Sentiment polarity classification using statistical data compression models

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Classification using compression models

Informal idea

- Compression algorithms build up extensive statistics
- Homogeneous data leads to better compression ratios
- Given categories $C_1, \ldots, C_n$ and corresponding training sets $T_1, \ldots, T_n$, affiliation of some document d can be determined by analyzing joint-compression ratio of each T_i with d

The information theoretic view

Cross entropy

- Measure for similarity of two sources (probability distributions)
- Gives average number of bits (per symbol) to identify an event using a probability distribution Q, rather than true distribution P
- Classification evaluates cross entropy between P for the source of document d and Q given by the compression model
- Exact value hard to compute $\rightarrow$ In practice mostly estimated

PPM (Cleary and Witten, 1984)

- Used in popular implementations such as RAR or 7Zip
- Remains among best compression algorithms for natural text

Basic concept

- Predict a symbol x_i by context $c_{i,j} = \{x_{i-j}, x_{i-j+1}, \ldots, x_{i-1}\}$ of order j using probability distribution p_j
- If $(c_{i,j}, x_i)$ not present in model of order j, add to model, update p_j, switch to order $j-1$ and encode order switch in output
- Else update p_j, encode x_i, reset order to j and restart with x_{i+1}

C-Measure (Hunnisett and Teahan, 2004)

- Based on the PPM compression algorithm but uses fixed order j
- Slightly outperforms PPM on the topic classification task

Basic Concept

- Extract all strings $c_{i,j} \circ x_i$ (features) from document d
- Add 1 to result if string is present in the training set T_i
- Assign d to class C_i with highest score

C_k-Measure (Ziegelmayer and Schrader, 2012)

- Keeps computational properties of C-measure
- Optimization for binary sentiment classification
- Omit features occurring in both classes (with similar frequencies)

Basic Concept

- Extraction and classification analogous to C-measure but:
- Add 1 to result if string is k-times more frequent in T_+ than in T_-

F_k-measure (Ziegelmayer and Schrader, 2012)

- Keeps computational properties of C-measure and (implicit) feature selection of C_k-measure
- Counts frequency of features rather than existence

Basic Concept

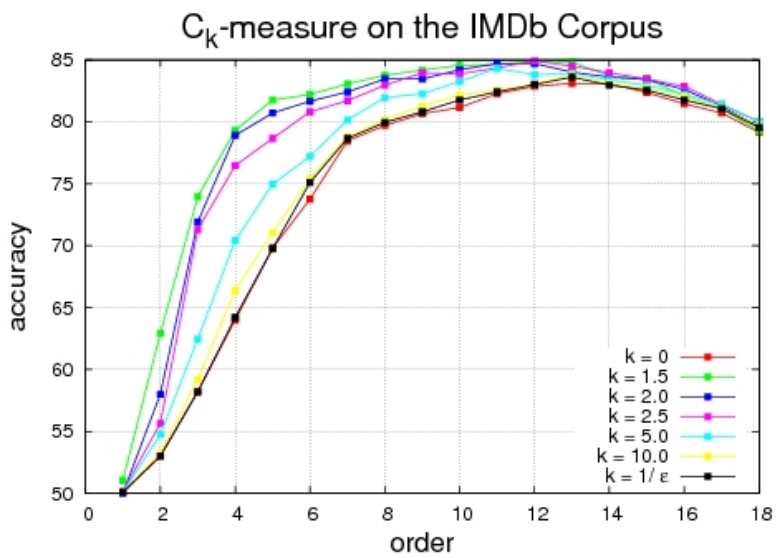
- Works analogous to C_k-measure but for each string $c_{i,j} \circ x_i$:
- Add absolute frequency of $c_{i,j} \circ x_i$ in corresponding model (T_-, T_+) to result instead of 1 for pure existence

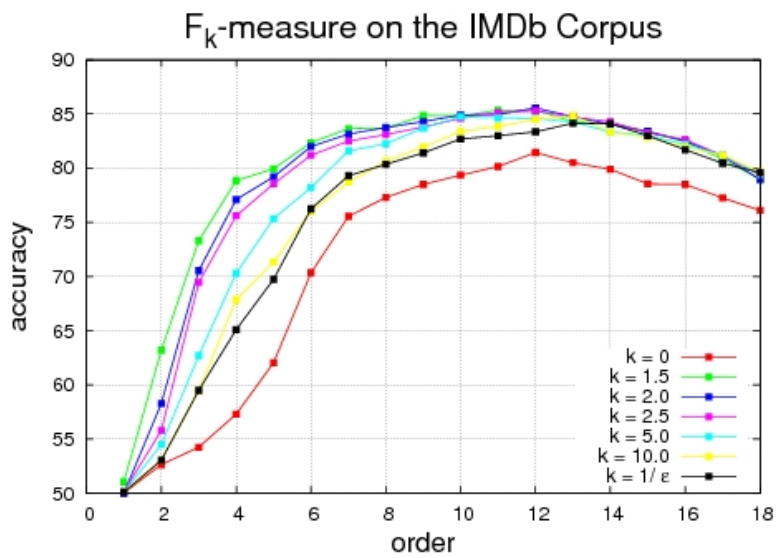
Corpora employed

- IMDb corpus (`polarity dataset v2.0` by Pang and Lee)
  - Large corpus (2,000 documents, 7,786,004 characters) with a rather versatile and complex language
- Amazon corpus (Custom dataset created from amazon.com)
  - Mid-Size corpus (2,000 documents, 682,124 characters) with mostly homogeneous and less complex language
- Twitter corpus (Public dataset from Sanders Analytics)
  - Small corpus (1,000 documents, 97,261 characters) with informal and rather simple language

Results on the IMDb corpus

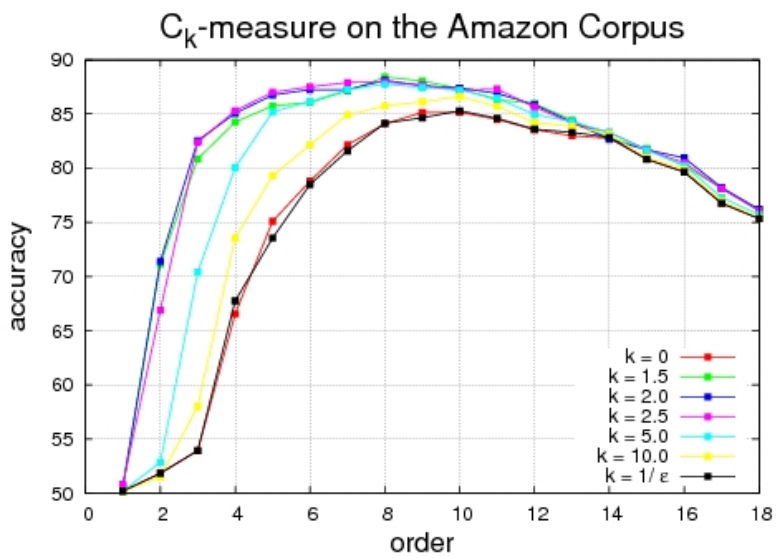
No	Method	Accuracy
(1)	PPMd	82.35%
(2)	C_0-measure	83.10%
(3)	$C_{2.5}$-measure	84.90%
(4)	$F_{2.5}$-measure	85.30%
(5)	**SVM (pres. unigram)**	**86.35%**

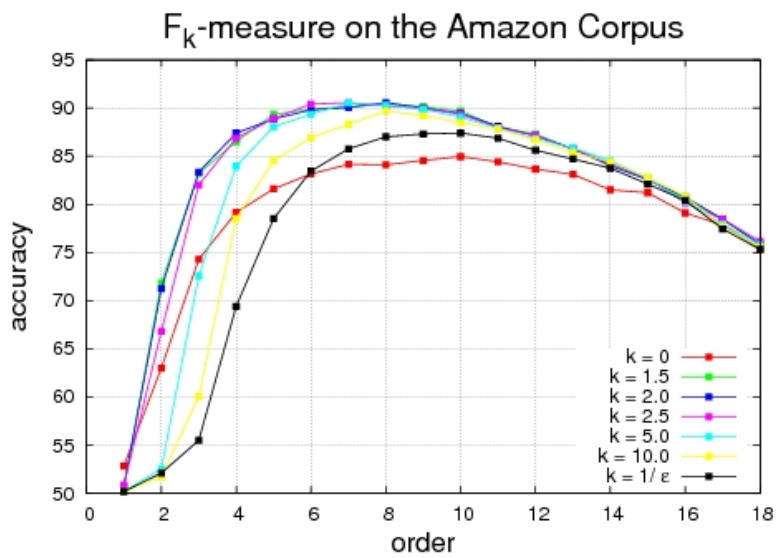




Results on the Amazon corpus

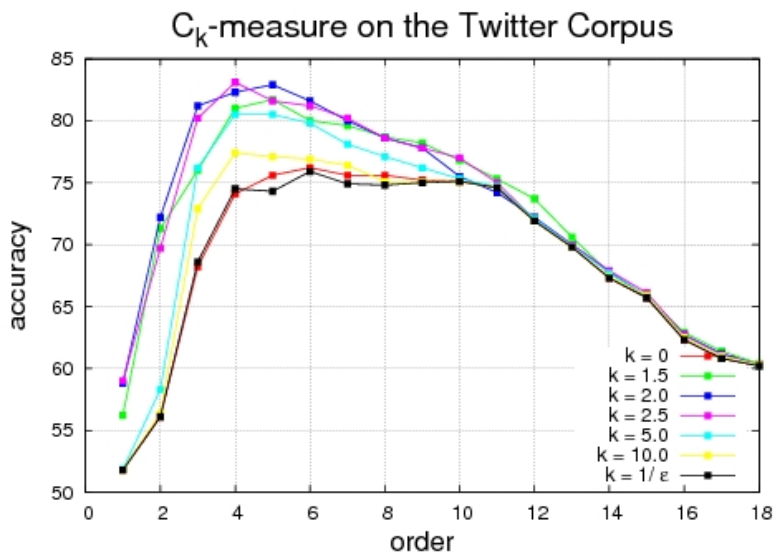
No	Method	Accuracy
(1)	PPMd	86.15%
(2)	C_0-measure	85.15%
(3)	$C_{2.5}$-measure	87.95%
(4)	**$F_{2.5}$-measure**	**90.55%**
(5)	SVM (pres. unigram)	86.35%

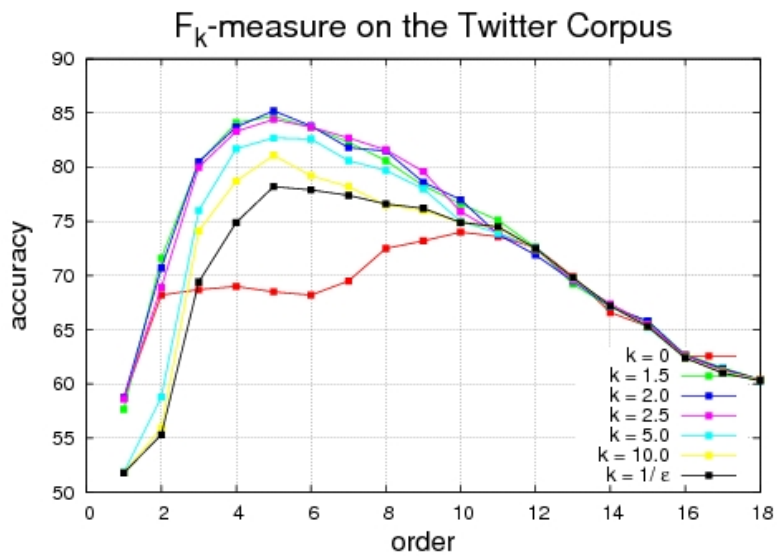




Results on the Twitter corpus

No	Method	Accuracy
(1)	PPMd	78.80%
(2)	C_0-measure	76.20%
(3)	$C_{2.5}$-measure	83.10%
(4)	**$F_{2.5}$-measure**	**84.40%**
(5)	SVM (pres. unigram)	77.80%





Discussion (1)

Why compression based sentiment classification?

- Requires no preprocessing and is easy to apply
- k-measures efficient in time and space complexity
- $F_{2.5}$-measure achieved 90.55% on Amazon corpus and outperformed SVM on the Twitter corpus by more than 6%

Discussion (2)

Why are *k*-measures performing better?

- We found misclassifications and spelling mistakes especially in Amazon and Twitter corpus

➨ *k*-measures effectively eliminate noise in the model

➨ Cope better with spelling mistakes and informal language

Discussion (3)

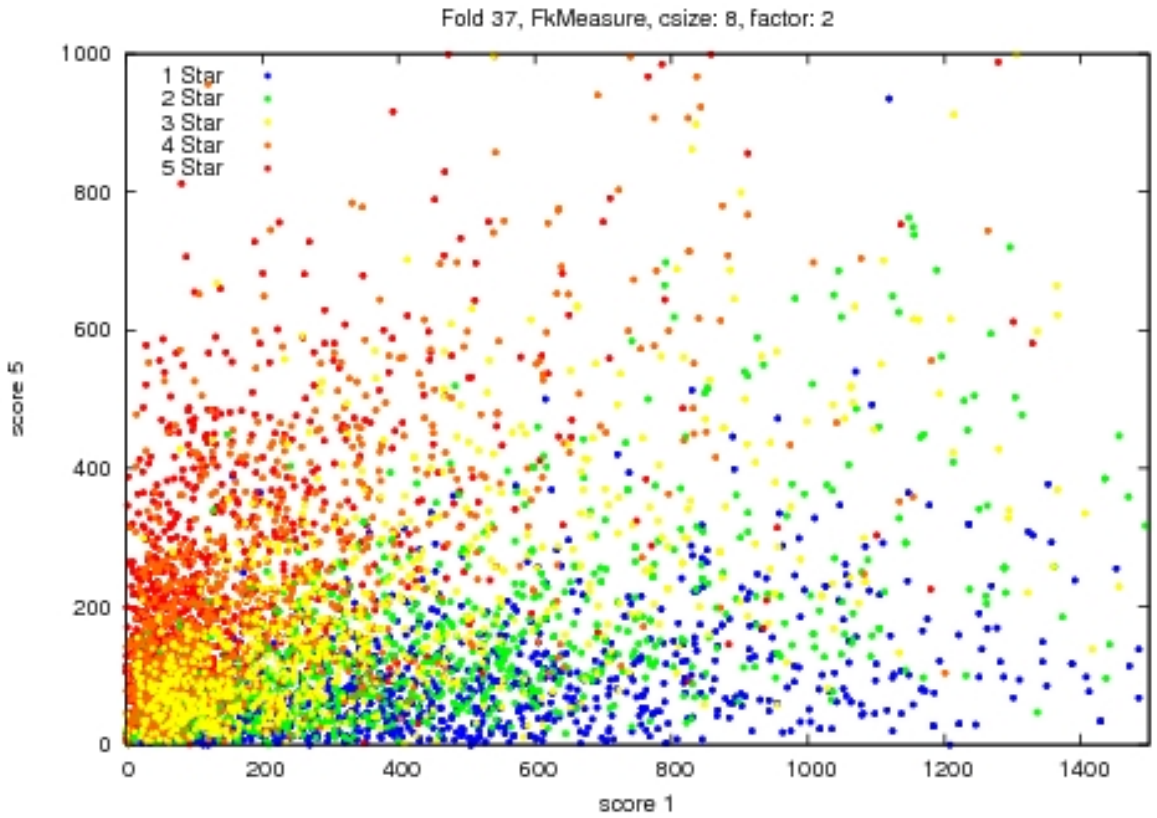
Interesting findings for future work

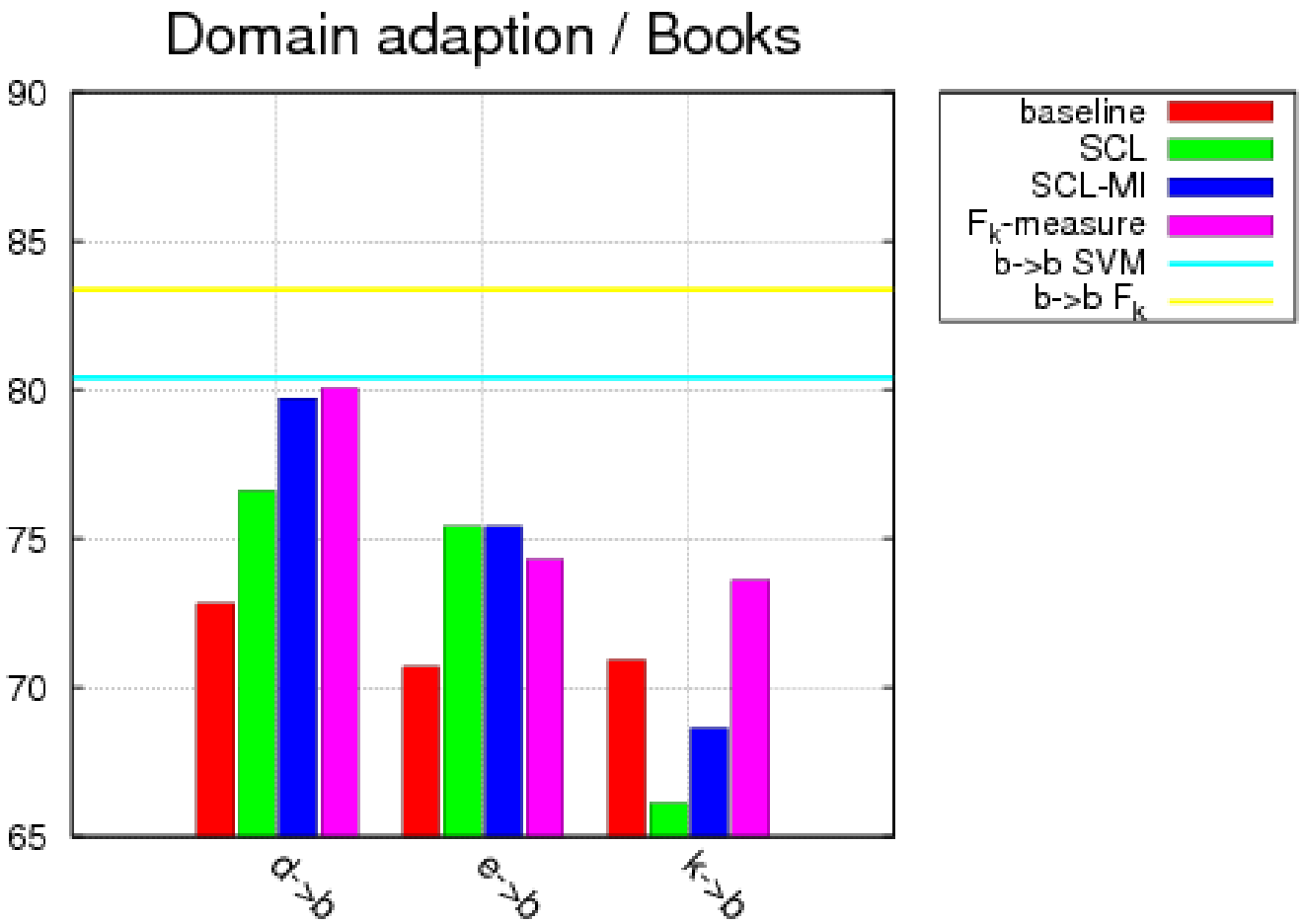
- Regression seems possible using ratio between positive and negative scores
- Cross-domain polarity classification performance seems to be slightly better than standard approach
- Character based approaches seem to obtain better results in inflective languages (McNamee et al.)

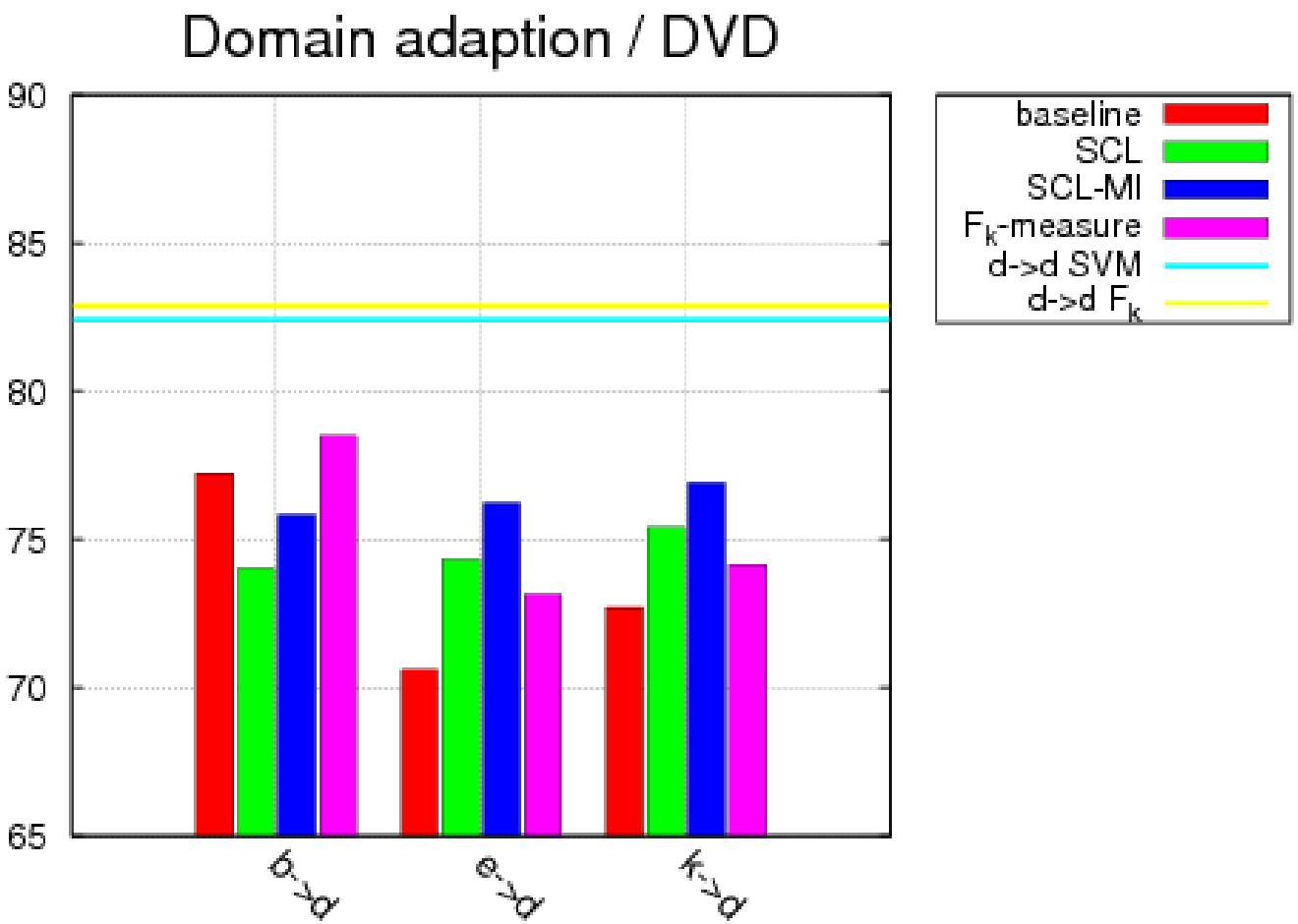
Backup

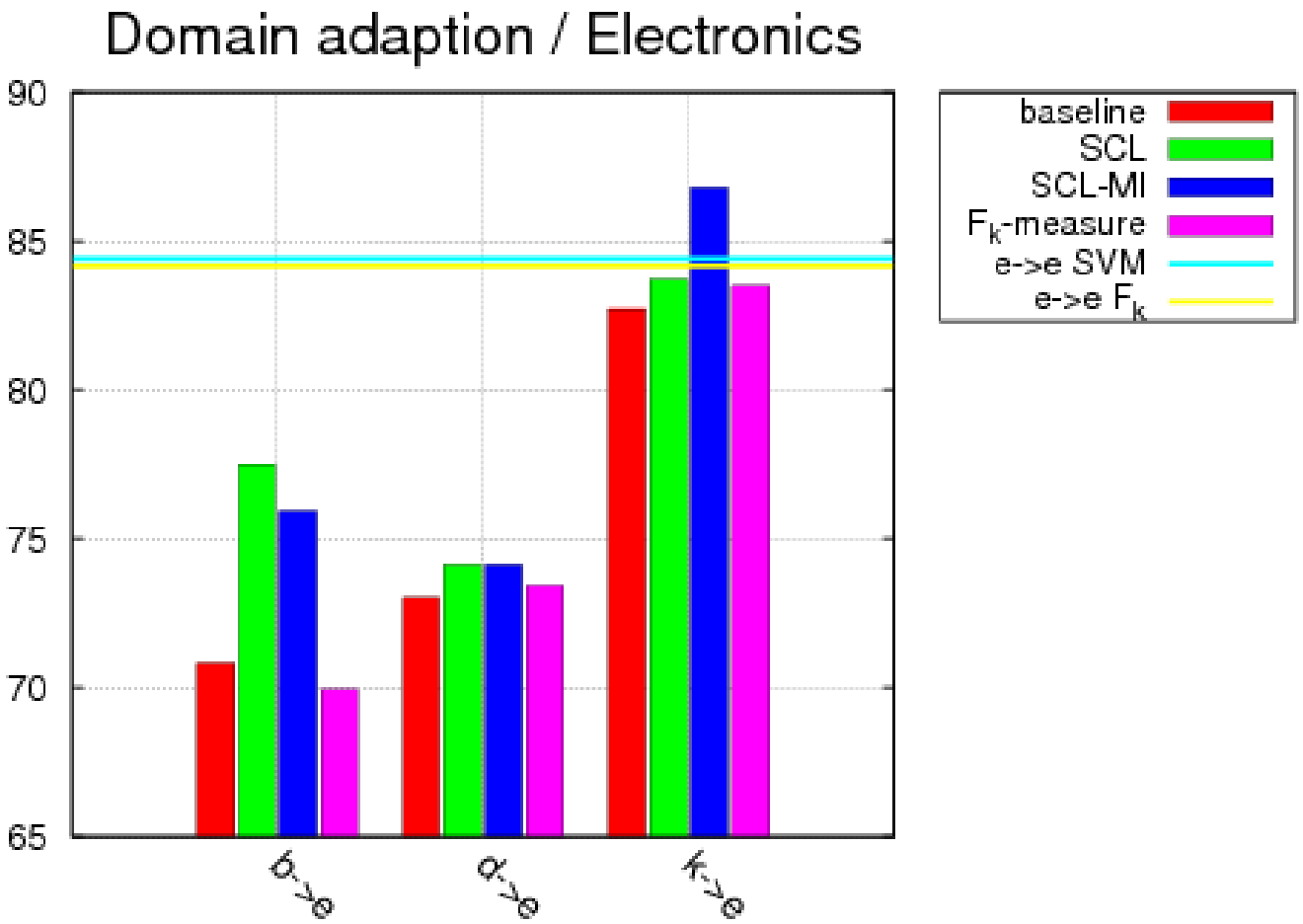
Regression using F_k-measure

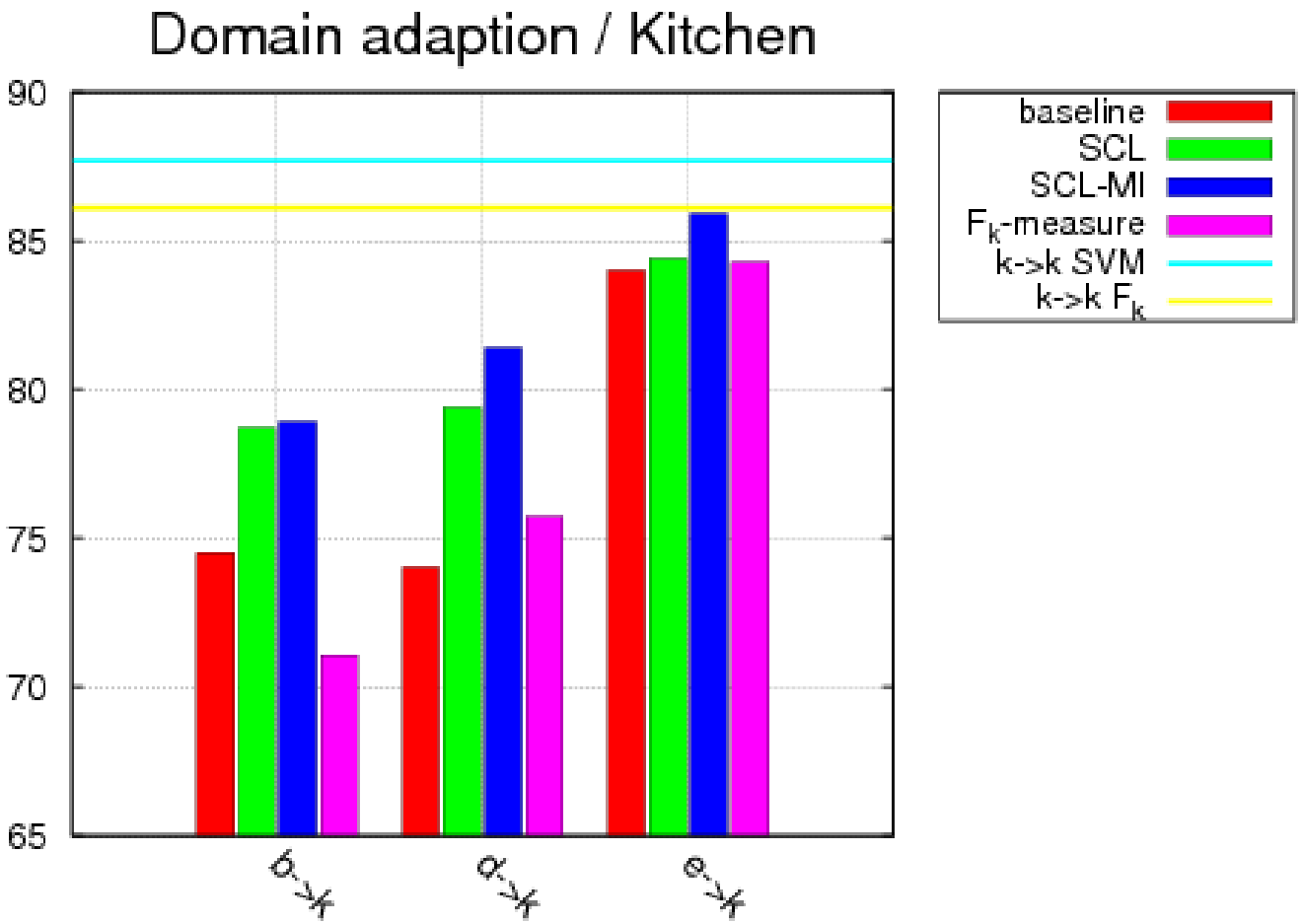
- Trained with 1-Star and 5-Star only, Tested with all reviews
- Star-rating shows linear order (1 < 2 < 3 < 4 < 5)




Domain adaption / Books
90
85
80
75
70
65
d->b
e->b
k->b
baseline
SCL
SCL-MI
F_k-measure
b->b SVM
b->b F_k


Domain adaption / DVD
90
85
80
75
70
65
b->d
e->d
k->d
baseline
SCL
SCL-MI
F_k-measure
d->d SVM
d->d F_k


Domain adaption / Electronics
90
85
80
75
70
65
b->e
d->e
k->e
baseline
SCL
SCL-MI
F_k-measure
e->e SVM
e->e F_k


Domain adaption / Kitchen
90
85
80
75
70
65
b->k
d->k
e->k
baseline
SCL
SCL-MI
F_k-measure
k->k SVM
k->k F_k

IMDb corpus

IMDb corpus (`polarity dataset v2.0` by Pang and Lee)

- 2,000 reviews written by 312 authors
- Average text length of 3,893 characters (755 words)
- Minimum of 91 characters, maximum of 14,957 characters
- Average length of 22 words per sentence
- 48,205 distinct words

➨ The language employed seems to be quite complex

Amazon corpus

Amazon corpus (Custom dataset created from amazon)

- 2,000 reviews written by 1,999 different authors
- Average text length of 341 characters (66 words)
- Minimum of 48 characters, maximum of 3,001 characters
- Average length of 13 words per sentence
- 9,380 distinct words

➨ The language employed seems less complex than the one employed in the IMDb corpus

Twitter corpus

Twitter corpus (Public dataset from sanders analytics)

- Only few tweets were labeled positive or negative
- 1,000 tweets written by an unknown number of authors
- Average text length of 97 characters (15 words)
- Minimum of 9 characters, maximum 140 characters
- Average length of 8 words per sentence
- 3,716 distinct words

➨ The language employed seems rather simple and informal

C-measure

Definition

- Let $g(T, s)$ denote the number of repetitions of a string s in a set of documents T. The C-measure is defined as:

$$C^{\{+,-\}} := \sum_{i=n}^{m} a_{i,n}^{\{+,-\}} \text{ with:}$$

$$a_{i,n}^{\{+,-\}} := \begin{cases} 1, & \text{if } g(T^{\{+,-\}}, c_{i,n}) > 0 \\ 0, & \text{otherwise} \end{cases}$$

C_k-measure

Definition

- Let $g(T, s)$ denote the number of repetitions of a string s in a set of documents T. The C_k-measure is defined as:

$C_k^{\{+,-\}} := \sum_{i=n}^{m} a_{i,n,k}^{\{+,-\}}$ with:

$$a_{i,n,k}^{+} := \begin{cases} 1, & \text{if } g(T^+, c_{i,n}) > k \cdot g(T^-, c_{i,n}) \\ 0, & \text{otherwise} \end{cases}$$

$$a_{i,n,k}^{-} := \begin{cases} 1, & \text{if } g(T^-, c_{i,n}) > k \cdot g(T^+, c_{i,n}) \\ 0, & \text{otherwise} \end{cases}$$

F_k-measure

Definition

- Let $g(T, s)$ denote the number of repetitions of a string s in a set of documents T. The F_k-measure is defined as:

$F_k^{\{+,-\}} := \sum_{i=n}^{m} b_{i,n,k}^{\{+,-\}}$ with:

$$b_{i,n,k}^{+} := \begin{cases} g(T^+, c_{i,n}), & \text{if } g(T^+, c_{i,n}) > k \cdot g(T^-, c_{i,n}) \\ 0, & \text{otherwise} \end{cases}$$

$$b_{i,n,k}^{-} := \begin{cases} g(T^-, c_{i,n}), & \text{if } g(T^-, c_{i,n}) > k \cdot g(T^+, c_{i,n}) \\ 0, & \text{otherwise} \end{cases}$$