Dual Teaching: A Practical Semi-supervised Wrapper Method

Fuqiaq LIU1 Chenwei DENG1 Fukun BI2 Yiding YANG1

1Department of Information and Electronic, Beijing Institute of Technology, Beijing
2College of Information Engineering, North China University of Technology, Beijing
fqliu@outlook.com, cwdeng@bit.edu.cn, bifukun@ncut.edu.cn, yangydi09g3@bit.edu.cn

Abstract

Semi-supervised wrapper methods are concerned with building effective supervised classifiers from partially labeled data. Though previous works have succeeded in some fields, it is still difficult to apply semi-supervised wrapper methods to practice because the assumptions those methods rely on tend to be unrealistic in practice. For practical use, this paper proposes a novel semi-supervised wrapper method, Dual Teaching, whose assumptions are easy to set up. Dual Teaching adopts two external classifiers to estimate the false positives and false negatives of the base learner. Only if the recall of every external classifier is greater than zero and the sum of the precision is greater than one, Dual Teaching will train a base learner from partially labeled data as effectively as the fully-labeled-data-trained classifier. The effectiveness of Dual Teaching is proved in both theory and practice.

Intruduction

Semi-supervised learning (SSL) is concerned with utilizing some labeled data as well as amounts of unlabeled data to train better classifiers and regressors (Balcan and Blum 2010; Zhu and Goldberg 2009). Some SSL methods are called “Semi-supervised wrapper methods” (Goldberg 2010) and they procedure external “wrappers” around the base learner, a supervised learning model. The purpose of semi-supervised wrapper methods is to train a supervised model from partially labeled data as effectively as the same model trained from fully labeled data. Compared with other semi-supervised methods, semi-supervised wrapper methods can use almost any user-specified supervised learner as a subroutine, which allows us to take advantage of advances in supervised learning without deriving new algorithms.

However, it is difficult to apply semi-supervised wrapper methods in practical learning cases (Li and Zhou 2016; Blum and Mitchell 2000; Singh, Nowak, and Zhu 2008). Though most of previous wrapper methods propose theoretical analysis to prove their effectiveness, there are still many gaps between realities and theories (Li and Zhou 2011a; Loog 2015; Sokolovska, Capp, and Yvon 2008). In real-world learning scenarios, assumptions those semi-supervised wrapper methods rely on might be untenable, which makes those methods ineffective. For instance, self-training (McClosky, Charniak, and Johnson 2006a) assumes that predictions of the base learner tend to be correct in early generation otherwise it would grow worse when using the unlabeled data. However for a base learner initialized from a few labeled data, making good predictions on amounts of unlabeled data is a tough job. More related semi-supervised wrapper methods including Co-Training (Blum and Mitchell 2000) and Cluster-Then-Label-Methods (Wang, Chen, and Zhou 2012) as well as the reason why they are hard to set up in practice are discussed in Related Work.

For practical use, this paper proposes a novel semi-supervised wrapper method named “Dual Teaching” whose assumptions are easy to set up in practical learning tasks. Dual Teaching only adopts two external classifiers outside the base learner. One assumption of Dual Teaching is that the recall of each auxiliary classifier is greater than zero. The other is that the sum of precision is greater than one. Compared with assumptions of previous works, these assumptions are much easier to set up in practice. The two assumptions themselves are so simple that they can be matched even by two weak classifiers. In addition, the assumptions have no relationship with the base learner so that Dual Teaching can choose a proper supervised learner as the base learner according to the practical data.

The above assumptions originate from a novel framework. Different from previous works, auxiliary wrappers in Dual Teaching estimate the error of the base learner rather than directly estimate the label of unlabeled data. One external classifier named “FP Teacher” picks out false positives from the positive outputs of the base learner. The other one named “FN Teacher” picks out false negatives from the negative outputs. To begin with, the base learner is zero-initialized. Then an effective learner would be trained by the following recursive processing. In every generation, the unlabeled data is classified by the base learner firstly; secondly the two teachers are tested on a validation set composed by part of labeled data and if the teachers do not match the assumptions, they will be tuned based on the rest labeled data until their performance on validation set matches the assumptions; thirdly the two teachers point out the unlabeled examples mis-classified by the base learner and then the base learner is re-trained using all previous mis-classified examples with their corrected labels. The base learner would grow...
better in every generation if the assumptions are valid. The rest of the paper is organized as follows. We first review related semi-supervised wrapper methods. Next, the proposed method is detailed. Then we analyzes the effectiveness of Dual Teaching in theory. This is followed by a number of experiments to show the effectiveness in practice. This paper finishes with conclusions and suggestions for future research.

Related Work
This section reviews a series of semi-supervised wrapper methods including Self-Training, Co-Training and Cluster-then-label-methods. Differences between Dual Teaching and the above methods are also discussed.

Self-Training (Mcclosky, Charniak, and Johnson 2006b) is characterized by the strategy that the learner uses its own predictions to teach itself. It starts by training a base learner from some labeled data and then evaluates the learner on the unlabeled data. Examples along with the labels predicted by the base learner are added to the training set and then the classifier is re-trained. Because the early mistakes made by the base learner would be reinforced by inputting the false labels to the early training set, self-training assumes that predictions of the base learner tend to be correct. However, it is unrealistic in some practical scenarios that a supervised model trained form a few labeled could classify amounts of unlabeled data successfully.

Co-Training (Balcan, Blum, and Yang 2004) is a wrapper method that works with two classifiers. The learning is initialized by training two classifiers from two separate feature sets of the labeled data. Then, one classifier make predictions on unlabeled data and then the data with their predicted labels are fed back for re-training another classifier. The two classifiers work as the above step alternately. The high performance of Co-Training relies on two independent feature-spaces. In addition, each classifier should make good predictions on unlabeled data in early generation. The above two assumptions tend to be violated in practice. First, two independent feature-spaces are difficult to be available because the diffusion of the real-world data is complicated. Second, it is difficult for the two classifiers to make good predictions on unlabeled data at the very start when they are trained from a few labeled data.

Cluster-then-label-Methods (Wang, Chen, and Zhou 2012) start by identifying clusters by unsupervised clustering algorithms and unlabeled data. Then supervised classifiers are learned from the labeled examples in each cluster. Each cluster should learn a classifier and if there is no labeled example falls into the cluster, the classifier would be trained from all labeled data. After that, the unlabeled examples in each cluster are labeled by the corresponding classifier. Cluster-then-label-methods will work effectively only if one cluster contains examples belong to a single class only. But in practice, one cluster usually contains examples from more than one class.

Dual Teaching is very different from previous works. Dual Teaching makes assumptions on its wrappers rather than the base learner or the data. Accordingly, the wrappers can be adjusted to match the assumptions in the process of Dual Teaching. The special assumptions are derived from a novel framework. Dual Teaching tries to estimate the error of the base learner, while previous works try to directly estimate the labels of unlabeled data. Thanks to this strategy, Dual Teaching can provide theoretical analysis for general cases with arbitrary inner base learners.

Description of Dual Teaching
We focus on binary classification. Suppose $x$ is an example from a feature-space $X$ and $y$ is its label from a label space $Y = \{1, -1\}$. Suppose $X_l$ is a labeled data set, $L_l$ is its corresponding label set and $X_u$ is an unlabeled data set, where $l \ll u$ and $R$ represent the number of labeled examples and that of unlabeled examples respectively. Assuming that $L_u$ is an in-existent label set that contains true labels of the unlabeled data, suppose $F : X \rightarrow Y$ be an supervised classifier learned from an assumed fully labeled data set $\{X_l, X_u\}$ with its label set $\{L_l, L_u\}$. Dual Teaching aims to train an effective classifier $f$ from a few labeled data $X_l$ with $L_l$ and amounts of unlabeled data $X_u$, where $l \ll u$. The classifier $f$ named the "base learner" is a supervised classification model parameterized by $\Theta$. Dual Teaching try to train the base learner as effectively as the fully-labeled-data-trained classifier.

Dual Teaching contains four base steps: zero-initialization, classification, teacher testing & tuning and error estimation & re-training. Dual Teaching adopts two external classifiers named ”FP Teacher” and ”FN Teacher” to estimate the false positives and false negatives respectively from the outputs of base learner. The assumptions of Dual Teaching are that the recall of each teacher is greater than zero and the sum of precision is greater than one. When the assumptions are valid, Dual Teaching can train a effective base learner from partially labeled data.

![Figure 1: The framework of Dual Teaching.](image)

Step1: Zero-Initialization For convenience, set the parameters of the base learner to zero, $\Theta^0 = \Theta$. In terms of Dual Teaching, how to initialize the base learner does not influence the performance of the base learner, which is different from Self-training and Co-training. Suppose $R$ represents the re-training data set for the base learner, it is an empty set initially, $R^0 = \emptyset$. This step is shown as Fig[1][1].

Step2: Classification In every generation, all unlabeled examples are classified by the base learner re-trained in last generation. $y^k = f(x, \Theta^{k-1})$ for $x \in X_u$, where $k$ represents the $k$th generation. This step is shown as Fig[1][2].
Step3: Teacher Testing & Tuning  First, the auxiliary classifiers are trained from half of the labeled data which is referred to as $TX_l$. The rest labeled data are reserved as a validation set named $VX_l$. Then before estimating the error of the base learner, the teachers are tested on the validation set to make sure they match the assumptions. We estimate the true precision and recall of auxiliary classifiers by their recall and precision on validation set. If teachers do not match the assumptions, we will increase the precision of teachers by reducing their recall. Take logistic regression for instance, the threshold of discrimination, referred to as $T$, is usually set to 0.5. But if we want to improve the precision, we will set $T$ greater than 0.5 and the recall will decrease accordingly.

This step, Teacher Testing & Tuning, is shown as Fig 1 ③. The specific strategy is detailed as algorithm 1. In the algorithm, $FP$ and $FN$ represent the FP teacher and FN teacher respectively. $p1$ and $r1$ represent the precision and recall of FP teacher. $p2$ and $r2$ represent the precision and recall of FN teacher. Allowing for a certain error, we empirically set the sum of precision should be greater than 1.1 rather than 1.

![Algorithm 1 Teaching Tuning](image)

As the base learner improves, it would be harder for teachers to correctly point out its mistakes because the proportion of mis-classified examples reduces. The two teachers gradually face a class imbalance problem as the base learner grows better. In practice, we construct each teacher by a balanced-weight logistic regression model (He and Garcia 2009). The threshold of discrimination is set to a small value initially for high recall. High recall means that teachers can pick out as many mis-classified examples as they could in step4: error estimation & re-training.

The proposed strategy on constructing teachers is compared with other two strategies. One comparative strategy abbreviated to LR(equal weight) is to construct the teachers using equal-weight logistic regression. Another one abbreviated to LR(balanced weight) is to construct the teachers using balanced-weight logistic regression with a constant threshold. LR(balanced weight+L/R tuned) is short for the proposed strategy. The precision and recall of the base learner on both labeled set and unlabeled set are recorded in every generation. The performance of the base learner on unlabeled data is also recorded.

As Fig 2 shows, the recall of the base learner when using LR(equal weight) drops fast because the FP teacher and FN teacher can not find any mis-classified example in early generation. The accuracy of the base learner when using LR(balanced weight) shakes because the teachers not only point out as many mis-classified examples as they can but also do not make too many mistakes (precision is always constant) as the base learner improves. Finally all of the outputs of two teachers are -1 which means the teachers think that the base learner makes no mistake. The performance of the base learner would be stable because the re-training set for the base learner does not change in next generation.

Step4: Error Estimation & Re-training  Dual Teaching adopts two external classifiers, FP Teacher and FN Teacher, to estimate the mis-classified examples in every generation. FP Teacher tries to pick out the false positives from the positive outputs of the base learner. FN Teacher tries to pick out the false negatives from the negative outputs. Then “add” these mis-classified examples with their estimated labels to the re-training set. The “add” is defined as follows: if the mis-classified example already exists in re-training set $R$, just change its label; if the mis-classified example does not exit in the re-training set $R$, add the example with its corrected label to the re-training set. Finally, re-train the base learner from the updated re-training data set $R'$. This step is shown as Fig 1 ④. Repeat steps 2-4 until the base learner is stable, then a strong classifier will be trained.
Effectiveness Analysis

To begin with, this section theoretically analyzes why Dual Teaching could train an effective classifier from partially labeled data. Then, we detail how to drive the assumptions Dual Teaching relies on. The assumptions are summarized as that the recall of each external classifier is greater than zero and the sum of precision is greater than one.

Effectiveness

This part theoretically derives that Dual Teaching could train an effective base learner from a few labeled data and amounts of unlabeled data just by two external classifiers.

Define \( \tilde{\varnothing}(k) \) as the error of the base classifier in kth generation,

\[
\tilde{\varnothing}(k) = [\alpha(k), \beta(k)]^T
\]

where \( \alpha(k) \) represents false positives and \( \beta(k) \) represents false negatives in the outputs of the base learner.

Define \( P^+, R^+ \) as the precision and the recall of FP Teacher respectively. Similarly, define \( P^-, R^- \) as the precision and the recall of FN Teacher. Assume that if the misclassified examples are pointed out and put into re-training set, the base learner will not make same mistakes in next generation. Assume that the base learner will classify the examples incorrectly if the examples along with wrong labels are contained in the re-training set. The recursive equations are shown as equation (2).

\[
\begin{align*}
\alpha(k + 1) &= \alpha(k) - R^+ \cdot \alpha(k) + \frac{1 - P^-}{P^-} R^- \cdot \beta(k) \\
\beta(k + 1) &= \beta(k) - R^- \cdot \beta(k) + \frac{1 - P^+}{P^+} R^+ \cdot \alpha(k)
\end{align*}
\]

(2)

where

• \( R^+ \cdot \alpha(k) \): the false positives that the FP Teacher pick out correctly.
• \( R^- \cdot \beta(k) \): the false negatives that the FN Teacher pick out correctly.
• \( \frac{1 - P^-}{P^-} R^- \cdot \alpha(k) \): examples incorrectly classified to be false positives by FP Teacher.
• \( \frac{1 - P^+}{P^+} R^+ \cdot \beta(k) \): examples incorrectly classified to be false negatives by FN Teacher.

Reconstruct equation (1) and (2),

\[
\tilde{\varnothing}(k + 1) = M \tilde{\varnothing}(k)
\]

(3)

where \( M = [ \begin{array}{cc} 1 - R^+ & \frac{1 - P^-}{P^-} R^- \\
\frac{1 - P^+}{P^+} R^+ & 1 - R^- \end{array} ] \).

Based on the well founded theory of dynamic system (MC Tsai 1996), \( \tilde{\varnothing}(k) \) would converge to zero if all magnitudes of eigenvalues of the transformation matrix are smaller than 1. The eigenvalues \( \lambda_1, \lambda_2 \) are shown as equation (4).

\[
\lambda_1, \lambda_2 = \frac{(2 - R^- - R^+) \pm \sqrt{\Delta}}{2}
\]

(4)

\[
\Delta = (R^+ - R^-)^2 + 4 \left( \frac{1 - P^+}{P^+} \right) \left( \frac{1 - P^-}{P^-} \right) R^+ R^-
\]

(5)

where \( P^+, P^+, P^-, R^- \in [0, 1] \) and \( \Delta \) is always greater than or equal to 0.

So, the maximum absolute value of the two eigenvalues is shown as equation (6).

\[
|\lambda|_{\text{max}} = \frac{(2 - R^- - R^+) + \sqrt{\Delta}}{2}
\]

(6)

Assuming that \( |\lambda|_{\text{max}} \) is smaller than 1, we can derive a conclusion as equation (7).

\[
\sqrt{\Delta} < R^- + R^+
\]

(7)

Simplify equation (7) and we can get equation (8).

\[
\frac{1 - P^+ - P^-}{P^+ P^-} R^+ R^- < 0
\]

(8)

Furthermore, the assumptions Dual Teaching makes are derived as equation (9).
\[
\begin{align*}
R^+ R^- & \neq 0 \\
P^++P^- & > 1
\end{align*}
\]  
Equation (9) proposes the requirement on the two external classifiers. When the recall of each classifier is greater than 0 and the sum of the precisions is greater than 1, the base learner will be trained effectively by Dual Teaching from partially labeled data.

**Experiments**

This section proposes a series of evaluations of the proposed method and previous works on a broad range of tasks including 4 semi-supervised benchmark data sets: bci, g241c, digit1, usps, and 6 UCI tasks: heart scale, car evaluation, wine quality, adult, housing, vehicle, and 2 image classification problems (Lecun 2010), mnist1v7, mnist4v9. The size of data ranges from 170 to more than 15000 and the dimensionality ranges from 6 to more than 600. The ratio of the number of positive examples to that of negative examples ranges from 0.25 to 1.149.

Every data set is separated into two parts. 75% data in each data set are reserved as training data. The testing data set is composed by the rest 25% data. Not all data in the training data set are labeled. Features in each data set are normalized beforehand.

**Comparison with Classical Semi-supervised Wrapper Methods**

This part compares Dual Teaching (DT) with previous semi-supervised wrapper methods, Self-Training (ST) and Co-Training (CT). To show the generalization of the proposed method, Logistical Regression (lr) (Hosmer Jr and Lemeshow 2004), Support Vector Machine with linear kernel (svm) (Suykens and Vandewalle 1999) and Adaboost (ada) (Ratsch, Onoda, and Muller 2001) serve as the base learner separately for every wrapper method. Every specific method is abbreviated to “the name of the base learner/the name of the wrapper method”. For instance, “lr/ST” means the base learner is a logistic regression model and the wrapper method is Self-Training. To show whether the wrapper methods can improve the performance of the base learner from unlabeled data, supervised models with the use of labeled data only, which are abbreviated to “name of the su-
Comparison with Productive Semi-supervised Methods

The proposed method is also compared with some of productive semi-supervised methods (no wrapper method): S3VM (Bennett and Demiriz 1999) and S4VM (Li and Zhou 2015) with linear kernel. The base learner of Dual Teaching is set to a SVM with linear kernel too. The ratio of the number of labeled data to that of training data ranges from 0.1 to 1. When the ratio is equal to 1, the base learner actually is a supervised classifier trained from fully-labeled data.

Dual Teaching is a wrapper method that can make full use of the supervised learning according to different data sets. For example, as shown in Fig 4, Dual Teaching with adaboost as the base learner performs better than Dual Teaching with svm as the base learner on bci and vehicle.

Conclusion and Future Work

Dual Teaching’s good performance relies on its easy assumptions and novel framework. The assumptions are easy to set up in practice. First, the assumptions themselves are not critical. For instance, with the base learner improves, the performance of teachers are usually worse than that in early generations. But the teachers can still match the assumptions just by reducing the recall to keep their precision in a satisfactory level. Then, the assumptions are well quantified so that we can monitor and tune the external teachers in the process of Dual Teaching to match the necessary conditions. Dual Teaching can effectively improve the performance of supervised learner from unlabeled data.

The above characters also improve the safety of Dual Teaching. By tuning the teachers, the base learner in Dual Teaching is able to be not worse than a same supervised model trained from labeled data only. When the recall of each teacher is equal to 0, the re-training set does not change anymore and the base learner is constant. To estimate the performance of teachers precisely, Dual Teaching needs enough labeled data reserved (at least 10% empirically). Unlike methods which focus on few labeled data training (Zhou, Zhan, and Yang 2007), Dual Teaching does not perform well in the cases where only few labeled data exist.

The easy assumptions originate from the carefully designed framework. Dual Teaching converts training an high performance base learner into training two qualified external classifiers in every generation. The re-training set of the base learner synthesizes the outputs of external classifiers in every generation and boosts the performance of the base learner. Even though the teachers in late generations are not critical. For instance, with the base learner improves, the performance of teachers are usually worse than that in early generations. But the teachers can still match the assumptions just by reducing the recall to keep their precision in a satisfactory level. Then, the assumptions are well quantified so that we can monitor and tune the external teachers in the process of Dual Teaching to match the necessary conditions. Dual Teaching can effectively improve the performance of supervised learner from unlabeled data.

Table 1 presents the accuracy of SVM and accuracy improvements of S3VM, S4VM and Dual Teaching on different numbers of labeled data. In the perspective of no matter effectiveness or safeness, Dual Teaching is competitive in this experiment. Different from S3VM and S4VM, Dual Teaching is able to be not worse than a same supervised learner from unlabeled data.

Table 1: Accuracy of svm and accuracy improvements of S3VM, S4VM and Dual Teaching on different numbers of labeled data

| Dataset       | 5% labeled data | 10% labeled data | 20% labeled data |
|---------------|-----------------|------------------|------------------|
|               | svm             | s3vm             | s4vm             | svm/DT | svm             | s3vm             | s4vm             | svm/DT | svm             | s3vm             | s4vm             | svm/DT |
| bci           | 56.2            | -1.0             | -1.1             | 1.8     | 62.7            | 1.2             | -0.6             | 0       | 64.3            | 0.9             | 0               | -0.9   |
| g241c         | 73.7            | 6.6              | 0.4              | 4.2     | 80.7            | 0.9             | 0.2              | 0.1     | 84.2            | 0.9             | 0.8             | 2.1    |
| digit1        | 90.9            | 0.6              | 2.0              | 1.0     | 93.7            | 0.2             | 0                | 0.4     | 93.9            | 0               | 0.1             | 0.2    |
| usps          | 86.9            | -0.2             | 8.3              | 1.7     | 86.9            | 0               | 8.4              | 1.8     | 90.4            | 0               | 0.1             | 0.4    |
| heart scale   | 71.2            | 0.9              | 1.3              | 1.0     | 78.9            | -0.6            | 0.7              | 1.9     | 80.8            | 0.3             | 0.2             | 5.7    |
| vehicle       | 65.3            | 0.2              | 2.3              | 0.8     | 74.2            | 2.3             | 3.4              | -0.1    | 77.0            | 3.0             | -0.9            | -1.2   |

Win/Tie/Loss against svm: (12/3/3)             13/2/3             14/1/3             7/4             
Best/Worst performance over all: (5/8)             6/5             7/4             7/4             

Table 1: Accuracy of svm and accuracy improvements of S3VM, S4VM and Dual Teaching on different numbers of labeled data.
Teaching.
In the future, it is worthy to extend Dual Teaching to solve multiple classification problems. Designing a more effective and efficient way to estimate the precision and the recall of auxiliary classifiers is also worthy.

References

[Balcan and Blum 2010] Balcan, M. F., and Blum, A. 2010. A discriminative model for semi-supervised learning. *Journal of the Acm* 57(3):517–527.

[Balcan, Blum, and Yang 2004] Balcan, M. F.; Blum, A.; and Yang, K. 2004. Co-training and expansion: Towards bridging theory and practice. *Advances in Neural Information Processing Systems* volume 8(1):29–58(30).

[Bennett and Demiriz 1999] Bennett, K. P., and Demiriz, A. 1999. Semi-supervised support vector machines. In *Conference on Advances in Neural Information Processing Systems II*, 368–374.

[Blum and Mitchell 2000] Blum, A., and Mitchell, T. 2000. Combining labeled and unlabeled data with co-training. In *Proceedings of the eleventh annual conference on Computational learning theory*, 92–100.

[Goldberg 2010] Goldberg, A. B. 2010. *New Direction in Semi-supervised Learning*. University of Wisconsin-Madison.

[He and Garcia 2009] He, H., and Garcia, E. A. 2009. Learning from imbalanced data. *IEEE Transactions on Knowledge & Data Engineering* 21(9):1263–1284.

[Hosmer Jr and Lemeshow 2004] Hosmer Jr, D. W., and Lemeshow, S. 2004. *Applied logistic regression*. John Wiley & Sons.

[Kalal, Matas, and Mikolajczyk 2010] Kalal, Z.; Matas, J.; and Mikolajczyk, K. 2010. Pn learning: Bootstrapping binary classifiers by structural constraints. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, 49–56. IEEE.

[Kalal, Mikolajczyk, and Matas 2012] Kalal, Z.; Mikolajczyk, K.; and Matas, J. 2012. Tracking-learning-detection. *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 34(7):1409–1422.

[Lecun 2010] Lecun, B. Y. 2010. et al., gradient-based learning applied to document recognition. In *Proceedings of the IEEE*.

[Li and Zhou 2011a] Li, Y.-F., and Zhou, Z. H. 2011a. Improving semisupervised support vector machines through unlabeled instances selection. In *Proceedings of 25th AAAI Conference on Artificial Intelligence* 386–391.

[Li and Zhou 2015] Li, Y. F., and Zhou, Z. H. 2015. Towards making unlabeled data never hurt. *IEEE Transactions on Pattern Analysis & Machine Intelligence* 37(1):1.

[Li and Zhou 2016] Li, Y. F., and Zhou, Z. H. 2016. Towards safe semi-supervised learning for multivariate performance measures. In *Proceedings of the 25th international conference on Machine learning*.

[Loog 2015] Loog, M. 2015. Contrastive pessimistic likelihood estimation for semi-supervised classification. *IEEE Transactions on Pattern Analysis & Machine Intelligence* 38(3):1.

[MC Tsai 1996] MC Tsai, D. G. 1996. Robust and optimal control. Springer.
[McClosky, Charniak, and Johnson 2006a] McClosky, D.; Charniak, E.; and Johnson, M. 2006a. Effective self-training for parsing. In Main Conference on Human Language Technology Conference of the North American Chapter of the Association of Computational Linguistics, 152–159.

[McClosky, Charniak, and Johnson 2006b] McClosky, D.; Charniak, E.; and Johnson, M. 2006b. Effective self-training for parsing. In Main Conference on Human Language Technology Conference of the North American Chapter of the Association of Computational Linguistics, 152–159.

[Rätsch, Onoda, and Müller 2001] Rätsch, G.; Onoda, T.; and Müller, K.-R. 2001. Soft margins for adaboost. Machine learning 42(3):287–320.

[Singh, Nowak, and Zhu 2008] Singh, A.; Nowak, R. D.; and Zhu, X. 2008. Unlabeled data: Now it helps, now it doesn’t. In Conference on Neural Information Processing Systems, Vancouver, British Columbia, Canada, December, 1513–1520.

[Sokolovska, Capp, and Yvon 2008] Sokolovska, N.; Capp, O.; and Yvon, F. 2008. The asymptotics of semi-supervised learning in discriminative probabilistic models. In Proceedings of the 25th international conference on Machine learning, 984–991.

[Suykens and Vandewalle 1999] Suykens, J. A., and Vandewalle, J. 1999. Least squares support vector machine classifiers. Neural processing letters 9(3):293–300.

[Wang, Chen, and Zhou 2012] Wang, Y.; Chen, S.; and Zhou, Z. H. 2012. New semi-supervised classification method based on modified cluster assumption. IEEE Transactions on Neural Networks & Learning Systems 23(5):689–702.

[Zhou, Zhan, and Yang 2007] Zhou, Z. H.; Zhan, D. C.; and Yang, Q. 2007. Semi-supervised learning with very few labeled training examples. In AAAI Conference on Artificial Intelligence, July 22-26, 2007, Vancouver, British Columbia, Canada, 675–680.

[Zhu and Goldberg 2009] Zhu, X., and Goldberg, A. B. 2009. Introduction to semi-supervised learning. Synthesis lectures on artificial intelligence and machine learning 3(1):1–130.