International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2017 IJSRCSEIT | Volume 2 | Issue 2 | ISSN : 2456-3307

Semisupervised Regression with Tangent Space Intrinsic Manifold Regularization

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ABSTRACT

Semisupervised learning is very important in machine learning for research processing. The main reason is small amount labeled examples and large amount unlabeled examples used. It reduce the expense of the process. In this paper, proposed a regression algorithm applied to the regularization method. Tangent space intrinsic manifold regularization method is dimensionality reduction technique.
Keywords: Semisupervised Classification, Regression, Tangent Space Intrinsic Manifold Regularization.

I. INTRODUCTION

Semisupervised classification used to estimate the decision function from small labeled examples and large unlabeled examples need to reduce the expensive or time-consuming label acquisition process. Regression analysis, a statistical technique for estimating the relationships among variables. The Linear Regression used to find the relationship between attributes. Tangent space intrinsic manifold regularization used to find the intersecting region of the data plotted region it is estimated by using the regularization. The dimensionality of the region can minimized for the process.

II. METHODS AND MATERIAL

1. Existing and Proposed System

A. Existing System

System In the previous paper they proposed the semisupervised support vector machine with tangent space intrinsic manifold regularization [1].The new algorithm is called as Tangent space intrinsic manifold regularization to approximate a manifold more subtly. From this regularization, we can learn a linear function f (x) on the manifold. Two learning machines tangent space intrinsic manifold regularized SVMs (TiSVMs) and tangent space intrinsic manifold regularized twin SVMs (TiTSVMs) are thus proposed.

Algorithm1 : Tangent Space Intrinsic Manifold Regularized Support Vector

Machines (TiSVMs)
1: **Input:** l labeled examples, u unlabeled examples.
2: Obtain $H1$, $h1$, $H2$, $h2$.
3: Solve the quadratic programming [3] by using cross validation to choose parameters.
4: **Output:**Predict the label of unlabeled training examples according to [4]; predict the label of a new example according to [5].

Algorithm2 : Tangent Space Intrinsic Manifold Regularized Twin Support Vector Machines (TiTSVMs).
1:**Input:** $l$labeled examples ($l1$ positive examples and $l2$ negative examples), u unlabeled examples.
2: Obtain $H+1$, $H-1$, $h+1$, $h-1$, $H+2$,
$H-2$,$h+2$, $h-2$.
3: Solve the quadratic programming [6] and [7] by using cross-validation to choose parameters.
4: **Output :** Predict the label of unlabeled training examples according to [8]; predict the label of a new example according to [4].

B. Proposed System

In my proposed system regression used for the manifold regularization for estimating the relationship among the variables. The processing can be classified into following sections: (i)Semisupervised Linear Regression (ii)Methodology of Tangent space intrinsic manifold regularization (iii)Regression with manifold regularization

2. Semisupervised Regression

In stastical modeling, regression analysis is a statistical process for estimating the relationships among variables.It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variables and one or more independent variables (or 'predictors'). In stastics, linear regression is an approach for modeling the relationship between a scalar dependent variables y and one or more explanatory (or independent variables) denoted X.linear regression can be used to fita predictive model to an observed data set of y and X values. In linear regression the following functions can be calculated.
(i)Covariance
(ii)Correlation coefficient

This two measures used to calculate the linear regression in the given data sets for identifying the relation.

$y \sim 1 + x1*x2 + x1^2 + x2^2 + (x1^2):x2 + x1:(x2^2) + x1^3 + x2^3$

	Estimate	SE	tStat	pValue
(Intercept)	15.292	1.8856	8.1097	2.1289e-12
x1^3	8.7219	1.2663	6.8876	6.8701e-10
x2^3	27.05	1.3828	19.562	1.5287e-34
x1^3:x2	6.0201	2.1132	2.8489	0.0054134
x1:x2^3	-1.1088	2.0991	0.52824	0.5986
x1^3:x2^2	6.039	1.7498	3.4513	0.00084441
x1^2:x2^3	0.70847	1.8158	0.39018	0.69731
x1^3:x2^3	3.7305	1.5761	2.3669	0.020032

Table 1. Correlation Coefficient

Cov(Y, X)=Cor(Y,X)/sy.sx

The covariance calculated from this formula.

3. Methodology of Tangent Space Intrinsic Manifold Regularization

In mathematics, the tangent space of a manifold define the generalization of vectors from affine configuration spaces to general manifolds, that gives the displacement of the one point to other. Fig.2.Tangent space The data lying in a high-dimensional space are assumed to be intrinsically of low dimensionality, data can be well characterized by far fewer parameters or degrees of freedom than the actual ambient representation. In manifold learning, distribution of data nears the low dimensional manifold. The regularization method contain the intrinsic to data manifold to prefers the linear functions on the manifold. The following fundamental elements involved in the regularization.

a)Local Tangent Space
b)Adjacent Tangent Space

We illustrate that this regularization method can obtain good and reasonable data embedding results[2].

Rd,where M is a smooth manifold on Rd Where f (x) is assumed to be a linear function with respect to the manifold M.Let m be the dimensionality of M.

$$f(x) \approx bz + w\_ z\, uz(x) + o(\_x - z\_2$$

locally around z, where uz(x) = Tz(x − z) is an m-dimensional vector representing x in the tangent space around z, and Tz is dimensional vector representing x in the tangent space around z, and Tz is an m × d matrix that projects x around z to a representation in the tangent space of M at z.

$$bz + w\_ z\, uz(x) \approx bz\_ + w\_ z\_ uz\_(x) + O(\_x - z\_\_2 + \_x - z\_2).$$

That is, $bz + w\_ z\, uz(x) \approx bz\_ + w\_ z\_ uz\_(x)$.

This means that $bz + w\_ z\, Tz(x - z) \approx bz\_ + w\_ z\_ Tz\_(x - z\_)$.

Setting x = z, we obtain $bz \approx bz\_ + w\_ z\_$

Tz_ (z − z_), and bz_ + w_ z_ Tz_ (z − z_) + w_ z Tz(x − z) ≈ bz_ + w_ z_ Tz_ (x − z_).

This implies that w_ z Tz(x − z) ≈ w_ z_

Tz_ (x − z) ≈ w_ z_ Tz_T_ z Tz(x − z) + O(_x − z__2 + _x − z_2).

III. RESULTS AND DISCUSSION

REGRSSION WITH TANGENT SPACE MANIFOLD REGULARIZATION

The linear regression identify the relation of attributes in the intersecting region of the tangent space. In this process implemented in the matlab for plotting the data set in the X and Y axis for the processing.

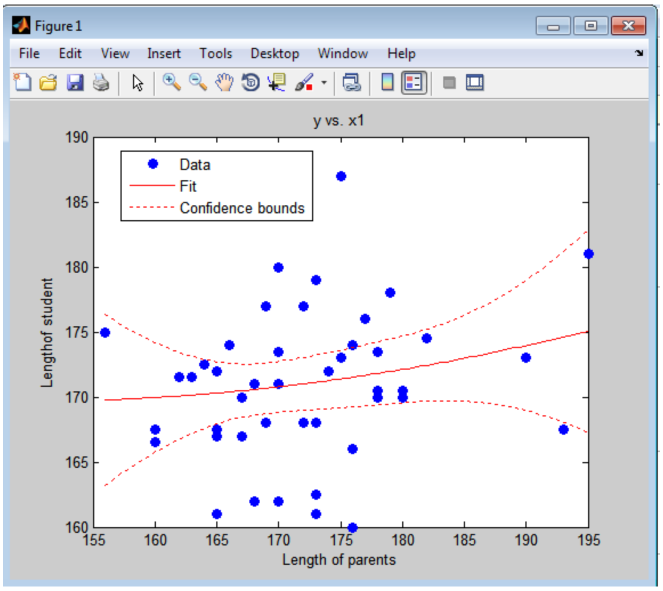

Figure 1. Calculation of tangent space

To remove the beyond the limit from the region for the manifold process then the data inside the region linear regression applied for finding the relation.

```
if all(is finite(xlim_))
xlim_ = xlim_ + [-1 1] * 0.01 * diff(xlim_);
set(ax_,'XLim',xlim_)
else
set (ax_, 'XLim',[155.61000000000001,
195.38999999999999]); end
```

IV. CONCLUSION

In this paper linear regression algorithm applied to the tangent space intrinsic manifold regularization. Linear regression efficient for the manifold processing, fitting process used to get the data inside the region.

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