Identifying Transferable Information Across Domains for Cross-domain Sentiment Classification

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Motivation

- Getting manually labeled data in each domain for sentiment analysis is always an expensive and a time consuming task, cross-domain sentiment analysis provides a solution.
- However, polarity orientation (positive or negative) and the significance of a word to express an opinion often differ from one domain to another.

*Changing Significance: "Entertaining, boring, one-n*ote, etc." are significant for classification in the movie domain.

Changing Polarity: "Unpredictable plot of a movie" //Positive sentiment

"Unpredictable behaviour of a machine" //Negative sentiment

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Problem Definition

- Significant Consistent Polarity (SCP) words represent the transferable (usable) information across domains.

- We present an approach based on χ^2 test and cosine-similarity between context vector of words to identify polarity preserving significant words across domains.

- Furthermore, we show that a weighted ensemble of the classifiers enhances the cross-domain classification performance.

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Technique: Find SCP

Significant Consistent Polarity (SCP): $S \cap T$

//Transferable information from the source (S) to the target (T) for cross-domain SA.

S: Significant words with their polarity orientation in the labeled source domain: $\chi 2$ test

H_0 : 'unpredictable' has equal distribution in the positive and negative corpora
H_a : 'unpredictable' has significantly different count in either positive or negative corpus
If X^2 score is greater than *3.85*

=> $p\text{-value} \leq 0.05$

=> *Probability of the observed value given null hypothesis is true* is less than *0.05*

=> Reject the Null hypothesis

=> 'unpredictable' has occurred significantly more often in one of the class with a $\chi 2$ score of *4.5*.

=> $C_{wP} > C_{wN}$, hence 'unpredictable' is positive

Technique: Find SCP (2)

T: Significant words with their polarity orientation in the unlabeled target domain:

Significance: $NormalizedCount_t(Significant_s(w)) > \theta \Rightarrow Significant_t(w)$

Polarity:

$$If(cosine(conVec(w),conVec(pos\text{-}pivot)) > cosine(conVec(w),conVec(neg\text{-}pivot))) \Rightarrow Positive$$

$$If(cosine(conVec(w),conVec(pos\text{-}pivot)) < cosine(conVec(w),conVec(neg\text{-}pivot))) \Rightarrow Negative$$

Note: We construct a 100 dimensional vector for each candidate word from the unlabeled target domain data.

Significant Consistent Polarity (SCP): $S \cap T$

//Transferable information from the source to the target for cross-domain SA.

Example: Inferred polarity orientation in the Target Domain

Word	Great (Pos-pivot)	Bad (Neg-pivot)	Polarity
Horrible	0.25	**0.31**	Negative
Awful	0.08	**0.31**	Negative
Terrible	0.05	**0.21**	Negative
Fantastic	**0.23**	0.04	Positive
Amazing	**0.24**	0.04	Positive
Wonderful	**0.25**	0.01	Positive

Cosine-similarity score with the Pos-pivot (great) and Neg-pivot (bad), and inferred polarity orientation of words in the movie domain.

F-score for SCP words identification task

E : Electronics
B : Books
K : Kitchen
D : DVD

Available at:
http://www.cs.jhu.edu/~mdredze/datasets/sentiment/index2.html

SCL: Structured Correspondence Learning (Bhatt et al., 2015)

Gold standard SCP words: Application of χ^2 test in both the domains considering target domain is also labeled gives us gold standard SCP words from the corpus. No manual annotation.

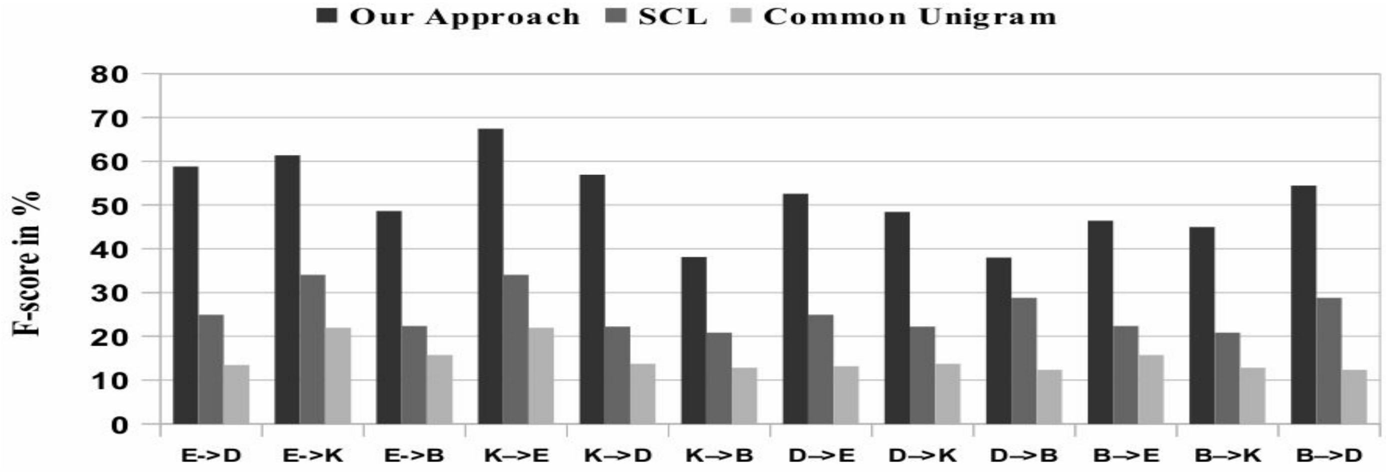

Figure-1: F-score for SCP words identification task (source -> target) with respect to gold standard SCP words.

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Domain Adaptation Algorithm

Input: $D_s^l = \{r_s^1, r_s^2, r_s^3, ...r_s^j\}$,
$D_t^u = \{r_t^1, r_t^2, r_t^3, ...r_t^k\}$,
$V_s = \{w_s^1, w_s^2, w_s^3, ...w_s^p\}$,
$V_t = \{w_t^1, w_t^2, w_t^3, ...w_t^q\}$

Output: Sentiment Classifier in the Target Domain.

Step-1 : SCP $= sigPol(D_s^l) \cap sigPol(D_t^u)$

Step-2 : C_s = Train-SVM(D_s^l), where f = SCP

Step-3 : Predict Label: $C_s(D_t^u) \rightarrow D_t^l$

Step-4 : Select: $R_t^n \mid \forall r_t^i \in D_t^u$, $C_s(r_t^i) > \phi$, where $i \in \{1, 2....k\}$ and $n <= k$

Step-5 : C_t = Train-SVM(R_t^n), where $f = \{unigrams(R_t^n)\}$

Step-6 : WSM $= (C_s * W_s + C_t * W_t)/(W_s + W_t)$

Step-7 : Sentiment Classifier in the Target Domain = WSM

C_s(exampleDoc) = -0.07 (wrong prediction, negative)
C_t(exampleDoc) = 0.33 (correct prediction, positive)

$W_s = 0.765$, $W_t = 0.712$

$$WSM(exampleDoc) = \frac{(-0.07*0.765+0.33*0.712)}{(0.765+0.712)} = 0.12$$

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Cross-domain Results

System Name: Transferred Info
System-1: Common-unigrams
System-2: SCL (Bhatt et al, 2015)
System-3: SCP
System-4: System-1 + iterations
System-5: System-2 + iterations
System-6: System-3 + iterations

- We obtained a strong positive correlation (r) of 0.78 between F-score (figure-1) and cross-domain accuracy (system-3).

	Sys1	Sys2	Sys3	Sys4	Sys5	Sys6
D->B	62	64.2	**67**	66	76.5	**78.5**
E->B	63	58.9	**68.3**	67	75.6	**76.3**
K->B	67	**68.75**	67.85	69	71.2	**74**
B->D	76	**81**	80.5	77	81.5	**81.5**
E->D	68	71	**77.5**	71.5	74	**80.4**
K->D	69	69	**74**	71	75.2	**77**
B->E	68	66	**73**	69	79	**81.2**
K->E	76	75.75	**80**	78	81	**82**
K->E	76	75.75	**80**	78	81	**82**
B->K	66	67.5	**72**	69	79.2	**80.5**
D->K	65.76	67	**71**	66	80	**81**
E->K	74.25	75	**85.75**	76	84	**85.75**

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Conclusion

- Significant Consistent Polarity (SCP) words shows a strong positive correlation of 0.78 with the sentiment classification accuracy achieved in the unlabeled target domain.

- Essentially, a set of less erroneous transferable features lead to a more accurate classification system in the unlabeled target domain.