Learning from Domain Complexity

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Abstract

Sentiment analysis is genre and domain dependent, i.e. the same method performs differently when applied to text that originates from different genres and domains. Intuitively, this is due to different language use in different genres and domains. We measure such differences in a sentiment analysis gold standard dataset that contains texts from 1 genre and 10 domains. Differences in language use are quantified using certain language statistics, viz. domain complexity measures. We investigate 4 domain complexity measures: percentage of rare words, word richness, relative entropy and corpus homogeneity. We relate domain complexity measurements to performance of a standard machine learning-based classifier and find strong correlations. We show that we can accurately estimate its performance based on domain complexity using linear regression models fitted using robust loss functions. Moreover, we illustrate how domain complexity may guide us in model selection, viz. in deciding what word n-gram order to employ in a discriminative model and whether to employ aggressive or conservative word n-gram feature selection.

Keywords: Domain complexity; model selection; sentiment analysis

1. Introduction

Sentiment Analysis (SA) is—just like natural language processing in general (Sekine, 1997; Escudero et al., 2000)—genre and domain dependent (Wang and Liu, 2011), i.e. the same SA method performs differently when applied to different genres and domains. Intuitively, this is due to different language use in different genres and domains. In this paper, we measure such differences in an SA gold standard dataset that contains texts from 1 genre—product reviews—and 10 domains, e.g. apparel and music. Differences in language use are quantified using certain language statistics, viz. domain complexity measures. We relate domain complexity to performance of a standard Machine Learning (ML)-based classifier and find strong correlations. We show that we can accurately estimate its performance based on domain complexity using linear regression models fitted using robust loss functions. Moreover, we illustrate how domain complexity may guide us in model selection.

1.1. Related Work

Related to our work are Ponomareva and Thelwall (2012), who estimate—using domain complexity and domain similarity—the accuracy loss when transferring an SA method from a source to a target domain. Van Asch and Daelemans (2010) estimate—using domain similarity—the accuracy loss when transferring a part of speech-tagger from one domain to another. Blitzer et al. (2007) compute an A-distance proxy and show that it correlates with accuracy loss when transferring their SA method from a source to a target domain.

1A genre is an identifiable text category (Crystal, 2008, p. 210) based on external, non-linguistic criteria such as intended audience, purpose, and activity type (Lee, 2001) as well as textual structure, form of argumentation, and level of formality (Crystal, 2008, p. 210).

2A domain is a genre attribute that describes the subject area that an instantiation of a certain genre deals with (Steen, 1999; Lee, 2001).

1.2. Outline

This paper is structured as follows: In Section 2. we describe domain complexity measures that we use to quantify differences in language use. In Section 3. we relate domain complexity to performance and show what we can learn from their relationship. In Section 4. we conclude and point out directions for future work.

2. Domain Complexity

Domain complexity is a measure that reflects the difficulty of [a] classification task for a given data set (Ponomareva and Thelwall, 2012). We use 4 approximations of domain complexity: 3 approximations proposed by Ponomareva and Thelwall (2012) and 1 proposed by Remus (2012).

2.1. Ponomareva and Thelwall (2012)

Ponomareva and Thelwall (2012) proposed 3 measures as approximations of domain complexity:

**Percentage of rare words.** The percentage of rare words is defined as in Equation (1)

\[
PRW = \frac{|\{w \in W \mid c(w) < 3\}|}{|W|}
\]  

(1)

where \(W\) is the vocabulary, vocabulary size \(|W|\) equals the number of types, i.e. the number of different words in a text sample, and \(c(w)\) is the number of occurrences of \(w\) in a text sample.

**Word richness.** The word richness is defined just as the type/token ratio \(TTR\) in Equation (2)

\[
TTR = \frac{|W|}{\sum_{w \in W} c(w)}
\]

(2)

where \(\sum_{w \in W} c(w)\) equals the number of tokens, i.e. the total number of words in a text sample (Crystal, 2008, p. 498). From hereon, we refer to word richness by type/token ratio.

2021
Relative entropy. The relative entropy is defined as in Equation (3)
\[
H_{\text{rel}} = \frac{H}{H_{\text{max}}}
\]
where \(H\) as in Equation (4)
\[
H = - \sum_{w \in W} p(w) \log_2 p(w)
\]
is the entropy of \(W\)’s distribution and \(H_{\text{max}}\) as in Equation (5)
\[
H_{\text{max}} = - \sum_{w \in W} \frac{1}{|W|} \log_2 \frac{1}{|W|} = \log_2 |W|
\]
is the maximum entropy of \(W\)’s distribution, i.e. its entropy if \(W\) was distributed uniformly.

2.2. Remus (2012)
Remus (2012) proposed corpus homogeneity (Kilgarriff, 2001) as another approximation of domain complexity. Corpus homogeneity or corpus self-similarity uses repeated random subsampling validation and is estimated as shown in Pseudocode 1.

Pseudocode 1: Corpus homogeneity.
```
for i = 1, ..., k |
shuffle corpus \(c\),
split \(c\) into \(2\) equally-sized subcorpora \(c_1, c_2\)
similarity \(s_i := \text{sim}(c_1, c_2)\)
```

We use Jensen-Shannon (JS) divergence as similarity function \(\text{sim}(c_1, c_2)\). The JS divergence (Lin, 1991) is based on the Kullback-Leibler (KL) divergence \(D_{\text{KL}}\) (Kullback and Leibler, 1951) as given in Equation (6)
\[
D_{\text{KL}}(Q||R) = \sum_{w \in W} Q(w) \log \frac{Q(w)}{R(w)}
\]
where \(Q\) and \(R\) are probability distributions over a finite set \(W\), e.g. words. The JS divergence \(D_{\text{JS}}\) is then defined as shown in Equation 7
\[
D_{\text{JS}}(Q||R) = \frac{1}{2} [D_{\text{KL}}(Q||M) + D_{\text{KL}}(R||M)]
\]
where \(M = \frac{1}{2}(Q + R)\) is the average distribution of \(Q\) and \(R\) and \(0 \leq D_{\text{JS}}(Q||R) \leq 1\). The larger \(D_{\text{JS}}\), the more the probability distributions diverge. For \(k \to \infty\), the homogeneity estimate approaches the “actual” corpus homogeneity. We set \(k\) to 10 (Remus, 2012).

2.3. Sample Size Normalization
The domain complexity measures described in the previous sections are sample size dependent (Remus and Bank, 2012). Therefore, we compute percentage of rare words, type/token ratio, and relative entropy on fixed length subsamples rather than on the full sample as shown in Pseudocode 2.

Using a sufficient number of iterations \(k\)—10,000 in our case—we obtain a stable approximation of the expected domain complexity value, which is normalized with respect to sample size.

To compute sample size-normalized homogeneity, we proceed as shown in Pseudocode 1. But instead of shuffling the corpus and splitting it into \(2\) equally-sized subcorpora, we randomly extract \(2\) fixed length subsamples \(s_1^i, s_2^i\) analogously to Pseudocode 2 with the constraint that \(s_1^i, s_2^i\) must not overlap. We then measure \(\text{sim}(s_1^i, s_2^i)\). In deviation from corpus homogeneity as described in Section 2.2, we here set \(k\) to 10,000 instead of 10.

### 3. Learning from Domain Complexity
In this section we learn from an SA gold standard dataset’s domain complexity: In Section 3.1, we relate differences in domain complexity in an SA gold standard dataset to the differences in performance of a standard ML-based classifier evaluated on the same SA gold standard dataset. In Section 3.2 and Section 3.3, we let domain complexity guide us in model selection, viz., in deciding what word \(n\)-gram order to employ in a discriminative model. In Section 3.3, we let domain complexity guide us in deciding whether to employ aggressive or conservative word \(n\)-gram feature selection.

We analyze a common SA subtask: document-level polarity classification. Our experimental setup for this subtask is as follows: We use Blitzer et al. (2007)’s Multi-Domain Sentiment Dataset v2.0 (MDSD v2.0)\(^3\) as gold standard dataset. MDSD v2.0 contains star-rated product reviews of various domains. We chose 10 domains: apparel, books, dvd, electronics, health & personal care, kitchen & housewares, music, sports & outdoors, toys & games, and videos. Those are exactly the domains for which a balanced amount of 1,000 positive and 1,000 negative reviews is available. Blitzer et al. (2007) considered reviews with more than 3 stars positive and less than 3 stars negative; so do we.

For sentence segmentation and tokenization of MDSD v2.0 we use OpenNLP\(^4\). As classifiers we employ Support Vector Machines (SVMs) (Vapnik, 1995) as implemented by LibSVM\(^5\) using a linear kernel with their optimal cost factor \(C\) chosen from \(\{2.0E-3, 2.0E-2, 2.0E-1, 2.0, 2.0E1, 2.0E2, 2.0E3\}\) via 10-fold cross validation (CV) on the training data. As features we use word uni-, bi-, and/or tri-grams extracted from the training data by a purely data-driven feature induction (Remus and Rill, 2013). We simply encode presence or absence of those word \(n\)-grams. We perform no feature selection; neither stop words nor punc-

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\(^3\)http://www.cs.jhu.edu/~mdredze/datasets/sentiment/
\(^4\)http://opennlp.apache.org
\(^5\)http://www.csie.ntu.edu.tw/~cjlin/libsvm/
10-fold CVs. In each fold 9/10 of the available data are used for training, the remaining 1/10 is used for testing. Training and testing data never overlap. As performance measure we report accuracy $A$. 

### 3.1. Performance Estimation

In this section we relate differences in domain complexity of an SA gold standard dataset to differences in performance of our SA method evaluated on the same SA gold standard dataset. Table 1 depicts the differences in performance when we evaluate our SA method—viz. SVM models based on word unigrams, uni- and bigrams, and uni-, bi-, and trigrams—on different domains from MDSD v2.0. Table 1 also depicts the differences in domain complexity of the same domains.

We correlate the accuracies achieved by our SVM models based on word unigrams and the corresponding domain complexity measurements. Table 2 shows the results. All correlations—except of unigram relative entropy—are strong ($|r| > 0.67$) and statistically significant ($p < 0.05$). From Table 2 we learn that:

- the smaller the percentage of rare unigrams, i.e. the less hapax legomena and dis legomena,
- the smaller the unigram type/token ratio, i.e. the more tokens per type,
- the smaller the unigram relative entropy, i.e. the farther the distribution from a uniform distribution and
- the smaller the unigram homogeneity value, i.e. the more homogeneous the corpus,

the higher the accuracy of our SA method.

Given such strong correlations, we perform an ordinary Linear Regression (LR) using squared error loss with single domain complexity measurements as predictors and accuracies of SVM models based on word unigrams as responses. We measure the mean residual standard error (MRSE) of the LR models in leave-one-domain-out CVs.

Table 3 shows the resulting MRSEs as well as the significance level $p$ of the predictor’s influence on the response. All predictors’ influences on the response—except of unigram relative entropy—are statistically significant ($p < 0.05$).

From Table 3 we learn that—analogously to the correlations we found—3 out of 4 domain complexity measures allow us to accurately estimate our SA method’s performance based solely on domain complexity measurement. Unigram homogeneity appears to be the most informative domain complexity measure: it yields the smallest MRSE (1.058).

As we can see in Figure 1 our data contains (at least) one outlier: the domain MUSIC with an accuracy of 76.4 and a unigram homogeneity of 0.451. Outliers such as MUSIC affect the slope of the LR fit. We counteract outliers by employing loss functions that are more robust than ordinary squared error loss: Huber loss (Huber, 1964) and Tukey’s biweight (Holland and Welsch, 1977). Using these robust loss functions in LR leads to small improvements in estimating accuracy—i.e. reduces the MRSEs—as shown in Table 4.

Figure 1 depicts LR models fitted to our data using squared error loss, Huber loss, and Tukey’s biweight.

Table 2: Pearson correlation $r$ between domain complexity measurements and accuracies of SVM models based on word unigrams as well as $r$’s significance level $p$.

| Domain complexity measure | $r$  | $p$  |
|---------------------------|------|------|
| Percentage of rare unigrams | -0.673 | 0.023 |
| Unigram type/token ratio | -0.723 | 0.012 |
| Unigram relative entropy | -0.425 | 0.192 |
| Unigram homogeneity | -0.708 | 0.015 |

Table 3: MRSEs of ordinary LR models fitted using squared error loss in leave-one-domain-out CVs with domain complexity measurements as predictors and accuracies of SVM models based on word unigrams as responses.

| Predictor | MRSE  | $p$  |
|-----------|-------|------|
| Percentage of rare unigrams | 1.238 | 0.033 |
| Unigram type/token ratio | 1.116 | 0.018 |
| Unigram relative entropy | 1.837 | 0.221 |
| Unigram homogeneity | 1.058 | 0.007 |

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We do not use more than one predictor in our LR models in accordance with Harrell (2001, p. 61), who suggests to obey the rule of thumb $p < n/10$ where $p$ is the number of predictors and $n$ is the total sample size. In our leave-one-domain-out CV experiments $n = 9$ (and hence $1 > n/10$).

Leave-one-(domain)-out CV (Hastie et al., 2009, p. 242) is a special case of a $K$-fold CV, where $K = n$ and $n$ is the number of instances—e.g. domains—in the data: we fit a model to $n - 1$ parts of the data and validate it on the held out $n$-th part. The $n$ results are then averaged.
Table 1: Accuracies on MDSD v2.0 of SVM models based on word unigrams, uni- and bigrams, or uni-, bi-, and trigrams as well as domain complexity measurements.

| Domain    | Our SA method's accuracy | Domain complexity measure |
|-----------|--------------------------|--------------------------|
|           | uni          | uni. bi | uni. bi. tri | PRW | TTR | H_rel | H_hom |           |
| APPAREL   | 83.25        | 85.55   | 85.05        | 0.6801 | 0.4294 | 0.8891 | 0.3923 |
| BOOKS     | 79.25        | 79.65   | 79.5         | 0.7261 | 0.4595 | 0.8871 | 0.4640 |
| DVD       | 78.55        | 79.8    | 79.25        | 0.7244 | 0.4631 | 0.8897 | 0.4695 |
| ELECTRONICS | 80.65   | 82.05   | 81.6         | 0.6916 | 0.4409 | 0.8888 | 0.4292 |
| HEALTH    | 80.35        | 83.55   | 83.45        | 0.6813 | 0.4306 | 0.888 | 0.4156 |
| KITCHEN   | 81.15        | 82.1    | 81.85        | 0.7155 | 0.4600 | 0.8926 | 0.4507 |
| MUSIC     | 76.4         | 78.45   | 78.9         | 0.6857 | 0.4361 | 0.8879 | 0.4240 |
| SPORTS    | 81.65        | 83      | 82.95        | 0.6765 | 0.4308 | 0.8916 | 0.4112 |
| TOYS      | 81.55        | 83.15   | 82.75        | 0.7248 | 0.4618 | 0.8882 | 0.4624 |
| VIDEO     | 81           | 81.65   | 81.65        | 0.6920 | 0.4595 | 0.8871 | 0.4640 |

Table 4: MRSEs of robust LR models fitted using Huber loss and Tukey’s biweight in leave-one-domain-out CVs with domain complexity measurements as predictors and accuracies of SVM models based on word unigrams as responses.

| Predictor                  | Huber | Tukey’s |
|----------------------------|-------|---------|
| Percentage of rare unigrams| 1.205 | 1.208   |
| Unigram type/token ratio   | 1.054 | 1.073   |
| Unigram relative entropy   | 1.959 | 2.050   |
| Unigram homogeneity        | 1.027 | 1.082   |

Performance estimation does not only work for SVM models based on word unigrams, but also for SVM models based on higher order word n-grams, i.e. SVM models based on word uni- and bigrams and SVM models based on word uni-, bi-, and trigrams: we just use higher order word n-gram domain complexity measurements as additional predictors in our LR models. E.g., to estimate the accuracy of an SVM model based on word uni- and bigrams, we measure both word unigram relative entropy and word bigram relative entropy, or both unigram type/token ratio and bigram type/token ratio etc. These additional predictors are either kept separately or averaged. Averaging predictors, e.g. averaging word uni-, bi-, and trigram relative entropy, results in a single predictor in our LR models. Keeping predictors separately results in multiple predictors in our LR models.

We then proceed as described earlier. Results of the accuracy estimation for SVM models based on word uni- and bigrams are shown in Table 5. Results of the accuracy estimation for SVM models based on word uni-, bi-, and trigrams are shown in Table 6.

For accuracy estimation of SVM models based on word uni- and bigrams using percentage of rare words as separate (i.e. not averaged) predictors and an LR model fitted using Tukey’s biweight yields the smallest MRSE (0.472). For accuracy estimation of SVM models based on word uni-

Table 5: MRSEs of LR models fitted using squared error loss, Huber loss, and Tukey’s biweight in leave-one-domain-out CVs with domain complexity measurements as predictors and accuracies of SVM models based on word unigrams as responses.

| Predictor(s) | Squared | Huber | Tukey’s |
|--------------|---------|-------|---------|
| PRW          | sep     | 0.94  | 0.506   | 0.472   |
|              | avg     | 0.963 | 0.905   | 0.907   |
| TTR          | sep     | 0.942 | 0.591   | 0.579   |
|              | avg     | 0.921 | 0.777   | 0.765   |
| H_rel        | sep     | 0.902 | 0.882   | 0.87    |
|              | avg     | 1.604 | 1.514   | 1.464   |
| H_hom        | sep     | 1.02  | 1.063   | 1.067   |
|              | avg     | 0.927 | 0.925   | 0.958   |

Table 6: MRSEs of LR models fitted using squared error loss, Huber loss, and Tukey’s biweight in leave-one-domain-out CVs with domain complexity measurements as predictors and accuracies of SVM models based on word uni-, bi-, and trigrams as responses. “sep” denotes separately kept predictors, “avg” denotes averaged predictors.

| Predictor(s) | Squared | Huber | Tukey’s |
|--------------|---------|-------|---------|
| PRW          | sep     | 1.143 | 0.867   | 0.738   |
|              | avg     | 0.913 | 0.943   | 0.928   |
| TTR          | sep     | 1.048 | 0.747   | 0.634   |
|              | avg     | 0.781 | 0.713   | 0.75    |
| H_rel        | sep     | 1.002 | 1.022   | 1.049   |
|              | avg     | 1.43  | 1.429   | 1.620   |
| H_hom        | sep     | 1.037 | 0.996   | 0.904   |
|              | avg     | 0.877 | 0.854   | 0.894   |

Discussion

Our performance estimates are not 100% accurate: on average we over- or underestimate our SA approach’s performance by about 1 accuracy point. Partly, this is because a discriminative model’s power ultimately also depends on
Table 7: Accuracies of our model selector for word n-gram model order. “1–2” denotes first vs. second order, “2–3” denotes second vs. third order. “sep” denotes separately kept predictors, “avg” denotes averaged predictors.

| Predictor(s) | Squared | | Huber | | Tukey’s | |
|--------------|---------|---|-------|---|---------|
|              | 1–2     | 2–3 | 1–2 | 2–3 | 1–2 | 2–3 |
| *PRW*        | sep     | 100 | 80 | 90 | 90 | 70 | 80 | 80 | 50 | 65 |
|              | avg     | 100 | 80 | 90 | 100 | 70 | 85 | 100 | 40 | 70 |
| *TTR*        | sep     | 90  | 90 | 90 | 90 | 80 | 85 | 90 | 80 | 85 |
|              | avg     | 100 | 90 | 90 | 100 | 60 | 80 | 90 | 40 | 65 |
| *Hrel*       | sep     | 60  | 80 | 70 | 60 | 70 | 65 | 60 | 70 | 65 |
|              | avg     | 90  | 80 | 85 | 90 | 70 | 80 | 80 | 60 | 70 |
| *Hnom*       | sep     | 100 | 80 | 90 | 100 | 80 | 90 | 90 | 70 | 80 |
|              | avg     | 100 | 80 | 90 | 100 | 90 | 95 | 90 | 90 | 90 |

We answer question 2 analogously to Section 3.2. A model selector estimates—based on domain complexity—how many features to select for our SA method.

Experiments We vary 3 parameters of our model selector’s accuracy estimation. (i) We compare 4 predictors: percentage of rare words, type/token ratio, relative entropy, and homogeneity. (ii) We compare separately kept and averaged predictors. (iii) We compare 3 LR loss functions: squared error loss, Huber loss, and Tukey’s biweight. Evaluation results of our leave-one-domain-out CV are shown in Table 7.

Results Our model selector yields an average accuracy between 60–100 when deciding between first or second order. It yields an average accuracy between 40–90 when deciding between second or third order. It yields an overall average accuracy between 65–95.

The most reliable model selector uses averaged homogeneity as predictor and fits the LR model using Huber loss: it yields an average accuracy of 100 when deciding between first or second order. It yields an average accuracy of 90 when deciding between second or third order. Thus, it yields an overall average accuracy of 95.

Note that for our data a naïve baseline also yields an overall average accuracy of 95: a naïve model selector that always decides for second order yields an average accuracy of 100 when deciding between first or second order. It yields an average accuracy of 90 when deciding between second or third order. Thus, its overall average accuracy is also 95.

3.3. Model Selection: Aggressive vs. Conservative Word n-gram Feature Selection

In this section we let domain complexity guide us in another model selection, viz. in deciding whether to employ aggressive or conservative word n-gram feature selection in our SA method for a given domain from MDSD v2.0. We face 2 questions when we perform word n-gram feature selection:

1. Which feature selection method should we use?
2. How many features should we select?

We answer question 1 up front: as feature selection method we use Information Gain (IG) (Yang and Pedersen, 1997), because it has been shown that IG is superior to other feature selection methods for word n-gram based text classification (Yang and Pedersen, 1997; Forman, 2003).

We answer question 2 analogously to Section 3.2. A model selector estimates—based on domain complexity—how many features to select for our SA method.
Table 8: Accuracies of SVM models based on word unigrams with (w/) and without (w/o) feature selection via IG based on the ideal CO in percent (and word unigram types).

| Domain     | w/o CO | w/ CO | Δ CO | CO% (Types) |
|------------|--------|-------|------|-------------|
| APPAREL    | 83.25  | 83.6  | 0.35 | 78% (7,927) |
| BOOKS      | 79.25  | 80.45 | 1.2  | 11% (3,136) |
| DVD        | 78.55  | 80.55 | 2    | 60% (18,169)|
| ELECTRONICS| 80.65  | 81.75 | 1.1  | 85% (13,139)|
| HEALTH     | 80.35  | 80.85 | 0.5  | 90% (11,778)|
| KITCHEN    | 81.15  | 82.8  | 1.65 | 17% (2,214) |
| MUSIC      | 76.4   | 78.45 | 2.05 | 2% (506)    |
| SPORTS     | 81.7   | 82.55 | 0.85 | 19% (2,715) |
| TOYS       | 81.5   | 82.45 | 0.95 | 4% (564)    |
| VIDEO      | 81.05  | 81.6  | 0.55 | 80% (20,301)|
| average    | 80.39  | 81.51 | 1.12 | 45% (8,044) |

Table 9: Pearson correlation $r$ between ideal CO and domain complexity measurements as well as $r$’s significance level $p$.

| Domain complexity measure                     | $r$  | $p$   |
|-----------------------------------------------|------|-------|
| Percentage of rare word unigrams              | -0.08| 0.814 |
| Word unigram type/token ratio                 | -0.119| 0.727 |
| Word unigram relative entropy                 | -0.35| 0.291 |
| Word unigram homogeneity                      | -0.095| 0.78  |

### 3.3.1. Evaluation

As in Section 3.2.1, we evaluate our model selector—which we develop in our experiments—in a leave-one-domain-out CV.

**Data**  Feature selection methods such as IG produce an implicit ranking with the most predictive features ranked highest and the least predictive features ranked lowest. To employ feature selection via IG we have to determine a cut off (CO): features ranked above the CO are kept, while features ranked below the CO are discarded.

To produce data for our leave-one-domain-out CV for each domain we determine the CO for which our SVM model’s accuracy peaks. First we rank a domain’s word unigrams via IG. We then set the CO to 1, 2, ..., 100% of the domain’s original word unigram vocabulary size. If it is set to 1% we keep its 1% highest ranked word unigrams, if it is set to 2% we keep its 2% highest ranked word unigrams etc. For each of the resulting 100 word unigram vocabularies we evaluate an SVM model based on this word unigram vocabulary size. If it is set to 1% we keep its 1% highest ranked word unigrams, if it is set to 2% we keep its 2% highest ranked word unigrams etc. For each of the resulting 100 word unigram vocabularies we evaluate an SVM model based on this word unigram vocabulary in a 10-fold CV. We call the CO for which our SVM model’s accuracy peaks ideal CO. Table 8 shows evaluation results of SVM models based on word unigrams with and without feature selection via IG. Feature selection is based on the ideal CO.

With feature selection using the ideal CO average accuracy is 1.12 higher than without feature selection. Ideal COs are scattered, with 85% (13,139 word unigram types) being the most conservative feature selection and 2% (506 word unigram types) being the most aggressive feature selection. The average ideal CO is 45% (8,045 word unigram types).

**Experiments**  Table 9 correlates domain complexity measurements of MDSD v2.0’s 10 domains with their ideal CO. Relative entropy correlates strongest with ideal CO (-0.35): the smaller the domain’s relative entropy, the larger its ideal CO. Hence, the less uniform a domain’s word unigram distribution, the more of its word unigrams are kept as features in our SVM model. Figure 2 plots relative entropy vs. ideal CO. Additionally, it shows an LR model fitted to the data using squared error loss. It achieves no perfect fit, but it still roughly estimates ideal CO.

Given its correlation with the ideal CO, we use as our model selector a robust LR model with relative entropy as single predictor and ideal CO as response. We compare LR models fitted using Huber loss and Tukey’s biweight. Table 10 shows the evaluation results of our leave-one-domain-out CV for Huber loss, Table 11 shows the evaluation results for Tukey’s biweight.

**Results and Discussion**  Our model selector over- or underestimates a domain’s ideal CO on average by 40%. But SVM models with feature selection using the estimated CO outperform SVM models without feature selection in 6 out of 10 domains. SVM models with feature selection using
the estimated CO yield an average accuracy of 80.55 (Huber loss) and 80.67 (Tukey’s biweight). Without feature selection average accuracy is 80.39. Thus, feature selection using the estimated CO yields an average accuracy gain of 0.16 and 0.28, respectively.

Compared to SVM models with feature selection using the ideal COs (81.51), using the estimated CO performs 0.95 and 0.83 lower, respectively. SVM models with feature selection using the average ideal CO (45%) yield an average accuracy of 80.56, which is on par with SVM models with feature selection using the estimated COs.

### Table 11: Ideal COs and COs estimated by our model selector fitted using Tukey’s biweight

| Domain     | Ideal CO | Ideal A | Estimated CO | Estimated A |
|------------|----------|---------|--------------|-------------|
| APPAREL    | 78%      | 83.6    | 41%          | 83.5        |
| BOOKS      | 11%      | 80.45   | 78%          | 79.2        |
| DVD        | 60%      | 80.55   | 37%          | 80.1        |
| ELECTRONICS| 85%      | 81.75   | 42%          | 80.45       |
| HEALTH     | 90%      | 80.85   | 46%          | 80.5        |
| KITCHEN    | 17%      | 82.8    | 62%          | 82.45       |
| MUSIC      | 2%       | 78.45   | 39%          | 77.65       |
| SPORTS     | 19%      | 82.55   | 62%          | 81.85       |
| TOYS       | 4%       | 82.45   | 37%          | 81          |
| VIDEO      | 80%      | 81.6    | 47%          | 80          |
| average    | 45%      | 81.51   | 49%          | 80.67       |

4. Conclusions & Future Work

We investigated domain dependencies in SA. We showed that our ML-based SA method—an SVM model based on word \( n \)-grams—performs differently when applied to different domains. We also showed that domains differ in their textual characteristics, viz. their domain complexity. We then showed that there is a clear relationship between performance of our SA method in certain domains and their domain complexity. Finally, we used their relationship to (i) estimate our SA method’s accuracy in certain domains based solely on its domains complexity and (ii) guide us in model selection for different domains.

In future work domain complexity may guide us in even more model selection or feature engineering tasks: whether to use super- or sub-word character \( n \)-gram representations (Raaijmakers and Kraaij, 2008) instead of word \( n \)-gram representations; whether to use non-binary word \( n \)-gram weighting, e.g. weighting using tf-idf (Manning and Schütze, 1999, p. 543); whether to employ non-lexical features, e.g. part of speech tags or dependency parses.

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