Job Title Classification Strategies for the German Labor Market

Masterthesis

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4.1 Baseline Algorithms

The developed algorithm should be compared against the current state-of-the art methods in order to check the improvements.

CNN-ALGORITHMUS

However, traditional methods like Support Vector Machine (SVM) also performed well for text classification. Especially for multiclass tasks, as mentioned in the literature review, often different versions of the algorithm are used and showed good performance (Aiolli and Sperduti, 2005; Angulo et al., 2003; Benabdeslem and Bennani, 2006; Guo and Wang, 2015; Mayoraz and Alpaydm, 1999; Tang et al., 2019; Tomar and Agarwal, 2015). In general SVM has several advantages for text classifcation. First, text classifcation usually has a high dimensional input space. SVM can handle these large features since they are able to learn independently of the dimensionality of the feature space. In addition SVMs are known to perform well for dense and sparse vectors, which is usually the case for text classification (Joachims, 1998). Empirical results, for example Joachims (1998) or Liu et al. (2010) confirm the theoretical expectations. It is, therefore, a reasonable option to use a basic version of the SVM algorithm as a baseline.

The general idea of a SVM is to map "the input vectors x into a high-dimensional feature space Z through some nonlinear mapping chosen a priori

[...], where an optimal separating hyperplane is constructed" (Vapnik, 2000, 138). In SVM this optimal hyperplane maximizes the margin, which is simply put the distance from the hyperplane to the closest points, so called Support Vectors, across both classes (Han et al., 2012). Formally, given a training data set with n training vectors $x_i \in R^n, i = 1, ..., n$ and the target classes $y_1, ...y_i$ with $y_i \in \{-1, 1\}$, the following quadratic programming problem (primal) has to be solved in order to find the optimal hyperplane:

$$\min_{w,b} \frac{1}{2} w^T w$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1$$

where $\phi(x_i)$ transforms x_i into a higher dimensional space, w corresponds to the weight and b is the bias (Chang and Lin, 2001; Jordan et al., 2006) The given optimzation function assumes that the data can be separated without errors. This is not always possible, which is why Cortes et al. (1995) introduce a soft margin SVM, which allows for missclassfication (Vapnik, 2000). By adding a regularization parameter C with $C > 0$ and the corresponding slack-variable ξ the optimization problem changes to (Chang and Lin, 2001; Han et al., 2012):

$$\min_{w,b} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i,$$

$$\xi_i \geq, i = 1, ..., n$$

Introducing Lagrange multipliers α_i and converting the above optimization problem into a dual problem the optimal w meets (Chang and Lin, 2001; Jordan et al., 2006):

$$w = \sum_{I=1}^{n} y_i \alpha_i \phi(x_i)$$

with the decision function (Chang and Lin, 2001):

$$\text{sgn } (w^T\phi(x) + b) = sgn(\sum_{i=1}^{n} y_i \alpha K(x_i, x) + b)$$

$K(x_i, x)$ corresponds to a Kernel function, which allows to calculate the dot product in the original input space without knowing the exact mapping into the higher space (Han et al., 2012; Jordan et al., 2006).

In order to apply SVM to multiclass problems several approaches have been proposed. One stratetgy is to divide the multi-classifcation problem into several binary problems. A common approach here is the one-against-all method. In this method as many SVM classifiers are constructed as there are classes k. The k-th classifier assumes that the examples with the k label are positive labels, while all the other examples treated as negative. Another popular approach is the one-against-one method. In this approach $k(k-1)/2$ classifiers are constructed allowing to train in each classifier the data of two classes (Hsu and Lin, 2002).

4.2 Approach

5 Results

6 Discussion and Limitations

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