

The LEXenstein Manual



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Chapter 1

Introduction

LEXenstein is a tool for the benchmarking of Lexical Simplification systems. It contains several methods, tools and resources for one to easily create Lexical Simplification systems and test them in various distinct ways. It takes Lexical Simplification as a process that can be modeled as a pipeline of sub-processes, as illustrated in Figure 1.1.

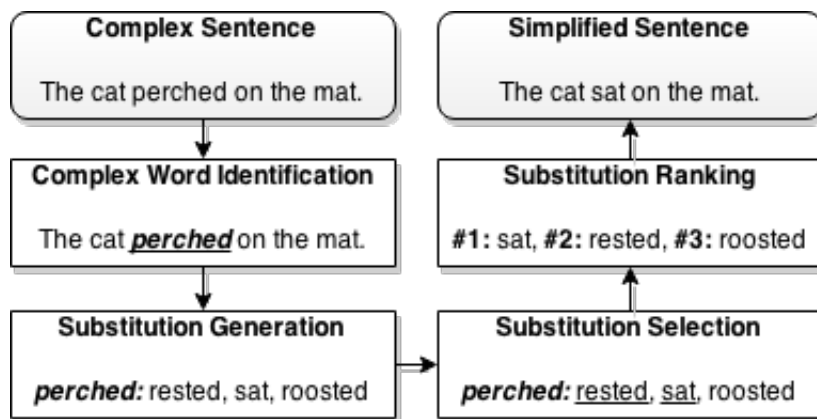


Fig. 1.1 Lexical Simplification pipeline

Each task in Figure 1.1 can be described as:

1. **Complex Word Identification:** Task of deciding which words of a given sentence may not be understood by a given target audience and hence must be simplified.
2. **Substitution Generation:** Task of finding pairs of words or expressions that share the same meaning and are interchangeable in some context.
3. **Substitution Selection:** Task of deciding which is the meaning of a given complex ambiguous word in a sentence to be simplified, and then selecting which substitutions available also represent that meaning.

4. **Substitution Ranking:** Task of ranking the remaining substitutions of a given complex word by their simplicity.

Its name is a reference to the *Frankenstein* novel, published by [21]. It refers to the fact that one can, as Victor Frankenstein did, create an entire Lexical Simplification “creature” by combining multiple “pieces” of the Lexical Simplification pipeline together.

LEXenstein is divided in several modules: Substitution Generation, Substitution Selection, Substitution Ranking, Feature Estimation, Evaluation and Text Adorning. In the next Sections, we describe the VICTOR file format (Section 3.1), explain how to properly setup LEXenstein (Section 2), and also describe in detail the components included in each module of the LEXenstein tool (Section 4).

Chapter 2

Installation

LEXenstein is a library written entirely in Python. It hence requires for Python 2.7.* to be installed in the user’s machine. We have not yet tried to run LEXenstein over Python 3.*. To install LEXenstein, please follow the steps below:

1. Download the tool from **omitted for review**.
2. Copy the “lexenstein” folder included in the package into the folder of your project.
3. Access LEXenstein by importing its modules in the following fashion:

```
from lexenstein.morphadorner import *  
from lexenstein.features import *  
from lexenstein.generators import *  
from lexenstein.selectors import *  
from lexenstein.rankers import *  
from lexenstein.evaluators import *
```

In the near future, we will allow for one to install LEXenstein by using standard installation routines, such as through a “setup.py” file, or pip. LEXenstein requires for several libraries and toolkits to be included in the user’s Python 2.7.* installation. The following Sections explain which libraries and toolkits are required, where to get them and how to install them.

2.1 Required Libraries

2.1.1 Morph Adorner Toolkit

The Morph Adorner Toolkit [16] is a set of Java applications that facilitate the access to Morph Adorner's functionalities [4]. This tool is used by LEXenstein's Substitution Generation module to create inflections for generated substitutions. To install it, follow the steps below:

1. Download the tool from <http://ghpaetzold.github.io/MorphAdornerToolkit/>
2. Place it in a folder of your choice

Since the tool does not require any compilation, all you need to do is use the path in which you installed it to create instances of the **MorphAdornerToolkit** class, which can be found in LEXenstein's Morph Adorning module.

2.1.2 NLTK

NLTK [2] is a set of resources and algorithms for tasks related, but not restricted to, Natural Language Processing. To install it, please follow the steps provided in: <http://www.nltk.org/install.html>. Once you have NLTK installed in your Python distribution, please download all additional resources available by following this tutorial: <http://www.nltk.org/data.html>.

2.1.3 KenLM

KenLM [9] is a tool for fast language model creation and querying. LEXenstein's modules use KenLM to access the data in binary language models for various tasks, such as feature calculation and substitution filtering. To install it, please follow the steps below:

1. Download or clone KenLM from <https://github.com/kpu/kenlm>
2. Place it in a folder of your choice
3. Navigate to the installation folder in a terminal and run: **python setup.py install**

If no problems occur, KenLM should now be installed in your Python distribution. To verify whether or not the installation was successful, open Python and try importing the library with the following line of code: **import kenlm**. If no errors occur, then the installation was successful.

2.1.4 Scipy and Numpy

Scipy and Numpy [13] are tools that offer great utility for projects and applications in the fields of mathematics, science, and engineering. To install them, please follow the instructions in: <http://www.scipy.org/install.html>.

2.1.5 Gensim

Gensim [19] is a set of algorithms for unsupervised semantic modeling. LEXenstein uses Gensim to read word vector models. To install it, follow the instructions in: <https://radimrehurek.com/gensim/install.html>.

2.1.6 PyWSD

PyWSD [23] is a library that offers access to several Word Sense Disambiguation algorithms. LEXenstein's uses this library to filter substitutions. To install it, follow the steps below:

1. Download or clone PyWSD from <https://github.com/alvations/pywsd>
2. Place it in a folder of your choice
3. Navigate to the installation folder in a terminal and run: **python setup.py install**

If no problems occur, PyWSD should now be installed in your Python distribution. To verify whether or not the installation was successful, open Python and try importing the library with the following line of code: **import pywsd**. If no errors occur, then the installation was successful.

2.1.7 Scikit-Learn

Scikit-Learn [18] is a set of tools for data mining, data analysis and machine learning. LEXenstein uses this library to learn ranking models. To install it, follow the instructions in: <http://scikit-learn.org/stable/install.html>.

2.1.8 SVM-Rank

SVM-Rank [12] is a tool that allows for one to use Support Vector Machines in ranking setups. LEXenstein uses this library to learn ranking models. To install it, follow the instructions in: http://www.cs.cornell.edu/people/tj/svm_light/svm_rank.html.

2.1.9 Other Libraries

LEXenstein also uses various other well-known Python modules, they are: xml, re, urllib2, subprocess, codecs and os.

Chapter 3

The VICTOR Format

In order to standardize input and output within the LEXenstein framework, we have conceived the VICTOR format: an elegant way of representing data for both the training and testing of Lexical Simplification models and systems. It is a reference to Victor Frankenstein, the main character in the Frankenstein novel [21], and creator of the ever so popular Frankenstein’s Monster. Each line of a file in VICTOR format is structured as illustrated in Example 3.1, where S_i is the i th sentence in the dataset, w_i a target complex word in the h_i th position of S_i , c_i^j a substitution candidate and r_i^j its simplicity ranking.

$$\langle S_i \rangle \langle w_i \rangle \langle h_i \rangle \langle r_i^1 : c_i^1 \rangle \langle r_i^2 : c_i^2 \rangle \dots \langle r_i^{n-1} : c_i^{n-1} \rangle, \langle r_i^n : c_i^n \rangle \quad (3.1)$$

Each bracketed component in the example above is separated by a tabulation marker. Examples of files with such notation can be found in “resources/victor_datasets”.

Chapter 4

Modules

4.1 Text Adorning

LEXenstein's Text Adorning module provides a Python interface to the Morph Adorner Toolkit [16], a set of Java tools that facilitates the access to Morph Adorner's functionalities. The class MorphAdornerToolkit provides easy access to word lemmatization, word stemming, syllable splitting, noun inflection, verb tensing and verb conjugation. Below is an example of how to create and use a MorphAdornerToolkit object:

```
from lexenstein.morphadorner import MorphAdornerToolkit

m = MorphAdornerToolkit('./morph/')

lemmas = m.lemmatizeWords(['doing', 'geese'])
print('Lemmas:')
print(str(lemmas)+'\n')

stems = m.stemWords(['doing', 'geese'])
print('Stems:')
print(str(stems)+'\n')

tenses = m.tenseVerbs(['do'], ['doing'])
print('Tenses:')
print(str(tenses)+'\n')

verbs = m.conjugateVerbs(['do', 'sit'], 'PRESENT_PARTICIPLE')
print('Verbs:')
```

```
print(str(verbs)+'\n')

nouns = m.inflectNouns(['goose', 'chair'], 'plural')
print('Nouns:')
print(str(nouns)+'\n')

syllables = m.splitSyllables(['persevere', 'sitting'])
print('Syllables:')
print(str(syllables)+'\n')
```

The output produced by the script above will be:

```
Lemmas:
['do', 'goose']

Stems:
['do', 'gees']

Tenses:
['PRESENT_PARTICIPLE']

Verbs:
['doing', 'sitting']

Nouns:
['geese', 'chairs']

Syllables:
['per-se-vere', 'sit-ting']
```

4.2 Feature Estimation

LEXenstein's Feature Estimation module allows the calculation of several features for LS related tasks. Its class `FeatureEstimator` allows the user to select and configure many types of features commonly used by LS approaches.

The `FeatureEstimator` object can be used either for the creation of LEXenstein's rankers, or in stand-alone setups. For the latter, the class provides a function called *calculateFeatures*, which takes as input a dataset in the VICTOR format (that can be built from generated/selected

substitutions) and returns as output a matrix $M \times N$ containing M feature values for each of the N substitution candidates listed in the dataset. Each of the 11 features supported must be configured individually. They can be grouped in four categories:

Lexicon-oriented: Binary features which receive value 1 if a candidate appears in a given vocabulary, and 0 otherwise.

Morphological: Exploit morphological characteristics of substitutions, such as word length and number of syllables.

Collocational: Estimate n-gram probabilities of form $P(S_{h-1}^{h-l} c S_{h+1}^{h+r})$, where c is a candidate substitution in the h th position in sentence S , and S_{h-1}^{h-l} and S_{h+1}^{h+r} are n-grams of size l and r , respectively.

Sense-oriented: Include several features which related to the meaning of a candidate substitution, such as: number of senses, lemmas, synonyms, hypernyms, hyponyms and maximum and minimum distance between all of its senses.

The code snippet below shows an example of how to configure and use a FeatureEstimator object:

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.features import *

m = MorphAdornerToolkit('./morph/')
fe = FeatureEstimator()
fe.addLexiconFeature('lexicon.txt', 'Simplicity')
fe.addLengthFeature('Complexity')
fe.addSyllableFeature(m, 'Complexity')
fe.addCollocationalFeature('lm.bin', 2, 2, 'Simplicity')
fe.addSentenceProbabilityFeature('lm.bin', 'Simplicity')
fe.addSenseCountFeature('Simplicity')
fe.addSynonymCountFeature('Simplicity')
fe.addHypernymCountFeature('Simplicity')
fe.addHyponymCountFeature('Simplicity')
fe.addMinDepthFeature('Complexity')
fe.addMaxDepthFeature('Complexity')
feats = fe.calculateFeatures('lexmturk.txt')
```

The output produced by the script above will be:

```
[1.0, 7, 2, 4.470454216003418, 6.206913948059082, 7.3130669593811035,
 10.297701835632324, 12.034161567687988, 13.140314102172852,
 11.422476768493652, 13.158936500549316, 14.26508903503418,
 51.03892517089844, 12, 51, 12, 83, 3, 8], [0.0, 6, 3, 4.487872123718262,
 7.389286041259766, 8.941888809204102, 10.315119743347168,
 13.216533660888672, 14.769136428833008, 11.439894676208496,
 14.34130859375, 15.893911361694336, 52.66774368286, 2, 6, 0, 0, 0, 0]
...
[0.0, 7, 2, 4.950876235961914, 8.496809005737305, 9.830375671386719,
 10.77812385559082, 14.324056625366211, 15.657623291015625,
 11.902898788452148, 15.448831558227539, 16.782398223876953,
 53.556236267089844, 6, 13, 1, 0, 0, 8]]
```

The lexicon file “lexicon.txt” used by a feature in the example above must be a plain text file with one word per line. The Language Model “lm.bin” used by some features in the example above must be binary, and must be produced by KenLM with the following command lines:

```
lmplz -o [order] <[corpus_of_text] >[language_model_name]
```

```
build_binary [language_model_name] [binary_language_model_name]
```

For more information on how to create a FeatureEstimator object, please refer to LEXenstein’s documentation.

4.3 Substitution Generation

We define Substitution Generation (SG) as the task of producing candidate substitutions for complex words. Authors commonly address this task by querying WordNet [8] and UMLS[3]. Some examples of authors who resort to this strategy are [7] and [6]. Recently however, learning substitutions from aligned corpora have become a more popular strategy [17] and [10].

In the Substitution Generation module of LEXenstein, one has access to several Substitution Generation methods available in literature. The module contains a series of classes, each representing a distinct approach in literature. Currently, it offers support for 5 distinct approaches. All approaches use LEXenstein’s Text Adorning module, described in Section 4.1,

to create substitutions for all possible inflections of verbs and nouns. The following Sections describe each one individually.

4.3.1 KauchakGenerator

Employs the strategy described in [10], in which substitutions are automatically extracted from parallel corpora. To be instantiated, this class requires as input an object of the MorphAdornerToolkit class, a parsed document of parallel sentences, the word alignments between them in Pharaoh format, and a list of stop words. As output, its *getSubstitutions* function produces a dictionary of complex-to-simple substitutions filtered by the criteria described in [10].

Parameters

The parsed parallel document, the alignments file, and the stop words list required by the KauchakGenerator class must be in a specific format. Each line of the parsed parallel document must be in the format described in Example 4.1, where w_i^s is a word in position i of a source sentence s , p_i^s its POS tag, w_j^t is a word in position j of a target sentence t , and p_j^t its POS tag.

$$\langle w_0^s \rangle ||| \langle p_0^s \rangle \cdots \langle w_n^s \rangle ||| \langle p_n^s \rangle \quad \langle w_0^t \rangle ||| \langle p_0^t \rangle \cdots \langle w_n^t \rangle ||| \langle p_n^t \rangle \quad (4.1)$$

All tokens of form $\langle w_i^s \rangle ||| \langle p_i^s \rangle$ are separated by a blank space, and the two set of source and target tokens $\langle w_0^s \rangle ||| \langle p_0^s \rangle \cdots \langle w_n^s \rangle ||| \langle p_n^s \rangle$ are separated by a tabulation marker. An example of file with such notation can be found in “resources/parallel_data/alignment_pos_file.txt”.

The alignments file must be in Pharaoh format. Each line of the alignments file must be structured as illustrated in Example 4.2, where $\langle i_h^s \rangle$ is an index i in source sentence s , and $\langle j_h^t \rangle$ is the index j in source sentence t aligned to it.

$$\langle i_0^s \rangle - \langle j_0^t \rangle \quad \langle i_1^s \rangle - \langle j_1^t \rangle \cdots \langle i_{n-1}^s \rangle - \langle j_{n-1}^t \rangle \quad \langle i_n^s \rangle - \langle j_n^t \rangle \quad (4.2)$$

All tokens of form $\langle i_h^s \rangle - \langle j_h^t \rangle$ are separated by a blank space. An example of file with such notation can be found in “resources/parallel_data/alignments.txt”.

Example

The code snippet below shows the KauchakGenerator class being used:

```
from lexenstein.morphadorner import MorphAdornerToolkit
```

```
from lexenstein.generators import *

m = MorphAdornerToolkit('./morph/')

kg = KauchakGenerator(m, 'parallel.txt', 'alignments.txt', 'stop_words.txt')
subs = kg.getSubstitutions('lexmturk.txt')
```

4.3.2 BiranGenerator

Employs the strategy described in [1], in which substitutions are filtered from the Cartesian product between vocabularies of complex and simple words. This approach requires as input vocabularies of complex and simple words, as well as two Language Models trained over complex and simple corpora. As output, it produces a dictionary linking words to a set of synonyms and hypernyms filtered by the criteria described in [1].

Parameters

The vocabularies of complex and simple words and Language Models trained over complex and simple corpora required by the BiranGenerator class must be in a specific format. The vocabularies must contain one word per line, and can be produced over large corpora with SRILM by running the following command line:

```
ngram-count -text [corpus_of_text] -write-vocab [vocabulary_name]
```

The Language Models must be binary, and must be produced by KenLM with the following command lines:

```
lmplz -o [order] <[corpus_of_text] >[language_model_name]
```

```
build_binary [language_model_name] [binary_language_model_name]
```

Complex and simple data can be downloaded from David Kauchak's page¹, or extracted from other sources.

Example

The code snippet below shows the BiranGenerator class being used:

¹<http://www.cs.pomona.edu/~dkauchak/simplification/>

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.generators import *

m = MorphAdornerToolkit('./morph/')

bg = BiranGenerator(m, 'vocabc.txt', 'vocabs.txt', 'lmc.bin', 'lms.bin')
subs = bg.getSubstitutions('lexmturk.txt')
```

4.3.3 YamamotoGenerator

Employs the strategy described in [25], in which substitutions are extracted from dictionary definitions of complex words. This approach requires as input an API key for the Merriam Dictionary², which can be obtained for free. As output, it produces a dictionary linking words in the Merriam Dictionary and WordNet to words with the same Part-of-Speech (POS) tag in its entries' definitions and usage examples.

Parameters

The YamamotoGenerator class requires a free Dictionary key to the Merriam Dictionary. To get the key, follow the steps below:

1. Visit the page <http://www.dictionaryapi.com/register/index.htm>.
2. Fill in your personal information.
3. In "Request API Key #1:" and "Request API Key #2:", select "Collegiate Dictionary" and "Collegiate Thesaurus".
4. Login in <http://www.dictionaryapi.com>.
5. Visit your "My Keys" page.
6. Use the "Dictionary" key to create a YamamotoGenerator object.

Example

The code snippet below shows the YamamotoGenerator class being used:

²<http://www.dictionaryapi.com/>

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.generators import *

m = MorphAdornerToolkit('./morph/')

yg = YamamotoGenerator(m, '0000-0000-0000-0000')
subs = yg.getSubstitutions('lexmturk.txt')
```

4.3.4 MerriamGenerator

Extracts a dictionary linking words to their synonyms, as listed in the Merriam Thesaurus.

Parameters

The YamamotoGenerator class requires a free Thesaurus key to the Merriam Dictionary. To get the key, follow the steps below:

1. Visit the page <http://www.dictionaryapi.com/register/index.htm>.
2. Fill in your personal information.
3. In "Request API Key #1:" and "Request API Key #2:", select "Collegiate Dictionary" and "Collegiate Thesaurus".
4. Login in <http://www.dictionaryapi.com>.
5. Visit your "My Keys" page.
6. Use the "Thesaurus" key to create a YamamotoGenerator object.

Example

The code snippet below shows the MerriamGenerator class being used:

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.generators import *

m = MorphAdornerToolkit('./morph/')

mg = MerriamGenerator(m, '0000-0000-0000-0000')
subs = mg.getSubstitutions('lexmturk.txt')
```

4.3.5 WordnetGenerator

Extracts a dictionary linking words to their synonyms, as listed in WordNet.

Parameters

The WordnetGenerator class requires only that you have the WordNet corpora from NLTK installed in your Python distribution.

Example

The code snippet below shows the WordnetGenerator class being used:

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.generators import *

m = MorphAdornerToolkit('./morph/')

wg = WordnetGenerator(m)
subs = wg.getSubstitutions('lexmturk.txt')
```

4.4 Selectors

Substitution Selection (SS) is the task of selecting which substitutions from a given list can replace a complex word in a given sentence without altering its meaning. Most work addresses this task referring to the context of the complex word by employing Word Sense Disambiguation (WSD) approaches [15, 20], or by discarding substitutions which do not share the same POS tag of the target complex word [17, 25].

LEXenstein's SS module provides access to 3 approaches, each represented by a Python class. The following Sections describe each one individually.

4.4.1 WordVectorSelector

Employs a novel strategy, in which a word vector model is used to determine which substitutions have the closest meaning to that of the sentence being simplified. It retrieves a user-defined percentage of the substitutions, which are ranked with respect to the cosine distance between its word vector and the sum of some, or all of the sentences' words, depending on the settings defined by the user.

Parameters

To create a WordVectorSelector object, you must provide a binary word vector model created with Word2Vec. To create the word vector, follow the steps below:

1. Download and install Word2Vec in your machine from <https://code.google.com/p/word2vec/>.
2. Gather large amounts of corpora (>10 billion words). You can find some sources of data in <https://code.google.com/p/word2vec/>.
3. With Word2Vec installed, run it with the following command line:

```
./word2vec -train <corpus> -output <binary_model_path> -cbow 1 -size  
300 -window 5 -negative 3 -hs 0 -sample 1e-5 -threads 12 -binary 1  
-min-count 10
```

The command line above creates word vectors with 300 dimensions and considers only a window of 5 tokens around each word. You can customize those parameters if you wish. Once you have produced a binary model, you can then use the “selectCandidates” function of the WordVectorSelector class to select substitutions from a generated dictionary for the instances of a VICTOR corpus. For more information on how to use the “selectCandidates” function please refer to LEXenstein’s documentation.

Example

The code snippet below shows the WordVectorSelector class being used:

```
from lexenstein.morphadorner import MorphAdornerToolkit  
from lexenstein.generators import *  
from lexenstein.selectors import *  
  
m = MorphAdornerToolkit('./morph/')  
  
kg = KauchakGenerator(m, 'parallel.txt', 'alignments.txt', 'stop_words.txt')  
subs = kg.getSubstitutions('lexmturk.txt')  
  
wordvecselector = WordVectorSelector('word_vector_model.bin')  
selected = wordvecselector.selectCandidates(subs, 'lexmturk.txt',  
    proportion=0.75, stop_words_file='stop_words.txt', onlyInformative=True,  
    keepTarget=True, onePerWord=True)
```

4.4.2 BiranSelector

Employs the strategy described in [1], in which a word co-occurrence model is used to determine which substitutions have meaning similar to that of a target complex word. It filters all substitutions which are estimated to be more complex than the target word, and also all those for which the distance between its co-occurrence vector and the target sentence's vector is higher than a threshold set by the user.

Parameters

To create a BiranSelector object, you must provide a word co-occurrence model. The model must be in plain text format, and each line must follow the format illustrated in Example 4.3, where $\langle w_i \rangle$ is a word, $\langle c_i^j \rangle$ a co-occurring word and $\langle f_i^j \rangle$ its frequency of appearance.

$$\langle w_i \rangle \langle c_i^0 \rangle : \langle f_i^0 \rangle \langle c_i^1 \rangle : \langle f_i^1 \rangle \cdots \langle c_i^{n-1} \rangle : \langle f_i^{n-1} \rangle \langle c_i^n \rangle : \langle f_i^n \rangle \quad (4.3)$$

Each component in the format above must be separated by a tabulation marker. To create a co-occurrence model, either create a script that does so, or follow the steps below:

1. Gather a corpus of text composed of one tokenized and truecased sentence per line.
2. Run the script `resources/scripts/Produce_Co-occurrence_Model.py` with the following command line:

```
python Produce_Co-occurrence_Model.py <corpus> <window> <model_path>
```

Where “<window>” is the number of tokens to the left and right of a word to be included as a co-occurring word.

To produce models faster, you can split your corpus in various small portions, run parallel processes to produce various small models, and then join them. Once you have produced the co-occurrence model, you can then use the “selectCandidates” function of the BiranSelector class to select substitutions from a generated dictionary for the instances of a VICTOR corpus. For more information on how to use the “selectCandidates” function please refer to LEXenstein’s documentation.

Example

The code snippet below shows the BiranSelector class being used:

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.generators import *
from lexenstein.selectors import *

m = MorphAdornerToolkit('./morph/')

kg = KauchakGenerator(m, 'parallel.txt', 'alignments.txt', 'stop_words.txt')
subs = kg.getSubstitutions('lexmturk.txt')

biranselector = BiranSelector('cooc_model.txt')
selected = biranselector.selectCandidates(subs, 'lexmturk.txt', 0.01, 0.75)
```

4.4.3 WSDSelector

Allows for the user to use many distinct classic WSD approaches in SS. It requires for the PyWSD [23] module to be installed, which includes the approaches presented by [14] and [24], as well as baselines such as random and first senses. The user can use any of the aforementioned approaches through the WSDSelector class by changing instantiation parameters.

Parameters

During instantiation, the WSDSelector class requires only for you to provide an id for the WSD method that you desire to use for Substitution Selection. For the options available, please refer to LEXenstein's documentation.

Example

The code snippet below shows the WSDSelector class being used:

```
from lexenstein.morphadorner import MorphAdornerToolkit
from lexenstein.generators import *
from lexenstein.selectors import *

m = MorphAdornerToolkit('./morph/')

kg = KauchakGenerator(m, 'parallel.txt', 'alignments.txt', 'stop_words.txt')
subs = kg.getSubstitutions('lexmturk.txt')
```



```
wsdselector = WSDSelector('lesk')
selected = wsdselector.selectCandidates(subs, 'lexmturk.txt')
```

4.5 Rankers

Substitution Ranking (SR) is the task of ranking a set of selected substitutions for a target complex word with respect to its simplicity. Approaches vary from simple word length and frequency-based measures [1, 5–7] to more sophisticated linear combination as scoring functions [11] and Machine Learning approaches [10].

LEXenstein’s SR module provides access to 3 approaches, each represented by a Python class. The following Sections describe each one individually.

4.5.1 MetricRanker

Employs a simple ranking strategy based on the values of a single feature provided by the user. By configuring the input FeatureEstimator object, the user can calculate values of several features for the candidates in a given dataset, and easily rank the candidates according to each of these features.

Parameters

During instantiation, the MetricRanker requires only a configured FeatureEstimator object, which must contain at least one feature that can be used as a metric for ranking. Once created, the user can retrieve rankings by using MetricRanker’s “getRankings” function, which requires a VICTOR corpus and the index of a feature to be used as a ranking metric.

Example

The code snippet below shows the WSDSelector class being used:

```
from lexenstein.features import *
from lexenstein.rankers import *

fe = FeatureEstimator()
fe.addCollocationalFeature('lm.txt', 0, 0, 'Complexity')
fe.addLengthFeature('Complexity')
fe.addSenseCountFeature('Simplicity')
```

```
mr = MetricRanker(fe)
frequency_ranks = mr.getRankings('lexmturk.txt', 0)
length_ranks = mr.getRankings('lexmturk.txt', 1)
sense_ranks = mr.getRankings('lexmturk.txt', 2)
```

4.5.2 SVMRanker

Use Support Vector Machines in a setup that minimizes a loss function with respect to a ranking model. In LS, this strategy is the one employed in the experiments of [10], yielding promising results.

Parameters

During instantiation, the SVMRanker requires for a FeatureEstimator object and a path to the root installation folder of SVM-Rank [12]. The user can then use the “getFeaturesFile”, “getTrainingModel”, “getScoresFile” and “getRankings” to train SVM ranking models and rank candidate substitutions. For more information on these functions’ parameters, please refer to LEXenstein’s documentation and the example in the following Section.

Example

The code snippet below shows the SVMRanker class being used:

```
from lexenstein.features import *
from lexenstein.rankers import *

fe = FeatureEstimator()
fe.addCollocationalFeature('lm.txt', 0, 0, 'Complexity')
fe.addLengthFeature('Complexity')
fe.addSenseCountFeature('Simplicity')

svmr = SVMRanker(fe, '/svm-rank/')
svmr.getFeaturesFile('lexmturk.txt', 'features.txt')
svmr.getTrainingModel('features.txt', 0.1, 0.1, 0, 'model.txt')
svmr.getScoresFile('features.txt', 'model.txt', 'scores.txt')
rankings = svmr.getRankings('features.txt', 'scores.txt')
```

4.5.3 BoundaryRanker

Employs a novel strategy, in which ranking is framed as a binary classification task. During training, this approach assigns the label 1 to all candidates of rank $1 \geq r \geq p$, where p is a range set by the user, and 0 to the remaining candidates. It then trains a stochastic descent linear classifier based on the features specified in the FeatureEstimator object. During testing, candidate substitutions are ranked based on how far from 0 they are.

Parameters

During instantiation, the BoundaryRanker requires only for a FeatureEstimator object. The user can then use the “trainRanker” function to train a ranking model, and the “getRankings” to rank the candidates of a VICTOR corpus. For more information on the training parameters supported by the “trainRanker” function, please refer to LEXenstein’s documentation.

Example

The code snippet below shows the BoundaryRanker class being used:

```
from lexenstein.features import *
from lexenstein.rankers import *

fe = FeatureEstimator()
fe.addCollocationalFeature('lm.txt', 0, 0, 'Complexity')
fe.addLengthFeature('Complexity')
fe.addSenseCountFeature('Simplicity')

br = BoundaryRanker(fe)
br.trainRanker('lexmturk.txt', 1, 'modified_huber', 'l1', 0.1, 0.1, 0.001)
rankings = br.getRankings('lexmturk.txt')
```

4.6 Evaluation

Since one of the goals of LEXenstein is to facilitate the benchmarking LS approaches, it is crucial that it provides evaluation methods. This module includes functions for the evaluation of all sub-tasks, both individually and in combination. It contains 4 classes, each designed for one form of evaluation. We discuss them in more detail in the following Sections.

4.6.1 GeneratorEvaluator

Provides evaluation metrics for SG methods. It requires a gold-standard in the VICTOR format and a set of generated substitutions. It returns the Potential, Precision and F-measure, where Potential is the proportion of instances in which at least one of the substitutions generated is present in the gold-standard, Precision the proportion of generated instances which are present in the gold-standard, and F-measure their harmonic mean.

The code snippet below shows the GeneratorEvaluator class being used:

```
from lexenstein.generators import *
from lexenstein.evaluators import *
from lexenstein.morphadorner import *

m = MorphAdornerToolkit('./morph/')

kg = WordnetGenerator(m)
subs = kg.getSubstitutions('lexmturk.txt')

ge = GeneratorEvaluator()
potential, precision, fmeasure = ge.evaluateGenerator('lexmturk.txt', subs)
```

4.6.2 SelectorEvaluator

Provides evaluation metrics for SS methods. It requires a gold-standard in the VICTOR format and a set of selected substitutions. It returns the Potential, Precision and F-measure of the SS approach, where Potential is the proportion of instances in which at least one of the substitutions generated is present in the gold-standard, Precision the proportion of generated instances which are present in the gold-standard, and F-measure their harmonic mean.

The code snippet below shows the SelectorEvaluator class being used:

```
from lexenstein.generators import *
from lexenstein.selectors import *
from lexenstein.evaluators import *
from lexenstein.morphadorner import *

m = MorphAdornerToolkit('./morph/')

kg = WordnetGenerator(m)
subs = kg.getSubstitutions('lexmturk.txt')
```

```

biranselector = BiranSelector('cooc_model.txt')
selected = biranselector.selectCandidates(subs, 'lexmturk.txt', 0.01, 0.75)

se = SelectorEvaluator()
potential, precision, fmeasure = se.evaluateSelector('lexmturk.txt',
    selected)

```

4.6.3 RankerEvaluator

Provides evaluation metrics for SR methods. It requires a gold-standard in the VICTOR format and a set of ranked substitutions. It returns the TRank-at-1 : 3 and Recall-at-1 : 3 metrics [22], where Trank-at- i is the proportion of instances in which a candidate of gold-rank $r \leq i$ was ranked first, and Recall-at- i the proportion of candidates of gold-rank $r \leq i$ that are ranked in positions $p \leq i$.

The code snippet below shows the RankerEvaluator class being used:

```

from lexenstein.rankers import *
from lexenstein.features import *

fe = FeatureEstimator()
fe.addCollocationalFeature('lm.txt', 0, 0, 'Complexity')

mr = MetricRanker(fe)
rankings = mr.getRankings('lexmturk.txt', 0)

re = RankerEvaluator()
t1, t2, t3, r1, r2, r3 = re.evaluateRanker('lexmturk.txt', rankings)

```

4.6.4 PipelineEvaluator

Provides evaluation metrics for the entire LS pipeline. It requires as input a gold-standard in VICTOR format and a set of ranked substitutions which have been generated and selected by a given set of approaches. It returns the approaches' Precision, Accuracy and Change Proportion, where Precision is the proportion of instances in which the highest ranking substitution is not the target complex word itself and is in the gold-standard, Accuracy is the proportion of instances in which the highest ranking substitution is in the gold-standard, and

Change Proportion is the proportion of instances in which the highest ranking substitution is not the target complex word itself.

The code snippet below shows the PipelineEvaluator class being used:

```
from lexenstein.generators import *
from lexenstein.selectors import *
from lexenstein.evaluators import *
from lexenstein.rankers import *
from lexenstein.features import *
from lexenstein.morphadorner import *

m = MorphAdornerToolkit('./morph/')

kg = WordnetGenerator(m)
subs = kg.getSubstitutions('lexmturk.txt')

bs = BiranSelector('cooc_model.txt')
selected = bs.selectCandidates(subs, 'lexmturk.txt', 0.01, 0.75)
bs.toVictorFormat('lexmturk.txt', selected, 'victor.txt',
    addTargetAsCandidate=True)

fe = FeatureEstimator()
fe.addCollocationalFeature('lm.txt', 0, 0, 'Complexity')

mr = MetricRanker(fe)
rankings = mr.getRankings('victor.txt', 0)

pe = PipelineEvaluator()
precision, accuracy, changed = pe.evaluatePipeline('lexmturk.txt', rankings)
```

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