Projecting Embeddings for Domain Adaptation: Joint Modelling of Sentiment in Diverse Domains

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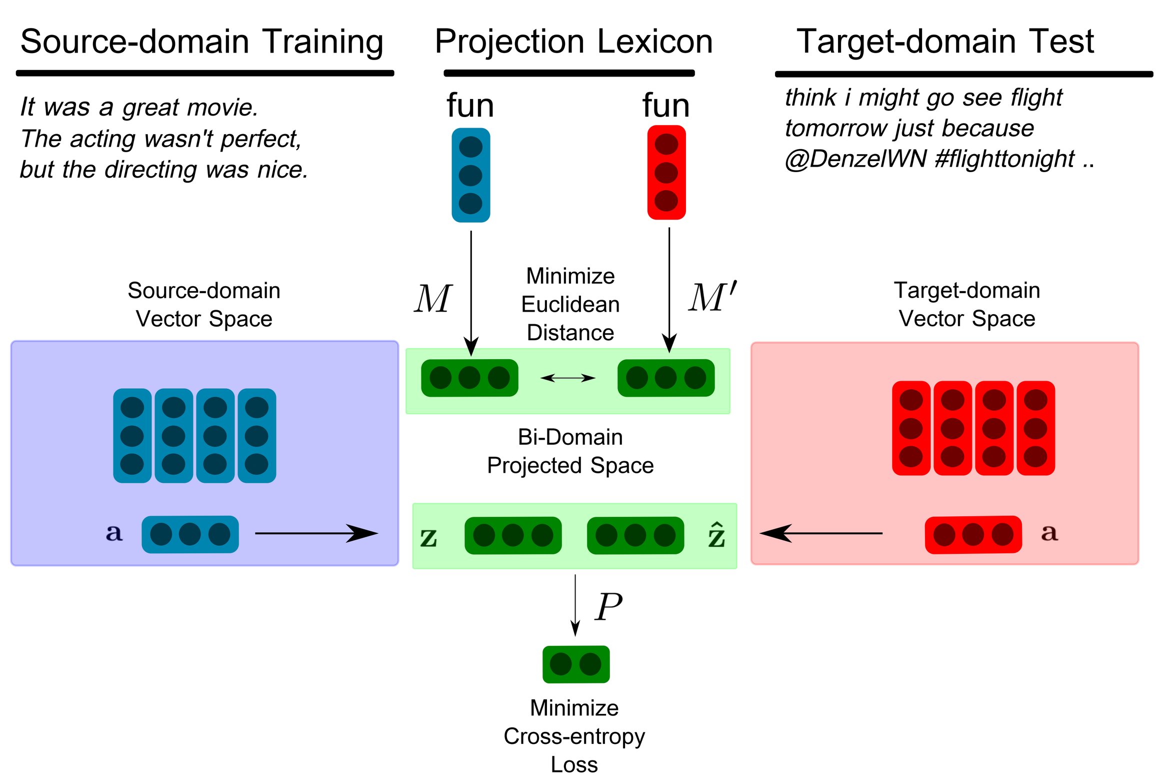
Projecting embeddings

Goal: How can we improve domain adaptation approaches for highly divergent domains?

Problem: Previous approaches disregard potentially relevant domain specific information when creating domain-independent representations.

Approach: We train a joint model to project embeddings between domains and to classify sentiment.

Proposed model



Setup

Datasets: Amazon domains datasets (**B**ooks, **D**VD, **E**lectronics, **K**itchen), as well as SemEval 2013 (**S13**) and SemEval 2016 (**S16**) twitter datasets.

Baselines: We compare to a non-adaptive baseline (NoAd), Neural Structural Correspondence Learning (NSCL), and Marginalized Stacked Denoising Autoencoders (mSDA).

Code available

`https://github.com/jbarnesspain/blse_domain`

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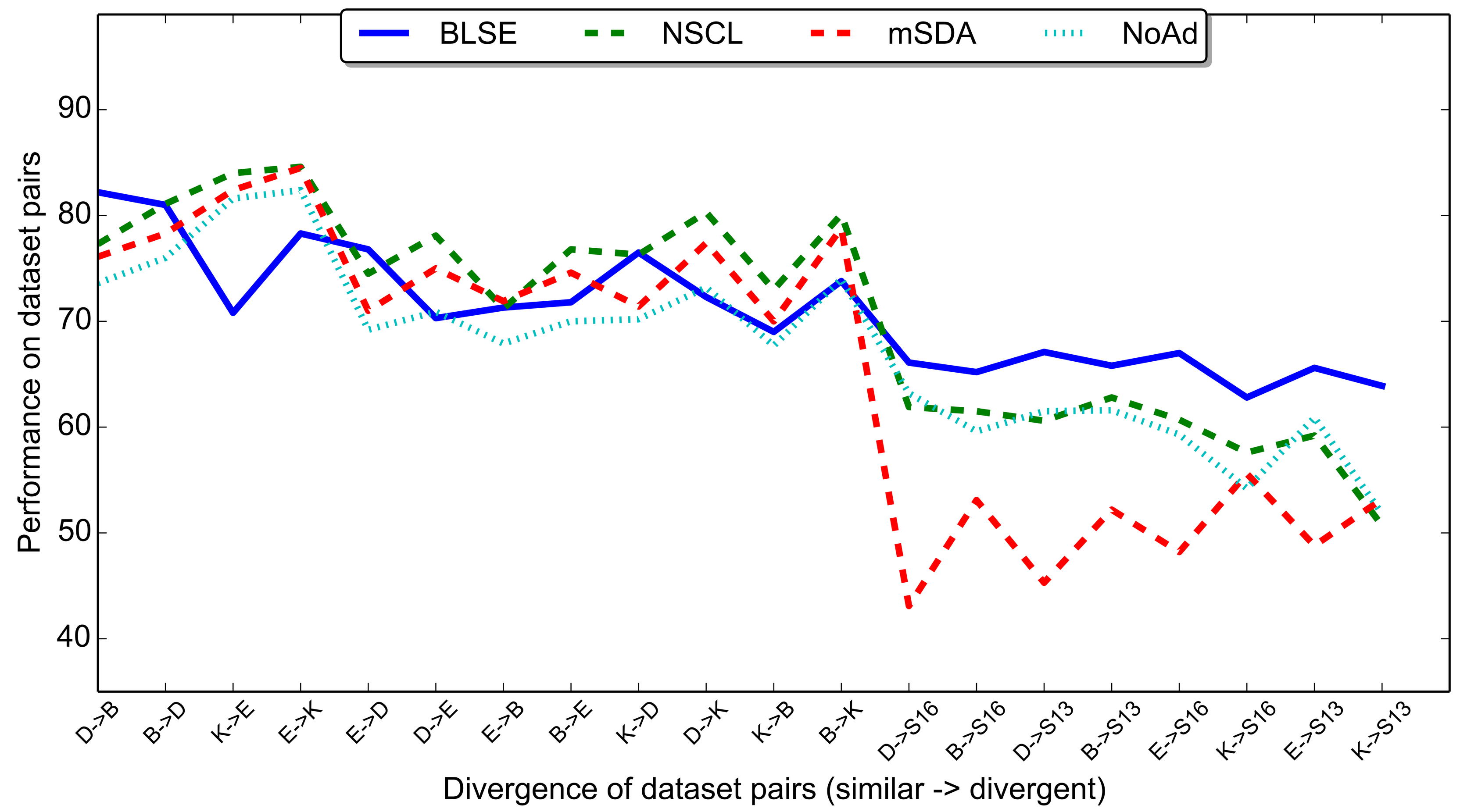
Results as function of domain similarity

BLSE performs better than NSCL and mSDA on highly divergent domains (measured as Jensen-Shannon divergence between unigram distributions).



Results for cross-domain sentiment classification

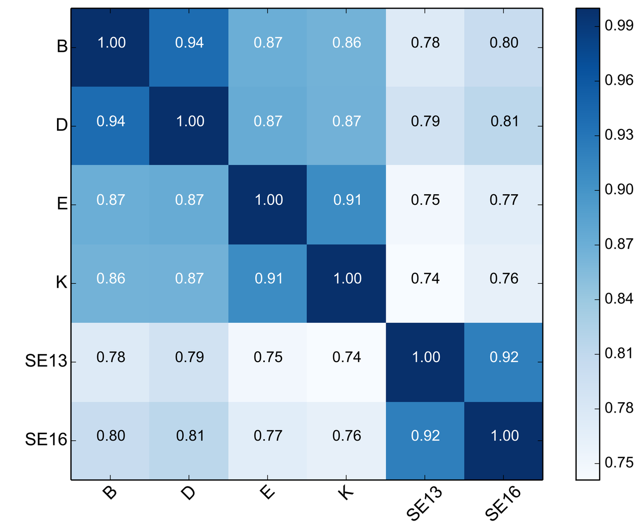
BLSE *outperforms other baseline methods* when training on Amazon data and testing on Twitter data. NSCL performs best when trained on Amazon data and tested on another Amazon domain. mSDA performs poorly on highly divergent data.

	D→B	E→B	K→B	B→D	E→D	K→D	B→E	D→E	K→E	B→K	D→K	E→K
BLSE	**82.2**	71.3	69.0	81.0	**76.8**	**76.5**	71.8	70.3	70.8	73.8	72.3	78.3
NSCL	77.3	71.2	**73.0**	**81.1**	74.5	76.3	**76.8**	**78.1**	**84.0**	**80.1**	**80.3**	**84.6**
mSDA	76.1	**71.9**	70.0	78.3	71.0	71.4	74.6	75.0	82.4	78.8	77.4	84.5
NoAd	73.6	67.9	67.7	76.0	69.2	70.2	70.0	70.9	81.6	74.0	73.2	82.4

	B→S13	D→S13	E→S13	K→S13	B→S16	D→S16	E→S16	K→S16
BLSE	**65.8**	**67.1**	**65.6**	**63.9**	**65.2**	**66.1**	**67.0**	**62.8**
NSCL	62.8	60.6	59.2	50.7	61.5	61.9	60.7	57.6
mSDA	52.2	45.3	48.8	53.2	53.1	43.1	48.2	55.6
NoAd	61.6	61.5	60.9	51.8	59.6	63.2	59.3	54.2

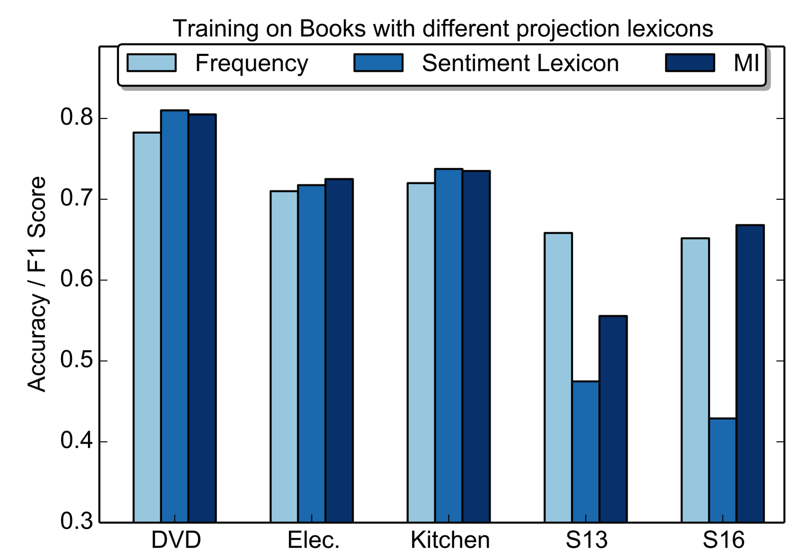
Domain similarity

We determine the pairwise similarity of domains as the Jensen-Shannon divergence between the unigram distributions of the 10,000 most frequent tokens.



Model analysis

Frequency-based projection lexicons give the best result on divergent datasets, while the sentiment lexicon performs slightly better on similar datasets.



Future work

- It would be useful to explore better domain-specific representations, which could then be projected.
- An interesting application could be the automatic mining of domain-specific concepts, , "not exciting" in the DVD domain ≈ "not reliable" in the Electronics domain.