Awesomeness with job ads

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Thesis submitted for examination for the degree of Master of Science in Technology.

Espoo 16.1.2015

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Aalto University
School of Science

AALTO UNIVERSITY
SCHOOL OF SCIENCE

ABSTRACT OF THE
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Your abstract in English. Try to keep the abstract short; approximately 100 words should be enough. The abstract explains your research topic, the methods you have used, and the results you obtained. Your abstract in English. Try to keep the abstract short; approximately 100 words should be enough. The abstract explains your research topic, the methods you have used, and the results you obtained.
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Keywords: NLP, bla bla, keyword

Preface

I want to thank bla bla bla

Otaniemi, 16.1.2015

Clemens Westrup

Contents

Symbols and abbreviations

Symbols

$\mathbf{B}$	magnetic flux density
c	speed of light in vacuum $\approx 3 \times 10^8$ [m/s]
ω_D	Debye frequency
ω_latt	average phonon frequency of lattice
$\uparrow$	electron spin direction up
$\downarrow$	electron spin direction down

Operators

$\nabla \times \mathbf{A}$	curl of vectorin $\mathbf{A}$
$\frac{\mathrm{d}}{\mathrm{d}t}$	derivative with respect to variable t
$\frac{\partial}{\partial t}$	partial derivative with respect to variable t
$\sum_i$	sum over index i
$\mathbf{A} \cdot \mathbf{B}$	dot product of vectors $\mathbf{A}$ and $\mathbf{B}$

Abbreviations

AC	alternating current
APLAC	an object-oriented analog circuit simulator and design tool (originally Analysis Program for Linear Active Circuits)
BCS	Bardeen-Cooper-Schrieffer
DC	direct current
TEM	transverse eletromagnetic

Todo list

0.1 TODO

- Describe the process of finding the problem

1 Introduction

1.1 Motivation

1.2 Structure

2 Background / Context

This thesis

"In the multiclass text classification task, we are given a training set of documents, each labeled as belonging to one of K disjoint classes, and a new unlabeled test document. Using the training set as a guide, we must predict the most likely class for the test document."[Do and Ng, 2006]

Meta-learning

other shit

2.1 Research objectives

main objective interim objectives

2.2 Related work

The problem of text classification has been studied from a variety of perspectives.

2.2.1 Feature extraction from Text

2.2.2 Text classification

3 Methods

3.1 TODO

- Linear machine
- explain metrics
- single class, multi-class and multi-label classification
- hard vs soft allocation (probabilistic vs discriminant)

3.2 Problem formalism

The problem at hand is to design a predictive function μ that best approximates the correct target response y_i for an input document d_i, given as

$$\{(d_1, y_1), (d_2, y_2), \ldots, (d_n, y_n)\}, \quad d_i \in \mathcal{D},\ y_i \in \mathcal{Y} \tag{1}$$

where $\mathcal{D}$ is a set of n documents, each of which is sequence of varying length that is composed of UTF-8 encoded characters, and $\mathcal{Y}$ is a the label space with $y_i \in \{0, 1\}^c$ indicating the presence of each of the c class labels to be predicted.

3.3 Metrics and Evaluation

3.3.1 Precision, Recall and F1 Score

In the field of Information Retrieval it is common practice to measure the effectiveness of a predictive system in terms of its precision and recall. This gives an improved The precision of such system is "the proportion of retrieved material that is actually relevant" whereas the recall measures "proportion of relevant material actually retrieved in answer to a search request" [Rijsbergen, 1979]. Formally these two measures are defined as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

As in [Powers, 2011] "True and False Positives (TP/FP) refer to the number of Predicted Positives that were correct/incorrect, and similarly for True and False Negatives (TN/FN)".

As both, high precision and recall, are important for an robust information retrieval system they are typically combined into a single measure such as the F-measure, also referred to as F-score. The F-score is the weighted harmonic mean between precision and recall, derived from the measure of effectiveness proposed

in [Rijsbergen, 1979]. The most common form is the F_1 score where precision and recall are assigned equal weight:

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The F_1 score has the advantage of its intuitive interpretability as both precision and recall are well understood measures and as it lives in the range $[0, 1]$, meaning that the effectiveness of the system is can be expressed in terms of percentage.

It is however important to point out that any version of the F-measure is a biased score as it "ignores TN which can vary freely without affecting the statistic" [Powers, 2011]. This can affect the evaluation of a classifier when the class distribution is skewed, motivating the use of unbiased measures in these cases, such as the ones described next.

3.3.2 Informedness, Markedness and Matthews Correlation Coefficient

3.3.3 Cross-entropy

3.4 Data

Describe data format

In order to perform supervised learning labelled data was needed for training. Together with the process of reframing of the research problem this was approached in an iterative way. First a quick prototypical tool was built to collect labels in a crowd-sourced fashion. This allowed getting more knowledge about the problem itself, especially with regards to how humans perform the task of labelling topics of text sections, and to perform first experiments of algorithmically achieving meaningful results in agreement to human behavior on this task. Then these learnings were taken into consideration when re-scoping the research problem and according to that data was collected using the microtasking service crowdflower.com [cro, 2016], leading to a quality dataset of labelled sentences from job ads.

3.4.1 Explorative Data Collection

Picture of software setup?

To collect first data a tool was build, consisting of a Node.js [nod, 2016] server using MongoDB[mon, 2016] as a database and communicating via a JSON with a simplistic website front-end using the mustache template engine [mus, 2016]. The tool is online[1] and it's source code is publicly available on GitHub[2] with it's API documentation hosted online as well[3].

The data generated by using the free text description of each job ad and splitting it into paragraphs as can be seen in the software package as well[4].

[1] http://thesis.cwestrup.de/jobad-tagger/
[2] https://github.com/cle-ment/thesis-tagger
[3] http://thesis.cwestrup.de/jobad-tagger/apidoc/
[4] https://github.com/cle-ment/thesis-tagger/blob/master/pre-processing.ipynb

The goal of this prototype tool for data collection was on the one hand to acquire data in order to carry our first experiments as fast as possible, and on the other hand to gain a deeper understanding about the research problem itself by giving an open, unbiased task to the participants. In particular the question at hand was how humans label the content of the different parts of a job ad.

The exact task given to the participants was "Describe what each section is about by adding one or more tags/keywords to it". They were shown a job ad that was split into paragraphs and besides each paragraph was a text field to enter 1 or more tags.

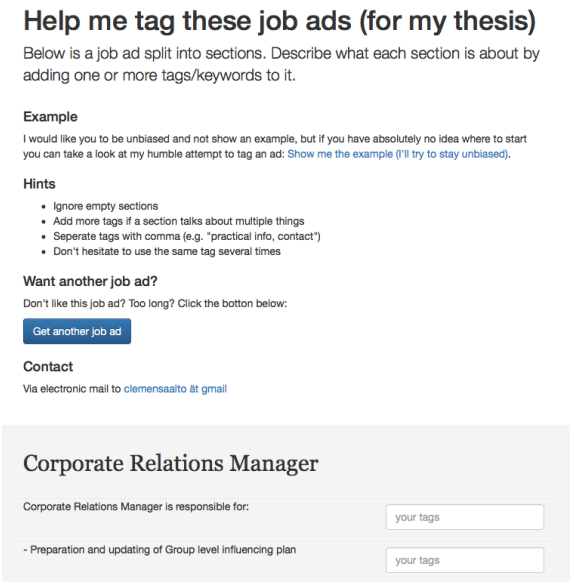


Figure 1: Interface of the tagging tool

In a first step the tool was only shown to 3 participants to get immediate feedback if the user interface had flaws and whether the task was understood. Based on this feedback the tool was improved by providing an example for the participants and then tested with a slightly larger group of 12 persons. After correcting a few minor details in the user interface a public link was then shared via social media and other channels with as many people as possible. A few days later the tool was then also shared internally within Sanoma where it was set up as a competition to tag the most possible job ads.

In total 91 job ads were tagged, resulting in 379 tagged text sections and 358 tags.

Describe data: Different characteristics

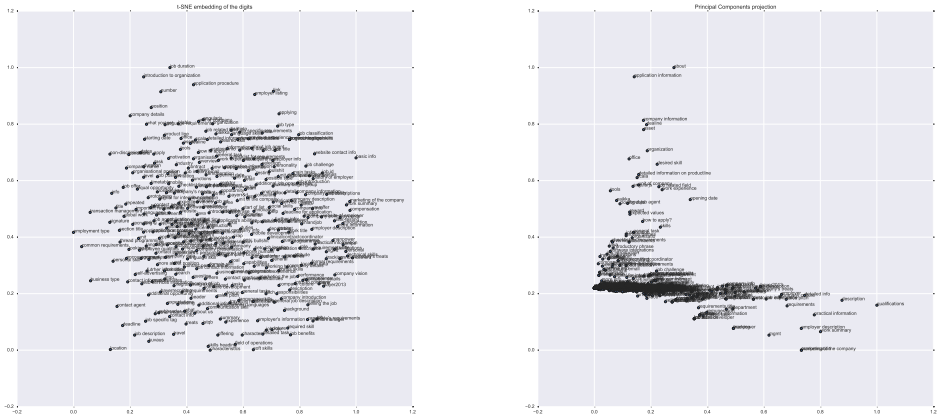
show distribution?

show em-

3.5 Crowdsourced Data Collection with Refined Research Problem

3.6 Discriminant Functions for Multi-class Classification

A simple approach to multi-class classification is to pose the learning problem as a combination of binary classification problems as described in [Bishop, 2006, Chapter

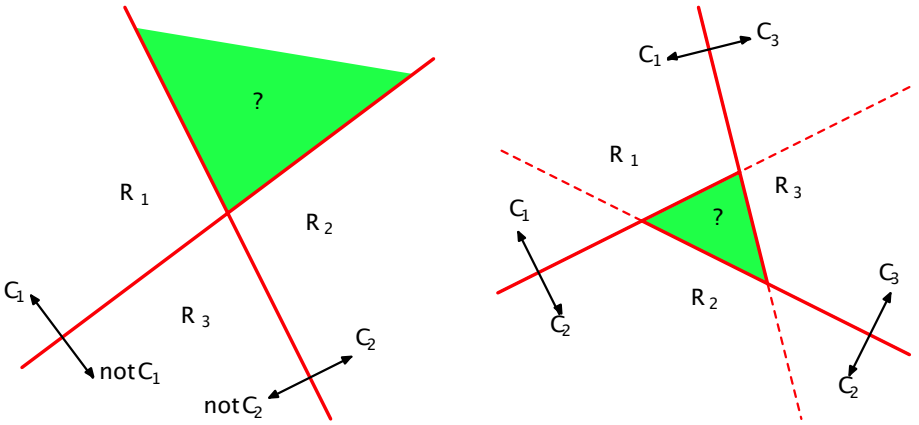


(a) t-SNE Embedding (b) Principal Components Projection

Figure 2: Visualizing the paragraph dataset. The data mapped into a vector space via a Unigram TF.IDF mapping.

4.1.2, p. 182]. This can be done by using K separate classifiers, each of which predicts one of the classes against all $K-1$ other classes, which is known as the *one-versus-the-rest* classification scheme. An alternative approach is to train $K(K-1)/2$ binary classifiers for each possible pair of classes, referred to as *one-versus-one* classification.

These extensions though have major drawbacks as pointed out by [Duda et al., 1973, Chapter 5.2.2]. As illustrated by 3 both of the classification schemes lead to ambiguous regions in the hypothesis space as their classification is undefined.



(a) One-Vs-Rest classification scheme (b) One-Vs-One classification scheme

Figure 3: : Ambiguous regions in the hypothesis space ([Bishop, 2006] Chapter 4, Figure 4.1)

[Bishop, 2006]

3.7 Vector-Space Models

Thus each document document vector has the same dimensionality its dimensions can be used as features to be fed into most popular classification metho

3.7.1 N-gram language models

N-gram language models are based on co-occurrences of word or character sequences, so-called N-grams or k-shingles as they are referred to in the Data Mining literature [Leskovec et al., 2014, Chapter 3.2, p. 72]. Formally an N-gram is defined as a sequence of n items, each of which consist of n characters or words, effectively used to capture sub-sequences of text. Common choices are N-grams of size 1, 2 or 3 – called "unigrams", "bigrams" and "trigrams" respectively – and can the definition can be extended to using a window size $[w_{\min}, w_{\max}]$, employing all combinations of N-grams in this interval.

N-grams are usually used to create a vector-space model by representing each document in a dataset as a *bag-of-words* or *bag-of-N-grams* vector so that each dimension of the vector represents statistics about the corresponding N-gram. For unigrams

- TF.IDF - simple wordcounts - show T-SNE embeddings of doc2vec vectors

Today N-gram models are still in wide use and considered as state of the art "not because there are no better techniques, but because those better techniques are computationally much more complex, and provide just marginal improvements" [Mikolov, 2012, p. 17].

Notable shortcomings of this method are it's inability to capture word-order

- vector space models
- bag of words
- "The most important weakness is that the number of possible n-grams increases exponentially with the length of the context, preventing these models to effectively capture longer context patterns. This is especially painful if large amounts of training data are available, as much of the patterns from the training data cannot be effectively represented by n-grams and cannot be thus discovered during training. The idea of using neural network based LMs is based on this observation, and tries to overcome the exponential increase of parameters by sharing parameters among similar events, no longer requiring exact match of the history H." [Mikolov, 2012, p. 17]

http://localhost:8888/notebooks/thesis/sandbox/crowdflower-data-collection/extract-data-crowdflower.ipynb

4 Experiments

4.1 TODO

- Comparison one-vs-rest and one-vs-one against linear machine
- Visualizations and embeddings of data in 2D (and decision boundaries?)
- show T-SNE embeddings of doc2vec vectors

4.2 Classification of paragraph labels

4.3 Unsupervised label detection

4.4 Classification of sentence labels

4.4.1 Experiment 1: Feature Extraction through Vector Space Models

4.4.2 N-gram models

4.4.3 Distributed Representations language models

Following an approach proposed by [Le and Mikolov, 2014], the rationale of this experiment was to find out it was possible to obtain a more expressive language model than the N-gram based methods described in 4.4.2.

The idea is based

4.5 Neural Networks

5 Results

5.1 TODO

- compare the two datasets in quality

Something

6 Discussion and Conclusions

Something

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A Appendix

Bla

B Appendix : Experiments

doc2vec

April 27, 2016

1 Classification using Distributed representations of sentences and documents

Testing paragraph vectors approach as proposed in [1].
Date: 22.04.2016

1.1 Context

Different language models lead to differente expressiveness in the feature space and thus alternatives were explored. This particular approach promised state-of-the-art results.

1.2 Experiment Rationale

The main goal of these experiments was to compare the performance of the approach in [1] with a simple bag-of-words model, especially given the rather small dataset.

1.3 Testing Procedure and Metrics

Using [4,5] a bag-of-words model was trained on the the labelled sentence dataset with a TF.IDF transformation applied to it and then classification was carried out by

1.4 Test Results

From manual judgement the word2vec mapping works exceptionally well to find relations between words, however simply adding up vectors to represent several words was an overly naive approach and does not work (Note: In retrospective this approach does not even make sense mathematically.)

1.5 Learnings

- Word2vec mapping has potential if the thesis scope will focus on NLP (natural language processing) since it is aware of the local context of words as opposed to a simple bag-of-words approach.
- Representing documents needs a more sophisticated approach.

1.6 References

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2 Code

```
In [8]: def warn(*args, **kwargs):
            pass
        import warnings
        warnings.warn = warn

In [9]: import pickle
        import datetime
        import logging
        import time
        import pandas as pd
        import numpy as np
        from random import shuffle
        import multiprocessing


        import sys
        sys.path.append('../joblearn-experiments/triton-experiments/workdir/')

        import joblearn.dataset
        import joblearn.gridsearch
        import joblearn.feat_extr
        import joblearn.feat_trans
        import joblearn.scoring
        import joblearn.target_trans
        import joblearn.estimation

        import sklearn.cross_validation
        import sklearn.feature_extraction
        import sklearn.linear_model
        import sklearn.neighbors

        import gensim
        from gensim import models

In [10]: ### Basic setup

         FEAT_DIM = 200

         # test set size
         TEST_SIZE = 0.3

         # timestamp at runtime
```

```
TIMESTAMP = str(int(time.time()))
EXP_NAME = "paragraph2vec"
```

In [11]:
```
### Dataset Initialization

df = pd.read_csv(
    "../joblearn-experiments/local-experiments/workdir/data/sentences_aggregated_50-249.csv")

# Use entries with label confidence over 0.6 and aren't test questions:
df_conf = df[df['0_label:confidence'] > 0.6]
df_conf = df_conf[df_conf['_golden'] == False]
df_conf = df_conf[['0_label', '0_label:confidence', '0-sentence',
         '0-context-after', '0-context-before']]

label_array = np.array(df_conf['0_label'])
le = sklearn.preprocessing.LabelEncoder()
le.fit(label_array)
data_Y = le.transform(label_array)
data_Y_labels = le.classes_


data_X = np.array(df_conf['0-sentence'])

### Train/Test Splits Setup

label_groupings = {}
data_splits = {}

# no grouping
label_groupings["none"] = joblearn.target_trans.LabelGrouping("No grouping",
                                                              data_Y,
                                                              data_Y_labels)
(X_train, X_test, Y_train, Y_test) = sklearn.cross_validation.train_test_split(
     data_X, data_Y, test_size=TEST_SIZE, random_state=0)
data_splits["none"] = joblearn.target_trans.DataSplit(X_train, X_test,
                                                      Y_train, Y_test)
```

2.1 Doc2Vec

In [12]:
```
alldocs = []
for line_no, document in enumerate(data_X):
    words = gensim.utils.to_unicode(document).split()
    alldocs.append(gensim.models.doc2vec.LabeledSentence(words, [line_no]))

Xdocs = alldocs[:]
```

In [13]:
```
# model = Doc2Vec(documents, size=100, window=8, min_count=5, workers=4)
# model = gensim.models.Doc2Vec.load_word2vec_format(
#     '../05.1-tag-classification-tfidf-clustered/data/word2vec/text8.bin',
#     binary=True)  # C binary format

cores = multiprocessing.cpu_count()
assert gensim.models.doc2vec.FAST_VERSION > -1, "this will be painfully slow otherwise"
model = gensim.models.Doc2Vec(dm=1, dm_concat=1, size=100, window=10, negative=5, hs=0, min_co
```

In [14]:
```
model.build_vocab(Xdocs)
```

```
In [15]: for i in range(0,20):
             shuffle(Xdocs)
             model.train(Xdocs)
```

```
WARNING:gensim.models.word2vec:under 10 jobs per worker: consider setting a smaller ‘batch_words’ for s
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```

```
In [16]: X_transformed_word2vec = np.matrix(model.docvecs)
```

2.2 N-grams BOW

```
In [17]: vectorizer = sklearn.feature_extraction.text.TfidfVectorizer(
             analyzer='word', max_features=100)
         X_transformed_bow = vectorizer.fit_transform(data_X).todense()
```

2.3 compare

```
In [18]: from sklearn import cross_validation
         from sklearn import linear_model
         from sklearn import neighbors
```

```
In [19]: (X_transformed_bow_train, X_transformed_bow_test,
          Y_bow_train, Y_bow_test) = cross_validation.train_test_split(
             X_transformed_bow, data_Y, test_size=0.3, random_state=0)

         (X_transformed_word2vec_train, X_transformed_word2vec_test, Y_word2vec_train,
          Y_word2vec_test) = cross_validation.train_test_split(
             X_transformed_word2vec, data_Y, test_size=0.3, random_state=0)
```

```
In [20]: # classifier_bow = linear_model.LogisticRegression().fit(X_transformed_bow_train, Y_bow_train)
         # classifier_word2vec = linear_model.LogisticRegression().fit(X_transformed_bow_train, Y_bow_t
         classifier_bow = neighbors.KNeighborsClassifier().fit(X_transformed_bow_train, Y_bow_train)
         classifier_word2vec = neighbors.KNeighborsClassifier().fit(X_transformed_bow_train, Y_bow_trai
```

```
In [21]: scores_word2vec = cross_validation.cross_val_score(
             classifier_word2vec, X_transformed_word2vec_test, Y_word2vec_test, cv=5,
             scoring='f1_weighted')

         print("Accuracy: %0.2f (+/- %0.2f)" % (scores_word2vec.mean(), scores_word2vec.std() * 2))
```

```
Accuracy: 0.34 (+/- 0.03)
```

```
In [22]: scores_bow = cross_validation.cross_val_score(
             classifier_bow, X_transformed_bow_test, Y_bow_test, cv=5,
             scoring='f1_weighted')

         print("Accuracy: %0.2f (+/- %0.2f)" % (scores_bow.mean(), scores_bow.std() * 2))
```

```
Accuracy: 0.63 (+/- 0.07)
```

3 Improved Doc2Vec

```
In [23]: model = gensim.models.Doc2Vec(dm=1, dm_concat=1, size=300, window=5, negative=5, hs=0, min_cou
         model.build_vocab(Xdocs)
         X_transformed_word2vec = np.matrix(model.docvecs)
```

```
In [24]: for i in range(0,20):
             shuffle(Xdocs)
             model.train(Xdocs)
```

```
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WARNING:gensim.models.word2vec:under 10 jobs per worker: consider setting a smaller 'batch_words' for s
```

```
In [30]: model.intersect_word2vec_format(
             '../05.1-tag-classification-tfidf-clustered/data/word2vec/GoogleNews-vectors-negative300.b
             binary=True)
```

```
In [31]: (X_transformed_bow_train, X_transformed_bow_test,
          Y_bow_train, Y_bow_test) = cross_validation.train_test_split(
             X_transformed_bow, data_Y, test_size=0.3, random_state=0)

         (X_transformed_word2vec_train, X_transformed_word2vec_test, Y_word2vec_train,
          Y_word2vec_test) = cross_validation.train_test_split(
             X_transformed_word2vec, data_Y, test_size=0.3, random_state=0)
```

```
In [32]: classifier_bow = linear_model.LogisticRegression().fit(X_transformed_bow_train, Y_bow_train)
         classifier_word2vec = linear_model.LogisticRegression().fit(X_transformed_bow_train, Y_bow_tra
         # classifier_bow = neighbors.KNeighborsClassifier().fit(X_transformed_bow_train, Y_bow_train)
         # classifier_word2vec = neighbors.KNeighborsClassifier().fit(X_transformed_bow_train, Y_bow_tr
```

```
In [33]: scores_word2vec = cross_validation.cross_val_score(
             classifier_word2vec, X_transformed_word2vec_test, Y_word2vec_test, cv=5,
             scoring='f1_weighted')

         print("Accuracy: %0.2f (+/- %0.2f)" % (scores_word2vec.mean(), scores_word2vec.std() * 2))
```

```
Accuracy: 0.23 (+/- 0.00)
```

```
In [34]: scores_bow = cross_validation.cross_val_score(
             classifier_bow, X_transformed_bow_test, Y_bow_test, cv=5,
             scoring='f1_weighted')

         print("Accuracy: %0.2f (+/- %0.2f)" % (scores_bow.mean(), scores_bow.std() * 2))
```

```
Accuracy: 0.68 (+/- 0.06)
```

```
In [ ]:
```