sklearn-crfsuite Documentation

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Contents

sklearn-crfsuite is thin a CRFsuite (python-crfsuite) wrapper which provides scikit-learn-compatible *sklearn_crfsuite.CRF* estimator: you can use e.g. scikit-learn model selection utilities (cross-validation, hyperparameter optimization) with it, or save/load CRF models using joblib.

License is MIT.

CHAPTER 1

Contents

1.1 Install Instructions

Make sure scikit-learn is installed, then run

```
pip install sklearn-crfsuite
```

sklearn-crfsuite requires Python 2.7+ or 3.3+.

1.2 Tutorial

Note: This tutorial is available as an IPython notebook here.

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

```
from itertools import chain

import nltk
import sklearn
import scipy.stats
from sklearn.metrics import make_scorer
from sklearn.cross_validation import cross_val_score
from sklearn.grid_search import RandomizedSearchCV

import sklearn_crfsuite
from sklearn_crfsuite import scorers
from sklearn_crfsuite import metrics
```

1.2.1 Let's use CoNLL 2002 data to build a NER system

CoNLL2002 corpus is available in NLTK. We use Spanish data.

```
nltk.corpus.conll2002.fileids()
```

```
['esp.testa', 'esp.testb', 'esp.train', 'ned.testa', 'ned.testb', 'ned.train']
```

```
%%time
train_sents = list(nltk.corpus.conll2002.iob_sents('esp.train'))
test_sents = list(nltk.corpus.conll2002.iob_sents('esp.testb'))
```

```
CPU times: user 2.91 s, sys: 108 ms, total: 3.02 s
Wall time: 3.13 s
```

```
train_sents[0]
```

```
[('Melbourne', 'NP', 'B-LOC'),
 ('(', 'Fpa', 'O'),
 ('Australia', 'NP', 'B-LOC'),
 (')', 'Fpt', 'O'),
 (',', 'Fc', 'O'),
 ('25', 'Z', 'O'),
 ('may', 'NC', 'O'),
 ('(', 'Fpa', 'O'),
 ('EFE', 'NC', 'B-ORG'),
 (')', 'Fpt', 'O'),
 ('.', 'Fp', 'O')]
```

1.2.2 Features

Next, define some features. In this example we use word identity, word suffix, word shape and word POS tag; also, some information from nearby words is used.

This makes a simple baseline, but you certainly can add and remove some features to get (much?) better results - experiment with it.

sklearn-crfsuite (and python-crfsuite) supports several feature formats; here we use feature dicts.

```
def word2features(sent, i):
    word = sent[i][0]
    postag = sent[i][1]

    features = {
        'bias': 1.0,
        'word.lower()': word.lower(),
        'word[-3:]': word[-3:],
        'word[-2:]': word[-2:],
        'word.isupper()': word.isupper(),
        'word.istitle()': word.istitle(),
        'word.isdigit()': word.isdigit(),
        'postag': postag,
        'postag[:2]': postag[:2],
    }
    if i > 0:
```

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```
        word1 = sent[i-1][0]
        postag1 = sent[i-1][1]
        features.update({
            '-1:word.lower()': word1.lower(),
            '-1:word.istitle()': word1.istitle(),
            '-1:word.isupper()': word1.isupper(),
            '-1:postag': postag1,
            '-1:postag[:2]': postag1[:2],
        })
    else:
        features['BOS'] = True

    if i < len(sent)-1:
        word1 = sent[i+1][0]
        postag1 = sent[i+1][1]
        features.update({
            '+1:word.lower()': word1.lower(),
            '+1:word.istitle()': word1.istitle(),
            '+1:word.isupper()': word1.isupper(),
            '+1:postag': postag1,
            '+1:postag[:2]': postag1[:2],
        })
    else:
        features['EOS'] = True

    return features


def sent2features(sent):
    return [word2features(sent, i) for i in range(len(sent))]

def sent2labels(sent):
    return [label for token, postag, label in sent]

def sent2tokens(sent):
    return [token for token, postag, label in sent]
```

This is what word2features extracts:

```
sent2features(train_sents[0])[0]
```

```
{'+1:postag': 'Fpa',
 '+1:postag[:2]': 'Fp',
 '+1:word.istitle()': False,
 '+1:word.isupper()': False,
 '+1:word.lower()': '(',
 'BOS': True,
 'bias': 1.0,
 'postag': 'NP',
 'postag[:2]': 'NP',
 'word.isdigit()': False,
 'word.istitle()': True,
 'word.isupper()': False,
 'word.lower()': 'melbourne',
 'word[-2:]': 'ne',
 'word[-3:]': 'rne'}
```

Extract features from the data:

```
%%time
X_train = [sent2features(s) for s in train_sents]
y_train = [sent2labels(s) for s in train_sents]

X_test = [sent2features(s) for s in test_sents]
y_test = [sent2labels(s) for s in test_sents]
```

```
CPU times: user 1.48 s, sys: 124 ms, total: 1.61 s
Wall time: 1.65 s
```

1.2.3 Training

To see all possible CRF parameters check its docstring. Here we are useing L-BFGS training algorithm (it is default) with Elastic Net (L1 + L2) regularization.

```
%%time
crf = sklearn_crfsuite.CRF(
    algorithm='lbfgs',
    c1=0.1,
    c2=0.1,
    max_iterations=100,
    all_possible_transitions=True
)
crf.fit(X_train, y_train)
```

```
CPU times: user 32 s, sys: 108 ms, total: 32.1 s
Wall time: 32.3 s
```

1.2.4 Evaluation

There is much more O entities in data set, but we're more interested in other entities. To account for this we'll use averaged F1 score computed for all labels except for O. `sklearn-crfsuite.metrics` package provides some useful metrics for sequence classification task, including this one.

```
labels = list(crf.classes_)
labels.remove('O')
labels
```

```
['B-LOC', 'B-ORG', 'B-PER', 'I-PER', 'B-MISC', 'I-ORG', 'I-LOC', 'I-MISC']
```

```
y_pred = crf.predict(X_test)
metrics.flat_f1_score(y_test, y_pred,
                      average='weighted', labels=labels)
```

```
0.76980231377134023
```

Inspect per-class results in more detail:

```
# group B and I results
sorted_labels = sorted(
```

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```
    labels,
    key=lambda name: (name[1:], name[0])
)
print(metrics.flat_classification_report(
    y_test, y_pred, labels=sorted_labels, digits=3
))
```

```
              precision    recall  f1-score   support

      B-LOC      0.775     0.757     0.766      1084
      I-LOC      0.601     0.631     0.616       325
     B-MISC      0.698     0.499     0.582       339
     I-MISC      0.644     0.567     0.603       557
      B-ORG      0.795     0.801     0.798      1400
      I-ORG      0.831     0.773     0.801      1104
      B-PER      0.812     0.876     0.843       735
      I-PER      0.873     0.931     0.901       634

avg / total      0.779     0.764     0.770      6178
```

1.2.5 Hyperparameter Optimization

To improve quality try to select regularization parameters using randomized search and 3-fold cross-validation.

I takes quite a lot of CPU time and RAM (we're fitting a model `50 * 3 = 150` times), so grab a tea and be patient, or reduce n_iter in RandomizedSearchCV, or fit model only on a subset of training data.

```
%%time
# define fixed parameters and parameters to search
crf = sklearn_crfsuite.CRF(
    algorithm='lbfgs',
    max_iterations=100,
    all_possible_transitions=True
)
params_space = {
    'c1': scipy.stats.expon(scale=0.5),
    'c2': scipy.stats.expon(scale=0.05),
}

# use the same metric for evaluation
f1_scorer = make_scorer(metrics.flat_f1_score,
                        average='weighted', labels=labels)

# search
rs = RandomizedSearchCV(crf, params_space,
                        cv=3,
                        verbose=1,
                        n_jobs=-1,
                        n_iter=50,
                        scoring=f1_scorer)
rs.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
```

```
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  4.1min
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed: 16.1min finished
```

```
CPU times: user 3min 34s, sys: 13.9 s, total: 3min 48s
Wall time: 16min 36s
```

Best result:

```
# crf = rs.best_estimator_
print('best params:', rs.best_params_)
print('best CV score:', rs.best_score_)
print('model size: {:0.2f}M'.format(rs.best_estimator_.size_ / 1000000))
```

```
best params: {'c2': 0.06146442424219609, 'c1': 0.30343585910230675}
best CV score: 0.748852160441
model size: 1.08M
```

Check parameter space

A chart which shows which `c1` and `c2` values have RandomizedSearchCV checked. Red color means better results, blue means worse.

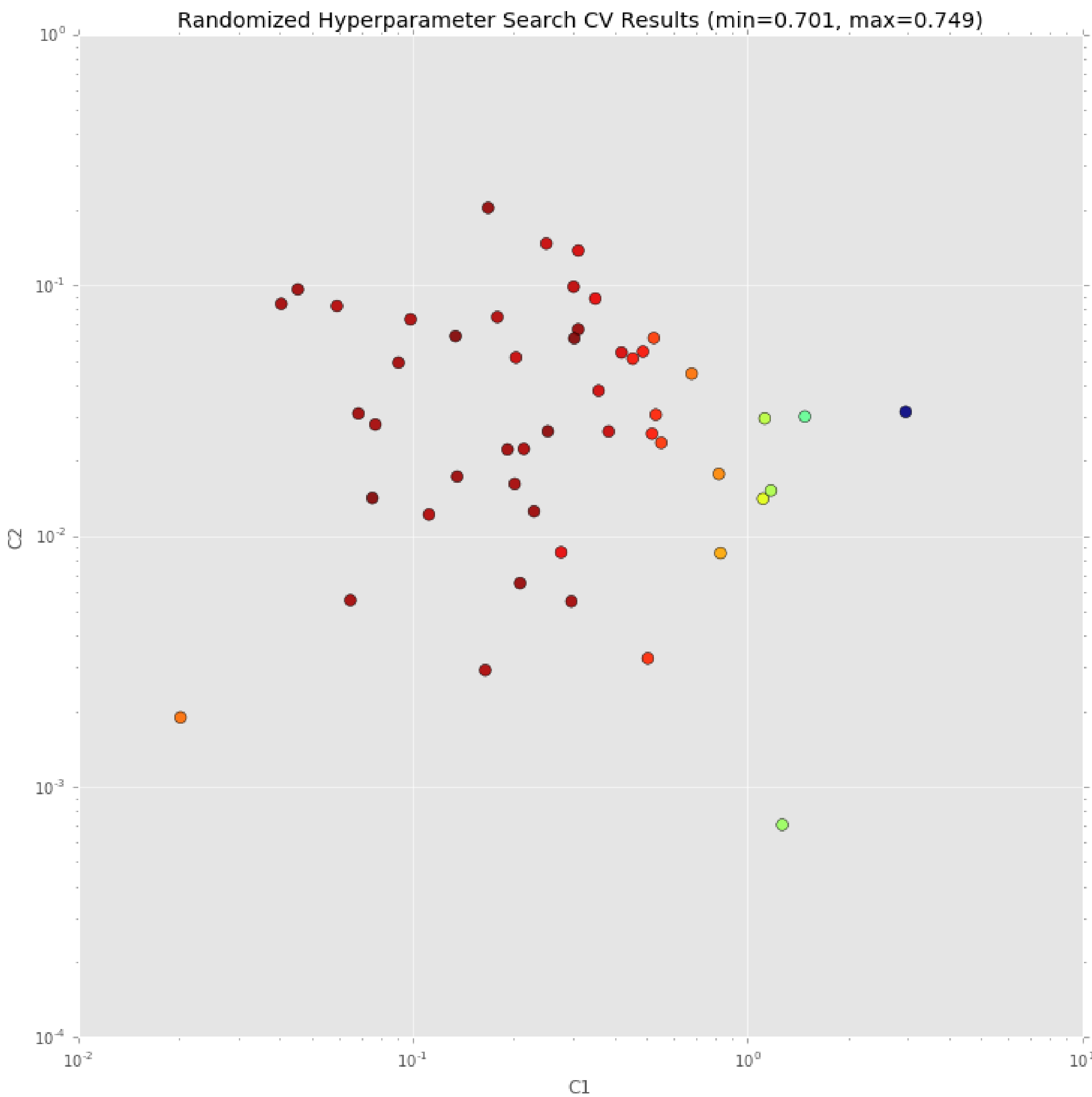
```
_x = [s.parameters['c1'] for s in rs.grid_scores_]
_y = [s.parameters['c2'] for s in rs.grid_scores_]
_c = [s.mean_validation_score for s in rs.grid_scores_]

fig = plt.figure()
fig.set_size_inches(12, 12)
ax = plt.gca()
ax.set_yscale('log')
ax.set_xscale('log')
ax.set_xlabel('C1')
ax.set_ylabel('C2')
ax.set_title("Randomized Hyperparameter Search CV Results (min={:0.3}, max={:0.3})".
↪format(
    min(_c), max(_c)
))

ax.scatter(_x, _y, c=_c, s=60, alpha=0.9, edgecolors=[0,0,0])

print("Dark blue => {:0.4}, dark red => {:0.4}".format(min(_c), max(_c)))
```

```
Dark blue => 0.7013, dark red => 0.7489
```



1.2.6 Check best estimator on our test data

As you can see, quality is improved.

```
crf = rs.best_estimator_
y_pred = crf.predict(X_test)
print(metrics.flat_classification_report(
    y_test, y_pred, labels=sorted_labels, digits=3
))
```

```
             precision    recall  f1-score   support

      B-LOC      0.800     0.780     0.790      1084
```

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```
       I-LOC      0.663     0.625     0.643       325
      B-MISC      0.729     0.555     0.630       339
      I-MISC      0.709     0.582     0.639       557
       B-ORG      0.808     0.824     0.816      1400
       I-ORG      0.849     0.783     0.814      1104
       B-PER      0.836     0.882     0.858       735
       I-PER      0.884     0.942     0.912       634

avg / total       0.804     0.781     0.791      6178
```

1.2.7 Let's check what classifier learned

```
from collections import Counter

def print_transitions(trans_features):
    for (label_from, label_to), weight in trans_features:
        print("%-6s -> %-7s %0.6f" % (label_from, label_to, weight))

print("Top likely transitions:")
print_transitions(Counter(crf.transition_features_).most_common(20))

print("\nTop unlikely transitions:")
print_transitions(Counter(crf.transition_features_).most_common()[-20:])
```

```
Top likely transitions:
B-ORG  -> I-ORG   7.029925
I-ORG  -> I-ORG   6.672091
B-MISC -> I-MISC  6.450077
I-MISC -> I-MISC  6.420227
B-PER  -> I-PER   5.898448
B-LOC  -> I-LOC   5.293131
I-LOC  -> I-LOC   4.669233
I-PER  -> I-PER   4.327948
O      -> O       3.773498
O      -> B-ORG   2.723333
O      -> B-PER   2.298990
O      -> B-LOC   1.753950
O      -> B-MISC  1.608865
B-ORG  -> O       0.373792
B-LOC  -> B-LOC   0.363950
B-MISC -> B-ORG   0.213808
B-ORG  -> B-LOC   0.122352
I-PER  -> B-LOC   0.055117
B-LOC  -> B-PER   -0.141696
B-MISC -> O       -0.170980

Top unlikely transitions:
I-ORG  -> B-LOC   -2.281004
I-LOC  -> I-PER   -2.285589
I-MISC -> B-LOC   -2.286738
I-LOC  -> B-MISC  -2.299090
B-LOC  -> B-MISC  -2.312090
I-ORG  -> I-PER   -2.636941
I-ORG  -> B-MISC  -2.673906
```

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```
B-ORG   -> B-MISC  -2.735029
I-PER   -> B-ORG   -2.822961
B-PER   -> B-MISC  -2.857271
I-MISC  -> I-LOC   -2.902497
I-PER   -> I-LOC   -2.931078
I-ORG   -> I-LOC   -2.943800
B-PER   -> B-PER   -3.063315
I-PER   -> B-MISC  -3.373836
B-MISC  -> B-MISC  -3.435245
O       -> I-MISC  -5.385205
O       -> I-ORG   -5.670565
O       -> I-PER   -6.003255
O       -> I-LOC   -6.680094
```

We can see that, for example, it is very likely that the beginning of an organization name (B-ORG) will be followed by a token inside organization name (I-ORG), but transitions to I-ORG from tokens with other labels are penalized.

Check the state features:

```
def print_state_features(state_features):
    for (attr, label), weight in state_features:
        print("%0.6f %-8s %s" % (weight, label, attr))

print("Top positive:")
print_state_features(Counter(crf.state_features_).most_common(30))

print("\nTop negative:")
print_state_features(Counter(crf.state_features_).most_common()[-30:])
```

```
Top positive:
11.005266 B-ORG    word.lower():efe-cantabria
9.385823 B-ORG    word.lower():psoe-progresistas
6.715219 I-ORG    -1:word.lower():l
5.638921 O        BOS
5.378117 B-LOC    -1:word.lower():cantabria
5.302705 B-ORG    word.lower():xfera
5.287491 B-ORG    word[-2:]:-e
5.239806 B-ORG    word.lower():petrobras
5.214013 B-MISC   word.lower():diversia
5.025534 B-ORG    word.lower():coag-extremadura
5.020590 B-ORG    word.lower():telefónica
4.804399 B-MISC   word.lower():justicia
4.729711 B-MISC   word.lower():competencia
4.705013 O        postag[:2]:Fp
4.695208 B-ORG    -1:word.lower():distancia
4.681021 I-ORG    -1:word.lower():rasd
4.636151 I-LOC    -1:word.lower():calle
4.618459 B-ORG    word.lower():terra
4.580418 B-PER    -1:word.lower():según
4.574348 B-ORG    word.lower():esquerra
4.537127 O        word.lower():r.
4.537127 O        word[-3:]:R.
4.536578 B-MISC   word.lower():cc2305001730
4.510408 B-ORG    +1:word.lower():plasencia
4.471889 B-LOC    +1:word.lower():finalizaron
4.451102 B-LOC    word.lower():líbano
```

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```
4.423293 B-ORG    word.isupper()
4.379665 O        word.lower():euro
4.361340 B-LOC    -1:word.lower():celebrarán
4.345542 I-MISC   -1:word.lower():1.9

Top negative:
-2.006512 I-PER    word[-3:]:ión
-2.020133 B-PER    word[-2:]:os
-2.027996 O        +1:word.lower():campo
-2.028221 O        +1:word.lower():plasencia
-2.043293 O        word.lower():061
-2.097561 O        postag:NP
-2.097561 O        postag[:2]:NP
-2.115992 O        word[-3:]:730
-2.156136 O        word.lower():circo
-2.173247 B-LOC    word[-3:]:la
-2.223739 I-PER    +1:word.lower():del
-2.323688 B-MISC   -1:word.isupper()
-2.347859 O        -1:word.lower():sánchez
-2.378442 I-PER    word[-3:]:ico
-2.404641 I-PER    +1:word.lower():el
-2.414000 O        word[-3:]:bas
-2.495209 O        -1:word.lower():británica
-2.539839 B-PER    word[-3:]:nes
-2.596765 O        +1:word.lower():justicia
-2.621004 O        -1:word.lower():sección
-2.981810 O        word[-3:]:LOS
-3.046486 O        word[-2:]:nd
-3.162064 O        -1:word.lower():españolas
-3.219096 I-PER    -1:word.lower():san
-3.562049 B-PER    -1:word.lower():del
-3.580405 O        word.lower():mas
-4.119731 O        word[-2:]:om
-4.301704 O        -1:word.lower():celebrarán
-5.632036 O        word.isupper()
-8.215073 O        word.istitle()
```

Some observations:

- **9.385823 B-ORG word.lower():psoe-progresistas** - the model remembered names of some entities - maybe it is overfit, or maybe our features are not adequate, or maybe remembering is indeed helpful;
- **4.636151 I-LOC -1:word.lower():calle:** “calle” is a street in Spanish; model learns that if a previous word was “calle” then the token is likely a part of location;
- **-5.632036 O word.isupper()**, **-8.215073 O word.istitle()** : UPPERCASED or TitleCased words are likely entities of some kind;
- **-2.097561 O postag:NP** - proper nouns (NP is a proper noun in the Spanish tagset) are often entities.

What to do next

```
* Load 'testa' Spanish data.
* Use it to develop better features and to find best model parameters.
* Apply the model to 'testb' data again.
```

The model in this notebook is just a starting point; you certainly can do better!

1.3 API Reference

1.3.1 CRF

class sklearn_crfsuite.**CRF**

python-crfsuite wrapper with interface siimlar to scikit-learn. It allows to use a familiar fit/predict interface and scikit-learn model selection utilities (cross-validation, hyperparameter optimization).

Unlike pycrfsuite.Trainer / pycrfsuite.Tagger this object is picklable; on-disk files are managed automatically.

Parameters

- **algorithm** (*str, optional (default='lbfgs')*) – Training algorithm. Allowed values:
  - `'lbfgs'` - Gradient descent using the L-BFGS method
  - `'l2sgd'` - Stochastic Gradient Descent with L2 regularization term
  - `'ap'` - Averaged Perceptron
  - `'pa'` - Passive Aggressive (PA)
  - `'arow'` - Adaptive Regularization Of Weight Vector (AROW)
- **min_freq** (*float, optional (default=0)*) – Cut-off threshold for occurrence frequency of a feature. CRFsuite will ignore features whose frequencies of occurrences in the training data are no greater than *min_freq*. The default is no cut-off.
- **all_possible_states** (*bool, optional (default=False)*) – Specify whether CRFsuite generates state features that do not even occur in the training data (i.e., negative state features). When True, CRFsuite generates state features that associate all of possible combinations between attributes and labels.

  Suppose that the numbers of attributes and labels are A and L respectively, this function will generate (A * L) features. Enabling this function may improve the labeling accuracy because the CRF model can learn the condition where an item is not predicted to its reference label. However, this function may also increase the number of features and slow down the training process drastically. This function is disabled by default.
- **all_possible_transitions** (*bool, optional (default=False)*) – Specify whether CRFsuite generates transition features that do not even occur in the training data (i.e., negative transition features). When True, CRFsuite generates transition features that associate all of possible label pairs. Suppose that the number of labels in the training data is L, this function will generate (L * L) transition features. This function is disabled by default.
- **c1** (*float, optional (default=0)*) – The coefficient for L1 regularization. If a non-zero value is specified, CRFsuite switches to the Orthant-Wise Limited-memory Quasi-Newton (OWL-QN) method. The default value is zero (no L1 regularization).

  Supported training algorithms: lbfgs
- **c2** (*float, optional (default=1.0)*) – The coefficient for L2 regularization.

  Supported training algorithms: l2sgd, lbfgs
- **max_iterations** (*int, optional (default=None)*) – The maximum number of iterations for optimization algorithms. Default value depends on training algorithm:
  - lbfgs - unlimited;
  - l2sgd - 1000;

  - ap - 100;
  - pa - 100;
  - arow - 100.

- **num_memories** (*int, optional (default=6)*) – The number of limited memories for approximating the inverse hessian matrix.

  Supported training algorithms: lbfgs

- **epsilon** (*float, optional (default=1e-5)*) – The epsilon parameter that determines the condition of convergence.

  Supported training algorithms: ap, arow, lbfgs, pa

- **period** (*int, optional (default=10)*) – The duration of iterations to test the stopping criterion.

  Supported training algorithms: l2sgd, lbfgs

- **delta** (*float, optional (default=1e-5)*) – The threshold for the stopping criterion; an iteration stops when the improvement of the log likelihood over the last *period* iterations is no greater than this threshold.

  Supported training algorithms: l2sgd, lbfgs

- **linesearch** (*str, optional (default='MoreThuente')*) – The line search algorithm used in L-BFGS updates. Allowed values:

  - `'MoreThuente'` - More and Thuente's method;
  - `'Backtracking'` - backtracking method with regular Wolfe condition;
  - `'StrongBacktracking'` - backtracking method with strong Wolfe condition.

  Supported training algorithms: lbfgs

- **max_linesearch** (*int, optional (default=20)*) – The maximum number of trials for the line search algorithm.

  Supported training algorithms: lbfgs

- **calibration_eta** (*float, optional (default=0.1)*) – The initial value of learning rate (eta) used for calibration.

  Supported training algorithms: l2sgd

- **calibration_rate** (*float, optional (default=2.0)*) – The rate of increase/decrease of learning rate for calibration.

  Supported training algorithms: l2sgd

- **calibration_samples** (*int, optional (default=1000)*) – The number of instances used for calibration. The calibration routine randomly chooses instances no larger than *calibration_samples*.

  Supported training algorithms: l2sgd

- **calibration_candidates** (*int, optional (default=10)*) – The number of candidates of learning rate. The calibration routine terminates after finding *calibration_samples* candidates of learning rates that can increase log-likelihood.

  Supported training algorithms: l2sgd

- **calibration_max_trials** (*int, optional (default=20)*) – The maximum number of trials of learning rates for calibration. The calibration routine terminates after trying *calibration_max_trials* candidate values of learning rates.

  Supported training algorithms: l2sgd

- **pa_type** (*int, optional (default=1)*) – The strategy for updating feature weights. Allowed values:

  – 0 - PA without slack variables;

  – 1 - PA type I;

  – 2 - PA type II.

  Supported training algorithms: pa

- **c** (*float, optional (default=1)*) – Aggressiveness parameter (used only for PA-I and PA-II). This parameter controls the influence of the slack term on the objective function.

  Supported training algorithms: pa

- **error_sensitive** (*bool, optional (default=True)*) – If this parameter is True, the optimization routine includes into the objective function the square root of the number of incorrect labels predicted by the model.

  Supported training algorithms: pa

- **averaging** (*bool, optional (default=True)*) – If this parameter is True, the optimization routine computes the average of feature weights at all updates in the training process (similarly to Averaged Perceptron).

  Supported training algorithms: pa

- **variance** (*float, optional (default=1)*) – The initial variance of every feature weight. The algorithm initialize a vector of feature weights as a multivariate Gaussian distribution with mean 0 and variance *variance*.

  Supported training algorithms: arow

- **gamma** (*float, optional (default=1)*) – The tradeoff between loss function and changes of feature weights.

  Supported training algorithms: arow

- **verbose** (*bool, optional (default=False)*) – Enable trainer verbose mode.

- **model_filename** (*str, optional (default=None)*) – A path to an existing CRFSuite model. This parameter allows to load and use existing crfsuite models.

  By default, model files are created automatically and saved in temporary locations; the preferred way to save/load CRF models is to use pickle (or its alternatives like joblib).

fit (*X*, *y*, *X_dev=None*, *y_dev=None*)

Train a model.

Parameters

- **X** (*list of lists of dicts*) – Feature dicts for several documents (in a python-crfsuite format).
- **y** (*list of lists of strings*) – Labels for several documents.
- **X_dev** (*(optional) list of lists of dicts*) – Feature dicts used for testing.

- **y_dev** (*(optional) list of lists of strings*) – Labels corresponding to X_dev.

predict(*X*)
Make a prediction.

Parameters **X** (*list of lists of dicts*) – feature dicts in python-crfsuite format

Returns **y** – predicted labels

Return type list of lists of strings

predict_single(*xseq*)
Make a prediction.

Parameters **xseq** (*list of dicts*) – feature dicts in python-crfsuite format

Returns **y** – predicted labels

Return type list of strings

predict_marginals(*X*)
Make a prediction.

Parameters **X** (*list of lists of dicts*) – feature dicts in python-crfsuite format

Returns **y** – predicted probabilities for each label at each position

Return type list of lists of dicts

predict_marginals_single(*xseq*)
Make a prediction.

Parameters **xseq** (*list of dicts*) – feature dicts in python-crfsuite format

Returns **y** – predicted probabilities for each label at each position

Return type list of dicts

score(*X*, *y*)
Return accuracy score computed for sequence items.

For other metrics check `sklearn_crfsuite.metrics`.

tagger_
pycrfsuite.Tagger instance.

classes_
A list of class labels.

size_
Size of the CRF model, in bytes.

num_attributes_
Number of non-zero CRF attributes.

attributes_
A list of known attributes.

state_features_
Dict with state feature coefficients – `{(attr_name, label) -- coef}`

transition_features_
Dict with transition feature coefficients – `{(label_from, label_to) -- coef}`

1.3.2 sklearn_crfsuite.metrics

`sklearn_crfsuite.metrics.`**`flat_accuracy_score`**(*y_true*, *y_pred*)
Return accuracy score for sequence items.

`sklearn_crfsuite.metrics.`**`flat_precision_score`**(*y_true*, *y_pred*, ***kwargs*)
Return precision score for sequence items.

`sklearn_crfsuite.metrics.`**`flat_recall_score`**(*y_true*, *y_pred*, ***kwargs*)
Return recall score for sequence items.

`sklearn_crfsuite.metrics.`**`flat_f1_score`**(*y_true*, *y_pred*, ***kwargs*)
Return F1 score for sequence items.

`sklearn_crfsuite.metrics.`**`flat_fbeta_score`**(*y_true*, *y_pred*, *beta*, ***kwargs*)
Return F-beta score for sequence items.

`sklearn_crfsuite.metrics.`**`flat_classification_report`**(*y_true*, *y_pred*, *labels=None*, ***kwargs*)
Return classification report for sequence items.

`sklearn_crfsuite.metrics.`**`sequence_accuracy_score`**(*y_true*, *y_pred*)
Return sequence accuracy score. Match is counted only when two sequences are equal.

1.4 Contributing

- Source code: https://github.com/TeamHG-Memex/sklearn-crfsuite
- Issue tracker: https://github.com/TeamHG-Memex/sklearn-crfsuite/issues

Feel free to submit ideas, bugs reports and pull requests.

In order to run tests install tox, then type

```
tox
```

from the source checkout.

1.4.1 Authors

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The code was initially extracted from webstruct and morphine projects and then cleaned up and improved.

1.4.2 License

License is MIT.

1.5 Changes

1.5.1 0.3.6 (2017-06-22)

- added `sklearn_crfsuite.metrics.flat_recall_score`.

1.5.2 0.3.5 (2017-03-21)

- Properly close file descriptor in `FileResource.cleanup`;
- declare Python 3.6 support, stop testing on Python 3.3.

1.5.3 0.3.4 (2016-11-17)

- Small formatting fixes.

1.5.4 0.3.3 (2016-03-15)

- scikit-learn dependency is now optional for sklearn_crfsuite; it is required only when you use metrics and scorers;
- added `metrics.flat_precision_score`.

1.5.5 0.3.2 (2015-12-18)

- Ignore more errors in `FileResource.__del__`.

1.5.6 0.3.1 (2015-12-17)

- Ignore errors in `FileResource.__del__`.

1.5.7 0.3 (2015-12-17)

- Added `sklearn_crfsuite.metrics.sequence_accuracy_score()` function and related `sklearn_crfsuite.scorers.sequence_accuracy`;
- `FileResource.__del__` method made more robust.

1.5.8 0.2 (2015-12-11)

- **backwards-incompatible**: `crf.tagger` attribute is renamed to `crf.tagger_`; when model is not trained accessing this attribute no longer raises an exception, its value is set to None instead.
- new CRF attributes available after training:
  - `classes_`
  - `size_`
  - `num_attributes_`
  - `attributes_`
  - `state_features_`
  - `transition_features_`
- Tutorial is added.

1.5.9 0.1 (2015-11-27)

Initial release.

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