
- Entity references span multiple tokens (incl. unitising task)
- Hack: Turn it into token-wise classification task
- B I O
  - B: Begin of an annotation
  - I: Inside of an annotation
  - O: Outside of an annotation
- Embedded annotations are not represented (only the longest)

Section 3

Hackatorial Setup

Hackatorial

Overview



D

D_{test}

eval-
uation

Mary	0.4
Peter	0.6

upload
results

feature set

D_{train}

`train.py`

`test.py`

prints

accuracy,
log files,
errors

edit

inspect

Hackatorial

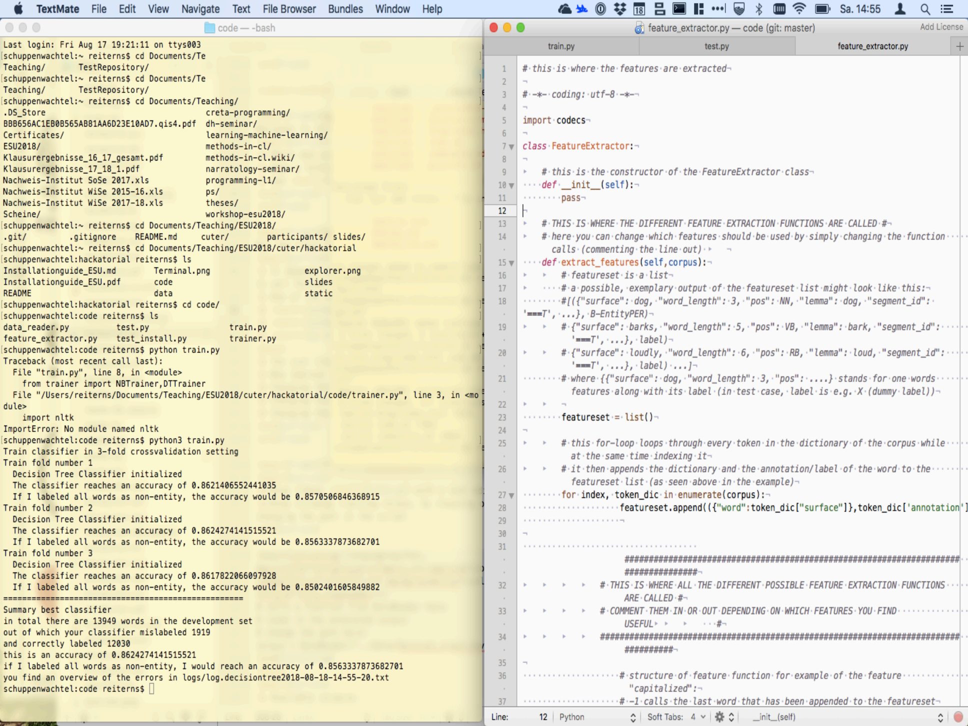
Playground options

- Choose a data set
    - Werther, Parzival, Bundestagsdebatten, Grimm folktales
- Choose a classifier
    - Decision tree, naive bayes
- Edit the feature set
    - Turn features on/off, add additional features

Hackatorial

Navigate to the correct folder

- Where did you save the `hackatorial` folder?
- Open a Terminal/Eingabeaufforderung
- Use `cd path/to/hackatorial/code` to navigate into the folder



TextMate File Edit View Navigate Text File Browser Bundles Window Help
Sa. 14:55
code — -bash
feature_extractor.py — code (git: master)
Add License
train.py
test.py
feature_extractor.py
Line: 12
Python
Soft Tabs: 4
__init__(self)

```
Last login: Fri Aug 17 19:21:11 on ttys003
schuppenwachtel:~ reiterns$ cd Documents/Te
Teaching/       TestRepository/
schuppenwachtel:~ reiterns$ cd Documents/Te
Teaching/       TestRepository/
schuppenwachtel:~ reiterns$ cd Documents/Teaching/
.DS_Store                                 creta-programming/
BBB656AC1EB0B565AB81AA6D23E10AD7.qis4.pdf dh-seminar/
Certificates/                             learning-machine-learning/
ESU2018/                                  methods-in-cl/
Klausurergebnisse_16_17_gesamt.pdf        methods-in-cl.wiki/
Klausurergebnisse_17_18_1.pdf             narratology-seminar/
Nachweis-Institut SoSe 2017.xls           programming-l1/
Nachweis-Institut WiSe 2015-16.xls        ps/
Nachweis-Institut WiSe 2017-18.xls        theses/
Scheine/                                  workshop-esu2018/
schuppenwachtel:~ reiterns$ cd Documents/Teaching/ESU2018/
.git/        .gitignore    README.md     cuter/        participants/ slides/
schuppenwachtel:~ reiterns$ cd Documents/Teaching/ESU2018/cuter/hackatorial
schuppenwachtel:hackatorial reiterns$ ls
Installationguide_ESU.md        Terminal.png                    explorer.png
Installationguide_ESU.pdf       code                            slides
README                          data                            static
schuppenwachtel:hackatorial reiterns$ cd code/
schuppenwachtel:code reiterns$ ls
data_reader.py          test.py                 train.py
feature_extractor.py    test_install.py         trainer.py
schuppenwachtel:code reiterns$ python train.py
Traceback (most recent call last):
  File "train.py", line 8, in <module>
    from trainer import NBTrainer,DTTrainer
  File "/Users/reiterns/Documents/Teaching/ESU2018/cuter/hackatorial/code/trainer.py", line 3, in <mo
dule>
    import nltk
ImportError: No module named nltk
schuppenwachtel:code reiterns$ python3 train.py
Train classifier in 3-fold crossvalidation setting
Train fold number 1
  Decision Tree Classifier initialized
  The classifier reaches an accuracy of 0.8621406552441035
  If I labeled all words as non-entity, the accuracy would be 0.8570506846368915
Train fold number 2
  Decision Tree Classifier initialized
  The classifier reaches an accuracy of 0.8624274141515521
  If I labeled all words as non-entity, the accuracy would be 0.8563337873682701
Train fold number 3
  Decision Tree Classifier initialized
  The classifier reaches an accuracy of 0.8617822066097928
  If I labeled all words as non-entity, the accuracy would be 0.8502401605849882
==================================================
Summary best classifier
in total there are 13949 words in the development set
out of which your classifier mislabeled 1919
and correctly labeled 12030
this is an accuracy of 0.8624274141515521
if I labeled all words as non-entity, I would reach an accuracy of 0.8563337873682701
you find an overview of the errors in logs/log.decisiontree2018-08-18-14-55-20.txt
schuppenwachtel:code reiterns$
```

```python
# this is where the features are extracted

# -*- coding: utf-8 -*-

import codecs

class FeatureExtractor:

	# this is the constructor of the FeatureExtractor class
    def __init__(self):
        pass

	# THIS IS WHERE THE DIFFERENT FEATURE EXTRACTION FUNCTIONS ARE CALLED #
	# here you can change which features should be used by simply changing the function calls (commenting the line out)
    def extract_features(self,corpus):
		# featureset is a list
	    # a possible, exemplary output of the featureset list might look like this:
        #[({"surface": dog, "word_length": 3, "pos": NN, "lemma": dog, "segment_id": '===T', ...}, B-EntityPER)
		#{"surface": barks, "word_length": 5, "pos": VB, "lemma": bark, "segment_id": '===T', ...}, label)
		#{"surface": loudly, "word_length": 6, "pos": RB, "lemma": loud, "segment_id": '===T', ...}, label) ...]
        # where {{"surface": dog, "word_length": 3, "pos": ....} stands for one words features along with its label (in test case, label is e.g. X (dummy label))

        featureset = list()

		# this for-loop loops through every token in the dictionary of the corpus while at the same time indexing it
		# it then appends the dictionary and the annotation/label of the word to the featureset list (as seen above in the example)
        for index, token_dic in enumerate(corpus):
                    featureset.append(({"word":token_dic["surface"]},token_dic['annotation']
                    

                                ################################################################################
				# THIS IS WHERE ALL THE DIFFERENT POSSIBLE FEATURE EXTRACTION FUNCTIONS ARE CALLED #
				# COMMENT THEM IN OR OUT DEPENDING ON WHICH FEATURES YOU FIND USEFUL			   #
				##########################################################################################

                    # structure of feature function for example of the feature "capitalized":
                    # -1 calls the last word that has been appended to the featureset
```

Hackatorial

Run the train script using Python

- It depends on your operating system and version, but you can try the following commands to call Python: py, python, python3
- One of the following should work:
  - `python train.py`
  - `python3 train.py`
  - `py train.py`

Hackatorial

Run the train script using Python

- It depends on your operating system and version, but you can try the following commands to call Python: py, python, python3
- One of the following should work:
  - `python train.py`
  - `python3 train.py`
  - `py train.py`
- You just trained your first machine learning model!
- Now improve its performance by
  - Changing the data set
  - Changing the algorithm
  - Changing the feature set

Hackatorial

How to change the data set

Step 1 Open `train.py` with a text editor (e.g. Notepad++)

Step 2 Change training corpus, by choosing one of the available corpora listed below and changing the path in the script

```python
# calls a function from DataReader here
# reads in the annotated corpus
# change the path here:
corpus = DataReader("../data/Parzival_train.tsv").read_corpus()
```

Hackatorial

How to change the data set

Step 1 Open `train.py` with a text editor (e.g. Notepad++)

Step 2 Change training corpus, by choosing one of the available corpora listed below and changing the path in the script

```
# calls a function from DataReader here
# reads in the annotated corpus
# change the path here:
corpus = DataReader("../data/Parzival_train.tsv").read_corpus()
```

- Available corpora:
  - `Grimm_train.tsv`
  - `Parzival_train.tsv`
  - `Werther_train.tsv`
  - `Bundestag_train.tsv`

Hackatorial

How to change the features

Step 1 Open `feature_extractor.py` with a text editor

Step 2 Comment or uncomment the features

- Commenting out (disable): Putting a # in front of the line
- Uncomment (enable the feature): Removing the #

```
...
####################################################################################
# THIS IS WHERE ALL THE DIFFERENT POSSIBLE FEATURE EXTRACTION FUNCTIONS ARE CALLED #
# COMMENT THEM IN OR OUT DEPENDING ON WHICH FEATURES YOU FIND USEFUL               #
####################################################################################

# structure of feature function for example of the feature "capitalized":
# -1 calls the last word that has been appended to the featureset
# 0 accesses the dictionary which is the first element of the tupel
# "capitalized" is the feature name

featureset[-1][0]["pos"] = self.pos(token_dic)
#featureset[-1][0]["surface"] = self.surface(token_dic)
#featureset[-1][0]["surface_backwards"] = self.surface_backwards(token_dic)
...
```

The full feature list is available as a PDF (with examples).

Hackatorial

What do features mean?

Available features and their meaning are listed in the table that you got on paper and further below in `feature_extractor.py`

```
#####################################################################
# THESE ARE ALL THE DIFFERENT POSSIBLE FEATURE EXTRACTION FUNCTIONS #
#####################################################################

# This function returns the part of speech tag of the word
def pos(self, word_dic):
    return word_dic["pos"]


# This function returns the word itself
def surface(self, word_dic):
    return word_dic["surface"]

# This function returns the word backwards
def surface_backwards(self, word_dic):
    return word_dic["surface"][::-1]
...
```

Hackatorial

How to change the training algorithm

Step 1 Open `train.py` with a text editor

Step 2 Comment out one of the lines starting with `trainer =`

```
    # THIS IS WHERE YOU CAN CHANGE THE ML ALGORITHM#
    # change this line for another ML algorithm (remove the # infront of a line to uncomment)
    # DTTrainer is the trainer for a Decision Tree classifier
    # NBTrainer is the trainer for a Naive Bayes classifier
    #
    trainer = DTTrainer(traincv)
    #trainer = NBTrainer(traincv)
```

Enjoy Training!