Language modeling for text classification

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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

kNN	k-Nearest Neighbors
SVM	Support Vector Machine
NN	Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory

one-hot or one-of-V encoding

Todo list

0.1 TODO

- Describe the process of finding the problem

1 Introduction

1.1 Motivation

1.2 Structure of the thesis

2 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]

2.1 Need Statement

2.2 Problem Statement

2.3 Research objectives

2.4 Related work

[Lodhi et al., 2002] string kernels

section on transfer learning and feature learning

text classification

explicit vs implicit feature representation

3 Research process and Design Development

3.1 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 [cro, 2016], leading to a quality dataset of labelled sentences from job ads.

3.1.1 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].

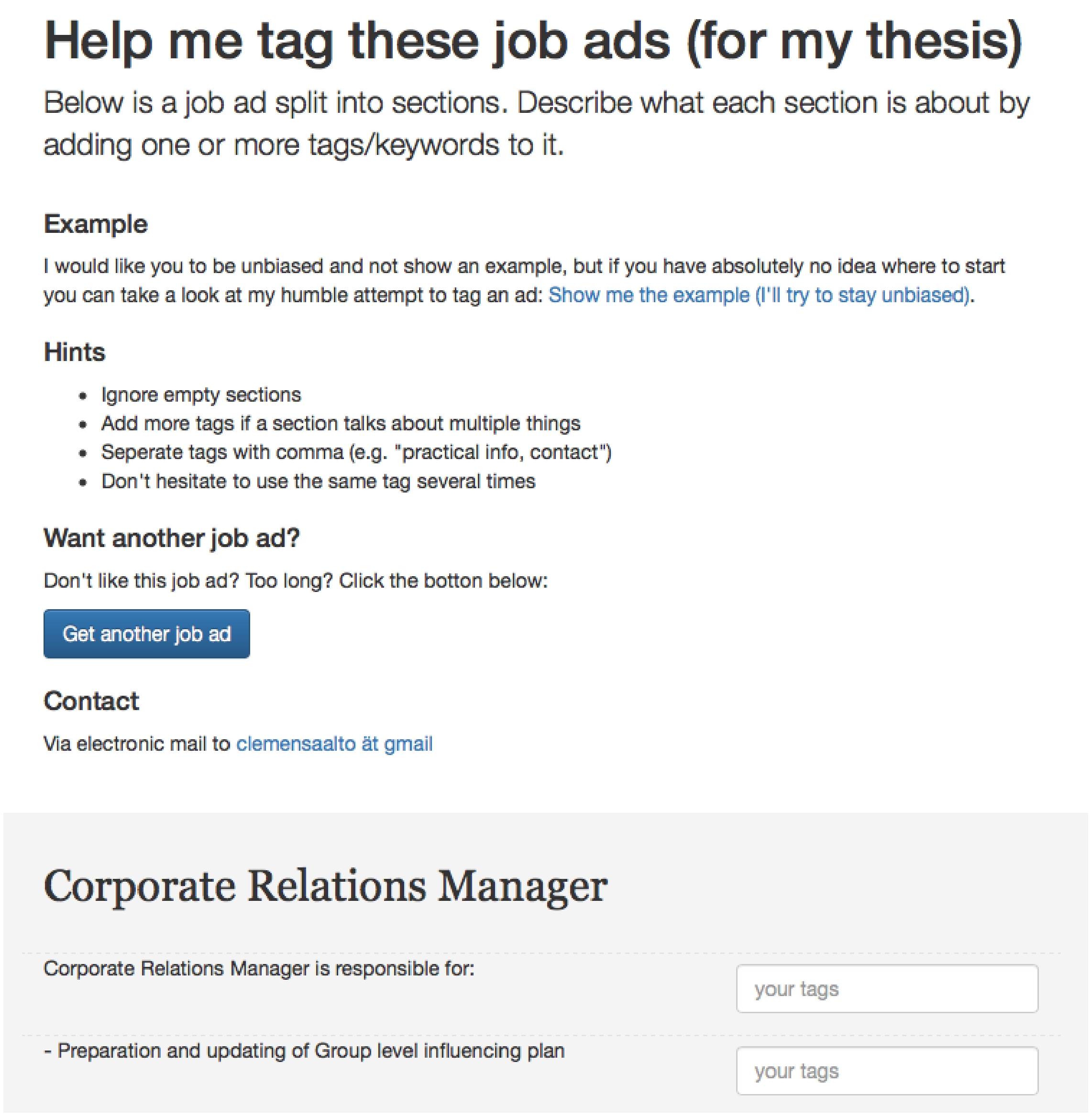
The data generated by using the free text description of each job ad and splitting it into paragraphs as can be seen in the software package as well[4].

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.

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.

[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



Help me tag these job ads (for my thesis)

Below is a job ad split into sections. Describe what each section is about by adding one or more tags/keywords to it.

Example

I would like you to be unbiased and not show an example, but if you have absolutely no idea where to start you can take a look at my humble attempt to tag an ad: Show me the example (I'll try to stay unbiased).

Hints

- Ignore empty sections
- Add more tags if a section talks about multiple things
- Seperate tags with comma (e.g. "practical info, contact")
- Don't hesitate to use the same tag several times

Want another job ad?

Don't like this job ad? Too long? Click the botton below:

Contact

Via electronic mail to clemensaalto ät gmail

Corporate Relations Manager

Corporate Relations Manager is responsible for:

- Preparation and updating of Group level influencing plan

Figure 1: Screen capture of the interface of the tagging tool

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

3.1.2 Crowdsourced Data Collection with Refined Research Problem

Describe data: Different characteristics

show distribution?

show em-

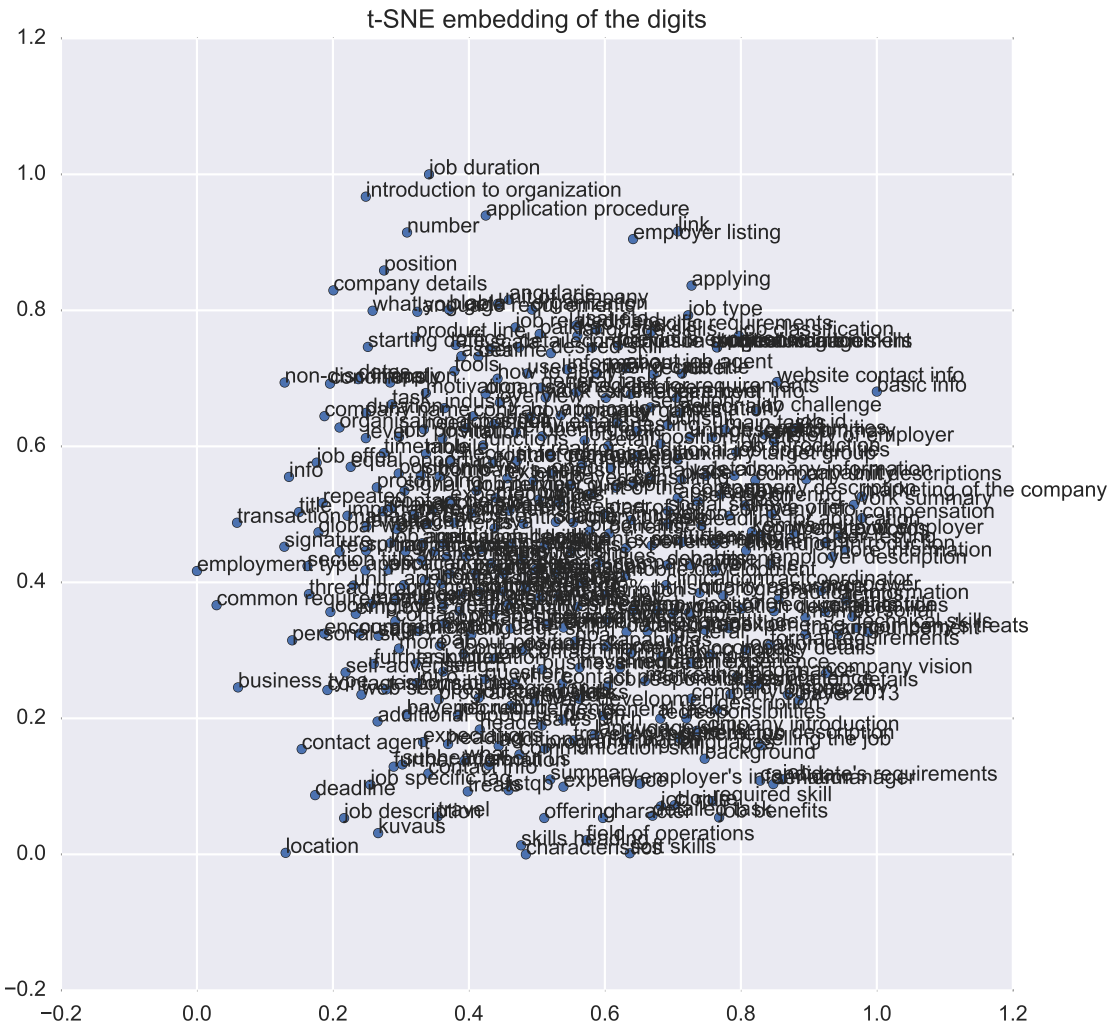


Figure 2: t-SNE Embedding

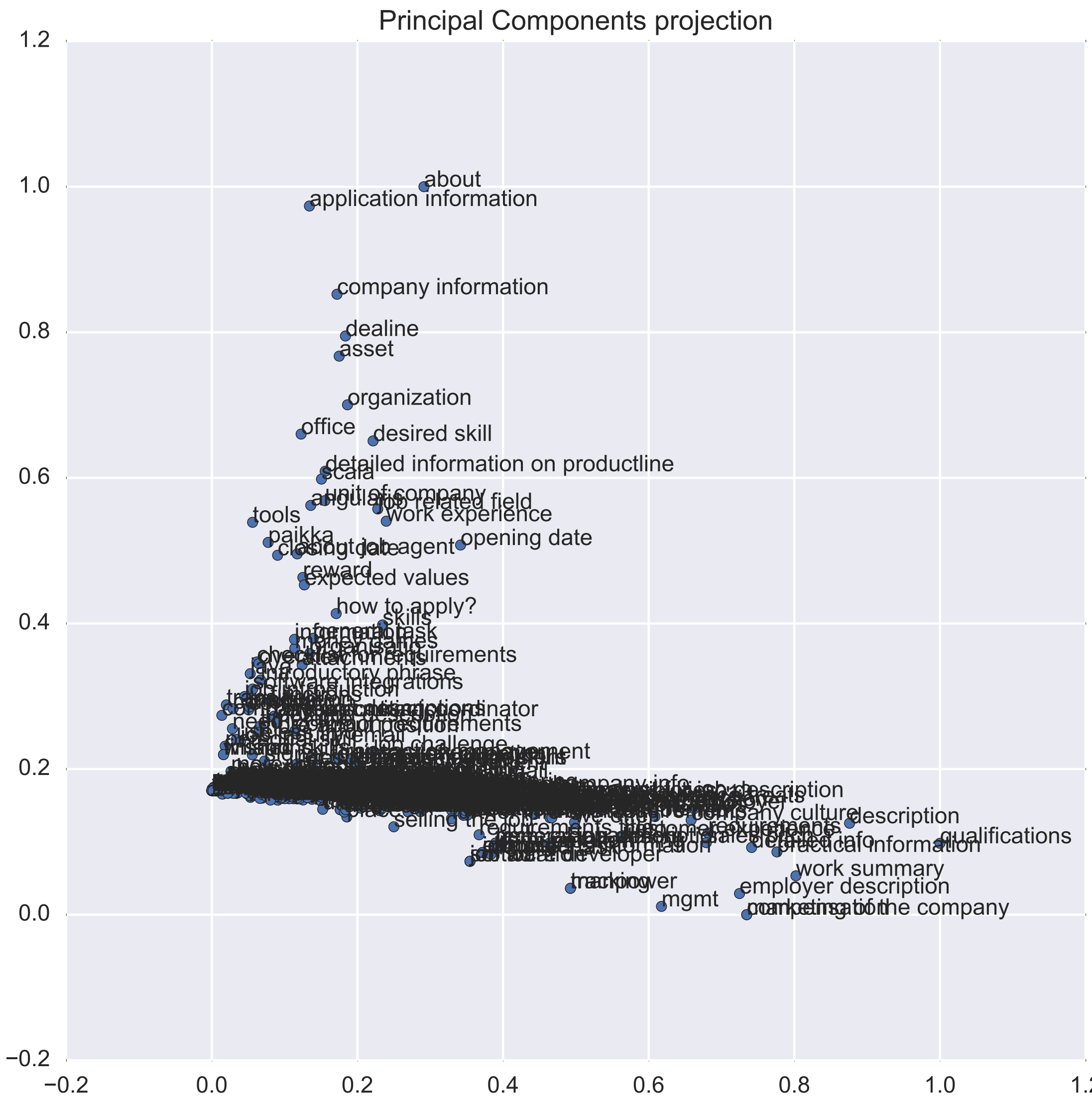
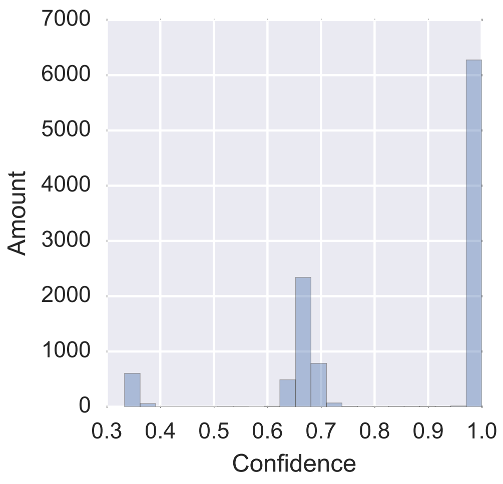
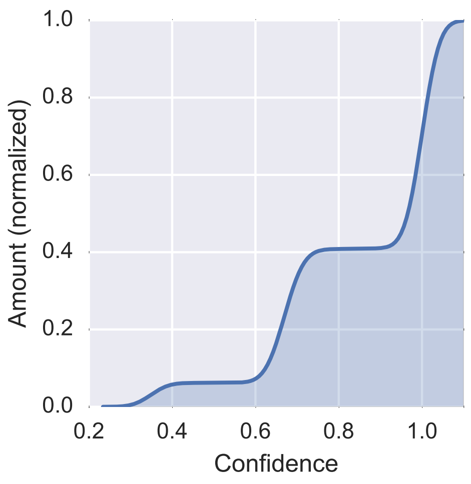


Figure 3: Principal Components Projection



(a) Confidence



(b) Cumulative Confidence

Figure 4: Amount of label judgements versus label confidence of the sentence label data collected via crowdflower

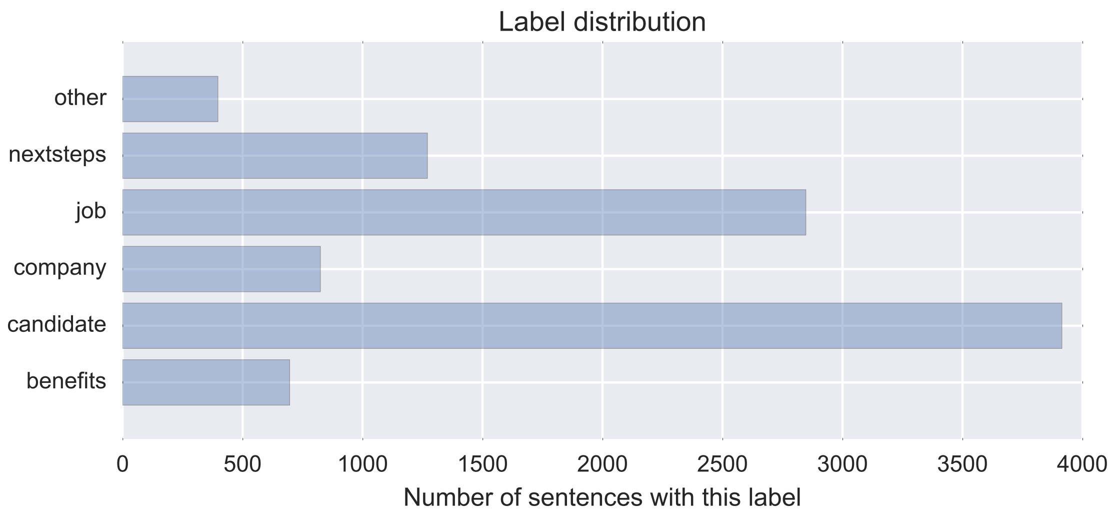


Figure 5: Distribution of labels in sentence data

4 Evaluation

explain suervised clas-sifi-ac-tion and bi-naty vs multi

4.1 Binary Classification

In binary or dichotomous case of classification we are given a single class k and a set of labelled data points $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ where targets $y_i \in \{0, 1\}$ encode whether a data point x_i belongs the class c or not. The task is then to achieve correct classification of new data points without knowing the true label via a model function or predictor $f(\cdot)$.

To evaluate such a predictor it is useful to present the results in form of a contingency table as shown in table Table 1, because it gives valuable insights about the performance of the prediction. The table shows the proportion of data points that belong to the class (RP) or not (RN) and were predicted correctly (TP) or incorrectly (FN), as well as the number of data samples that do not belong to the class (RN) and were falsely predicted to be in the class (FP) or correctly predicted to not be in the class (TN), and the same proportions for the positively (PP) and negatively (PN) predicted cases with respect to the true assignments to the data. N refers to the total amount of data points.

	Real Positives (RP)	Real Negatives (RN)
Predicted Positives (PP)	True Positives (TP)	False Positives (FP)
Predicted Negatives (PN)	False Negatives (FN)	True Negatives (TN)

Table 1: Contingency table for binary classification

An intuitive choice towards classification is to simply ask which data points were correctly classified to belong to the class or not. In terms of the contingency table above the ratio of $(\mathrm{TP} + \mathrm{FP})/(\mathrm{N})$, commonly referred to as the “accuracy” of the classifier.

This choice can give a good intuition and it does capture the effectiveness on both true positives as well as true negatives, but it is strongly influenced by bias of the true and predicted class distribution (known as prevalence RP/N and label bias) as pointed out by [Powers, 2011]. For example given a population of 900 positive and 100 negative examples, a predictor that simply always chooses a positive assignment can achieve accuracy of 90% while it obviously is not a great predictor.

“There is a good reason why accuracy is not an appropriate measure for information retrieval problems. In almost all circumstances, the data is ex- tremely skewed: normally over 99.9% of the documents are in the nonrele- vant category. A system tuned to maximize accuracy can appear to perform well by simply deeming all documents nonrelevant to all queries. Even if the system is quite good, trying to label some documents as relevant will almost always lead to a high rate of false positives. However, labeling all documents as nonrelevant is completely unsatisfying to an information retrieval system user. ”[Manning et al., 2008, Chapter 8.3, p. 155]

4.1.1 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. 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:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

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:

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The F_1 score has the advantage of its intuitive interpretability as both precision and recall are well understood measures and, analogous to recall, precision and accuracy, as it lives in the range $[0, 1]$, giving a single number that can express the effectiveness of the system in terms of percentage.

The F1 score is widely used in the field of Machine Learning and Data Mining and thus it is an important measure to consider to compare results to outcomes of prior publications by others. 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 (prevalence) or the classifier develops a bias towards certain classes (label bias), motivating the use of unbiased measures in these cases, such as the ones described next.

4.1.2 Informedness, Markedness and Matthews Correlation Coefficient

[Powers, 2011] introduces unbiased analogue measures to Recall and Precision, called "Informedness" and "Markedness" respectively. As [Powers, 2011] lays out, "Informedness quantifies how informed a predictor is for the specified condition, and specifies the probability that a prediction is informed in relation to the condition (versus chance).":

$$\begin{aligned} \text{Informedness} &= \text{Recall} + \text{Inverse Recall} - 1 \\ &= 1 - \text{Miss Rate} - \text{Fallout} \\ &= 1 - \frac{\text{FN}}{\text{RN}} - \frac{\text{FP}}{\text{RP}} \end{aligned} \tag{4}$$

Further he defines: "Markedness quantifies how marked a condition is for the specified predictor, and specifies the probability that a condition is marked by the predictor (versus chance)."

$$\begin{aligned} \text{Informedness} &= \text{Recall} + \text{Inverse Recall} - 1 \\ &= 1 - \text{Miss Rate} - \text{Fallout} \\ &= 1 - \frac{\text{FN}}{\text{RN}} - \frac{\text{FP}}{\text{RP}} \end{aligned} \tag{5}$$

Based on Informedness and Markedness we can then see that *Matthews Correlation Coefficient* r_G, first proposed by [Matthews, 1975], is a score that balances these two measures:

$$\begin{aligned} r_G &= \pm\sqrt{\text{Informedness} \cdot \text{Markedness}} \\ &= \frac{(\text{TP} \cdot \text{TN} - \text{FP} \cdot \text{FN})}{(\text{TP} + \text{FN})(\text{FP} + \text{TN})(\text{TP} + \text{FP})(\text{FN} + \text{TN})} \end{aligned} \tag{6}$$

Matthews Correlation Coefficient can thus be used as unbiased alternative to the F-measure and offers a similar ease of interpretability as it ranges from -1 to 1, the former indicating a negative correlation or adverse estimation and the latter indicating a perfect prediction, while a coefficient of 0 reflects chance.

4.2 Multi-class classification

Multi-class classification refers to a generalization of the binary case where we aim to predict for each datapoint x_i one of K labels for the classes at hand. The target space $\mathcal{Y}$ can be represented with each $y_i \in \{0,1\}^k$, known as *one-hot encoding*, where each target is c-dimensional vector. Alternatively we can encode the targets as categorical variables $y_i \in c_1, c_2, \ldots, c_k$. The contingency table from the binary case can be extended as in table 2, which is then commonly known as *Confusion Matrix* or *Error Matrix* .

citation for Confusion Matrix?

	Real Class 1	Real Class 2	...	Real Class k
Predicted Class 1	...	...		...
Predicted Class 2	...	...		...
...				
Predicted Class k	...	...		...

Table 2: Contingency table for k classes, also referred to as Confusion Matrix

4.2.1 Averaging for Multi-class Recall, Precision and F1-Score

A way to evaluate

4.2.2 Matthews Correlation Coefficient for K classes

4.2.3 Categorical Cross-entropy / Multi-class Log-loss

4.3 Multi-label classification

5 Vector Space Language Models

write vector space models introduction

"Contiguity hypothesis. Documents in the same class form a contiguous region and regions of different classes do not overlap." [Manning et al., 2008, Chapter 14, p. 289]

Vector space model [Manning et al., 2008, Chapter 6.3, p. 120]

"the document 'Mary is quicker than John' is, in this view, identical to the document 'John is quicker than Mary'"[Manning et al., 2008, Chapter 6.2, p. 117]

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

5.1 N-gram language models

explain language modeling as approach for text classification

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 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. Specifically, a common way to compute the word count vectors for a document is the following:

is the term language model right for ngram vector space models?

$$\mathrm{TF}_{ij} = \frac{f_{ij}}{\max_k f_{kj}} \tag{7}$$

Where f_{ij} is "the *frequency* (number of occurences) of a term (word) i in document j" and TF_{if} is the *term frequency*, i.e. "f_{ij} normalized by dividing it by the maximum number of occurrences of any term [...] in the same document" [Leskovec et al., 2014, Chapter 1.3.1, p. 8].

5.1.1 Variants

As this approach has been studied for decades there is quite an extensive amount

example with 2 vectors and

of variants and thus hyper-parameters to tune. The most important ones will be explained in the following sections:

Words vs. Characters The first choice when building an N-gram language model is to use characters or words as the atomic unit. In practically every case there are less characters than words in a dataset, but to capture expressive substrings usually larger N-gram window sizes or ranges have to be chosen, which leads to a combinatorial explosion. In case of word-based models on the other hand the maximal size of the feature space is the size of the vocabulary $\mathcal{V}$ in the case of unigrams or V^k in case of k-grams.

Stop words For creating N-gram models, so-called stop word lists are often used which are lists of frequent words that will be excluded as they do not carry much meaning [Leskovec et al., 2014, Chapter 1.3.1, p. 7]. The stop-word list used in these experiments is the standard list used for the Scikit-learn framework [Pedregosa et al., 2011] which is a list gathered by the University of Glasgow Information Retrieval group [5].

N-gram range The N-gram range, also known as window size or shingle size, refers to combinations of the atomic units of the model (words or characters) and defines an upper and lower limit for these combinations. For example a range of $[1, 1]$ specifies a unigram model, $[2, 2]$ a bigram model and $[1, 2]$ a combination of both including all unigrams and all bigrams. A larger range allows the model to capture an increasing amount of word order and thus context, but again leads to a combinatorial explosion in terms of feature space.

Vector size The vector size imposes an upper limit to the vector size and therefor the number of N-grams that can be encoded in the feature space. Commonly this simply uses the words with the highest frequency to reduce the vector size from the full length — the size of the vocabulary — to the desired size.

TF.IDF weighting A common extension to using word-counts is to weight the term frequencies by the so-called inverse document frequency, i.e. the inverse of the frequency of an term or N-gram in all documents. This method is commonly referred to as *TF.IDF* and specifically the inverse document frequency is defined as $\mathrm{IDF}_i = \log_2(N/n_i)$, where logarithmic smoothing is applied. The TF.IDF value for a term or N-gram is then computed as $\mathrm{TF}_{ij} \cdot \mathrm{IDF}_i$.

Sublinear TF scaling As [Manning et al., 2008, Chapter 6.4.1, p. 126] suggests "[it] seems unlikely that twenty occurrences of a term in a document truly carry twenty times the significance of a single occurrence". Hence a common variant is

[5]`http://www.gla.ac.uk/schools/computing/research/researchoverview/informationretrieval/`. The full stop word list can be found at `http://ir.dcs.gla.ac.uk/resources/linguistic_utils/stop_words` and in the appendix in section B.

sublinear scaling where we down-weigh the increase in term importance by applying a logarithmic function to it, resulting in the sub-linear term frequency subTF_{ij}:

$$\text{subTF}_{ij} = \left\{ \begin{array}{ll} 1 + \log \text{TF}_{ij} & \text{TF}_{ij} > 0 \\ 0 & \text{otherwise} \end{array} \right\}$$

Normalization Often the term vectors are globally normalized using the L_1 or L_2 norm to remove the effect of statistical differences between the terms.

There are, of course, various other variants and modifications to the N-gram model, but within the scope of this thesis only the most notable ones were introduced and will be used for experiments later. For further material on this subject refer for example to [Manning et al., 2008].

5.1.2 Shortcomings

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]. As [Mikolov, 2012] points out further "[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 [Language Models] 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]

5.2 Language Models using Distributed Representations

To overcome the shortcomings of popular language models such as the ones of the N-gram model mentioned above, lots of recent work went into the study of so-called distributed language models. One branch of research that gained significant attention is the work on Neural Network based Language models (NNLMs), popularized largely through the work of T. Mikolov and his software realization of such a model dubbed *word2vec* with interest coming not only from the academic community but also from open source community (Figure 6 shows the search relevance of the term "word2vec" in the

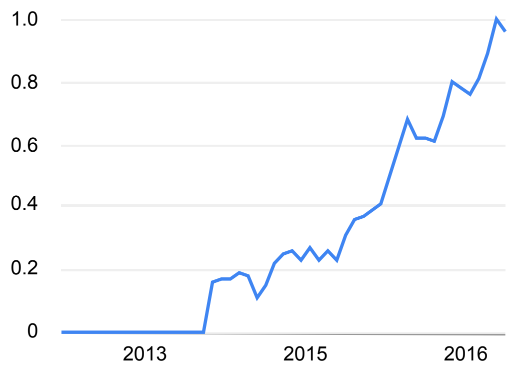


Figure 6: Google Trends statistics on relative search interest in the term "word2vec". Retrieved on 22.05.2016.

recent years). His work builds on ideas
introduced in [Bengio and Bengio, 2000]
where a neural network based model was
proposed for modeling high-dimensional discrete data, which was then applied to the domain of language modeling in [Bengio et al., 2003]. Following the description in this paper, the approach is as follows:

1. Associate with each word in the vocabulary a distributed *word feature vector* (a real-valued vector in $\mathbb{R}^m$),
2. Express the joint *probability function* of word sequences in terms of the feature vectors of these words in the sequence, and
3. Learn simultaneously the *word feature vectors* and the parameters of that *probability function*.

To achieve this, a feedforward neural network model is trained to learn these *word feature vectors* or *word embeddings*. As input a sequence of n words is given, each encoded using one-hot encoding or one-of-V encoding where the corresponding indicator vectors for each word have the size of the vocabulary V. The input word vectors are then projected linearly into a projection layer of significantly lower dimensionality D, using a global projection matrix for across all words, and concatenated, forming the input of size $D \times N$ to a hidden layer of size H. The hidden layer then feeds non-linearly into the output layer that is again of size V, modeling the probability distribution for a word given its context $P(w_t \mid w_{t-n}, \ldots, w_{t-2}, w_{t-1})$.

for his PhD thesis [Mikolov, 2012] and in his follow-up publications, e.g. [Mikolov et al., 2013b], [Mikolov et al., 2013c], [Mikolov et al., 2013a], whose approach dubbed "word2vec"

Building on ideas of [Bengio and Bengio, 2000]

5.3 Word2Vec

mention GloVe

[]

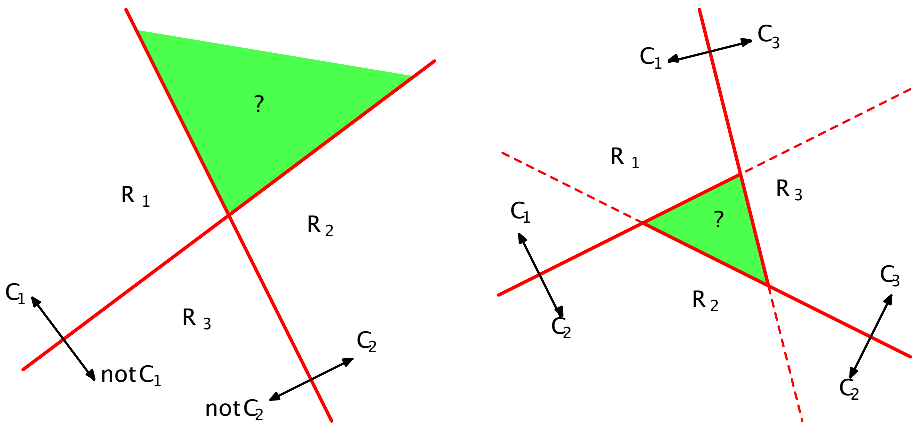
5.4 Doc2Vec

6 Classification Approaches

6.1 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 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 7 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 7: : Ambiguous regions in the hypothesis space ([Bishop, 2006] Chapter 4, Figure 4.1)

[Bishop, 2006]

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

7 Experiments

7.1 Effectiveness and Expressiveness of Statistical (Vector Space) Language Models

As section 5 explains, a popular way to approach text classification and other tasks in natural language processing is to build a language model by creating explicit representations of the objects or entities to be processed in a vector space. Such vectors can be used as features for a learning algorithm. Depending on the representation they can also further meaning, such as to encode notions of similarity of associativity between the objects.

In order to determine effective vector space representations for the task of sentence classification, a set of experiments was carried out to study and compare different approaches. Each method was studied with regards to the effect of its hyper-parameters on effectiveness when producing an input space to different classifiers, but also time and memory requirements at training and inference time are taken into account .

In order to compare the effectiveness for the sentence classification task as discussed in ?each labelled document was transformed into a vector space representation using the different methods and then used for classification with a simple logistic regression classifier(). Performance was then compared with regards to Matthews Correlation Coefficient for multi-class problems and Accuracy.

7.1.1 Baselines Classifiers: Uniform and Stratified Guessing

As a baseline for comparing the performance of classification two different guessing strategies were used, namely uniform and stratified guessing. Uniform guessing refers to a predictor that samples from the given classes assuming a uniform distribution whereas stratified guessing takes the label distribution in the data as the underlying probability distribution. Then both methods just sample from these distributions to produce “predictions”, while ignoring the actual input data. Both, uniform and stratified guessing achieve a Matthews Correlation Coefficient score of around 0 (averaged over 1000 runs) as expected for such guessing strategies (see section 4.1.2). On the other hand the accuracy for uniform guessing is around 0.16 which corresponds to 1/K for the K classes and around 0.26 for stratified guessing which reflects the skew of the label distribution. Figure 8 shows the confusion matrices for these baseline variants in absolute and normalized form which, revealing the properties of these guessing strategies.

7.1.2 N-gram Language Models

The first class of language models that was investigated for the task of multi-class classification are N-gram models that were explained in section 5.1. As mentioned

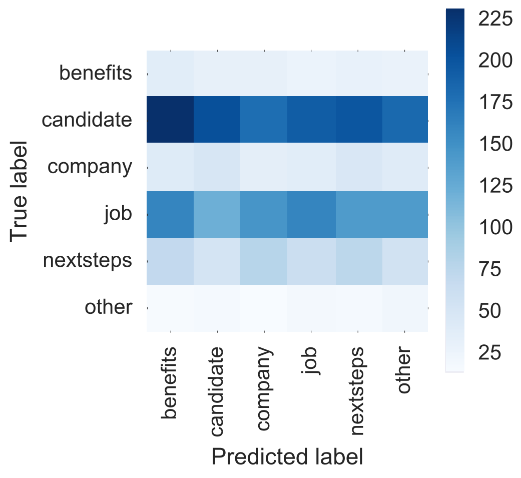
Compariso one-vs-rest and one-vs-one against linear machine

Visualizatio and embeddings of data in 2D (and decision boundaries?)

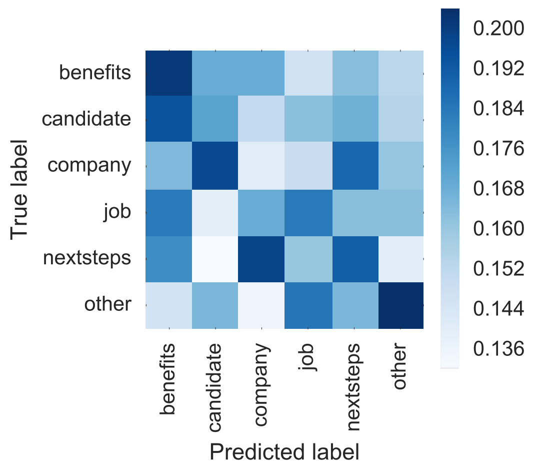
show T-SNE embeddings of doc2vec vectors

say why using the sentence dataset here

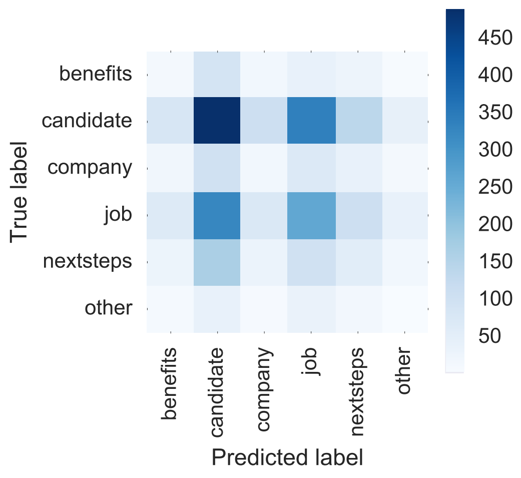
reference jupyter note-



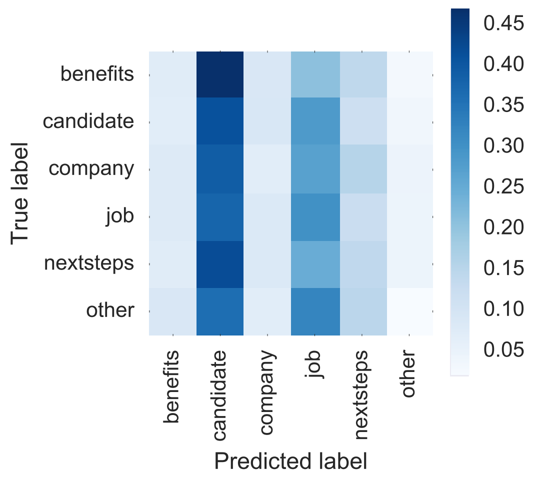
(a) Uniform, absolute



(b) Uniform, normalized



(c) Stratified, absolute



(d) Stratified, normalized

Figure 8: Confusion matrices of uniform and stratified guessing strategies.

earlier this type of model relies on simple statistics makes for straightforward computation but at the same time comes at cost of expressiveness in terms of temporal dependencies between words.

To compare the effects of these hyper-parameters for the different N-gram models a grid search was performed, searching over a large parameter space.

show T-SNE embeddings of doc2vec vectors

7.1.3 Distributed Language Models

- word2vec averaged - par2vec - inversed baysian

show influence of

Parameter	Search Space N-grams Words	Search Space N-grams Characters
N-gram range	[1,1], [1,2], [1,3], [2,3], [3,3]	[1,5], [1,10], [5,10], [5,15]
Stop words	English, None	N/A
Vector size	10, 100, 300	10, 100, 300
IDF	Yes, No	Yes, No
Norm	L1, L2, None	L1, L2, None
Sublinear TF	Yes, No	Yes, No

Table 3: Parameter search space for word and character level N-gram models

8 Results

8.1 TODO

- compare the two datasets in quality

Something

9 Discussion and Conclusions

9.1 Conclusions

- As in many areas of machine learning much work has been going into feature engineering but it seems that feature learning, while much more computationally expensive, surpasses the potential of engineered feature representations. Deep learning and meta-learning are mature enough to make up for the gap that has been there for years: To achieve performance that is good enough to make an algorithmic system usable in production, huge amounts of research and engineering went into feature engineering and finally the performance of these methods can be matched and even surpassed by automated methods or learning features. (link here NG's transfer learning work, also Schmidhubers work of meta-learning and on function prediction etc)
- There is more need to understand the representations of such feature learning systems though, statistics are quite easy to understand but weights of a neural network don't tell much. There is however potential for learning "better statistics" ourselves, e.g. how to efficiently learn a language (by looking at explicit indermediate representations of the states of a NN)
-

9.2 Contributions

- compare n-gram and doc2vec (?)
-

9.3 Further research

- how well do word2vec and comparable methods generalize: e.g. initialize a text corpus with word vectors from a bigger corpus (Google News), then train an RNN to predict the next word vector using the small corpus but use the bigger corpus to validate and see if words in bigger corpus can be inferred
- trajectory based algorithms (word trajectory through space for a sentence)

9.4 Learnings

- focusing on both, building a working system (engineering) and exploring new directions (science), is hard
- problem framing is hard

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A Appendix

Add list of en-glish stop words used for ngrams (sklearn list)

Add first Ngram TF.IDF ex-peri-ment

B Stopwords for N-grams

a about above across after afterwards again against all almost alone along already also although always am among amongst amoungst amount an and another any anyhow anyone anything anyway anywhere are around as at back be became because become becomes becoming been before beforehand behind being below beside besides between beyond bill both bottom but by call can cannot cant co computer con could couldnt cry de describe detail do done down due during each eg eight either eleven else elsewhere empty enough etc even ever every everyone everything everywhere except few fifteen fify fill find fire first five for former formerly forty found four from front full further get give go had has hasnt have he hence her here hereafter hereby herein hereupon hers herself him himself his how however hundred i ie if in inc indeed interest into is it its itself keep last latter latterly least less ltd made many may me meanwhile might mill mine more moreover most mostly move much must my myself name namely neither never nevertheless next nine no nobody none noone nor not nothing now nowhere of off often on once one only onto or other others otherwise our ours ourselves out over own part per perhaps please put rather re same see seem seemed seeming seems serious several she should show side since sincere six sixty so some somehow someone something sometime sometimes somewhere still such system take ten than that the their them themselves then thence there thereafter thereby therefore therein thereupon these they thick thin third this those though three through throughout thru thus to together too top toward towards twelve twenty two un under until up upon us very via was we well were what whatever when whence whenever where whereafter whereas whereby wherein whereupon wherever whether which while whither who whoever whole whom whose why will with within without would yet you your yours yourself yourselves

C 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)

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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)
```

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

```
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 [ ]:
```