APPLYING A MACHINE LEARNING TECHNIQUE TO CLASSIFICATION OF JAPANESE PRESSURE PATTERNS

H Kimura [1]*, H Kawashima [1,2], H Kusaka [2] and H Kitagawa [1,2]

*[*1] Graduate School of Systems and Information Engineering, University of Tsukuba, Tsukuba, Ibaraki, Japan*
Email: hkimu@kde.cs.tsukuba.ac.jp; kawasima@kde.cs.tsukuba.ac.jp; kitagawa@kde.cs.tsukuba.ac.jp
[2] Center for Computational Sciences, University of Tsukuba, Tsukuba, Ibaraki, Japan
Email: kusaka@ccs.tsukuba.ac.jp

ABSTRACT

In climate research, pressure patterns are often very important. When a climatologists need to know the days of a specific pressure pattern, for example "low pressure in Western areas of Japan and high pressure in Eastern areas of Japan (Japanese winter-type weather)," they have to visually check a huge number of surface weather charts. To overcome this problem, we propose an automatic classification system using a support vector machine (SVM), which is a machine-learning method. We attempted to classify pressure patterns into two classes: "winter type" and "non-winter type". For both training datasets and test datasets, we used the JRA-25 dataset from 1981 to 2000. An experimental evaluation showed that our method obtained a greater than 0.8 F-measure. We noted that variations in results were based on differences in training datasets.

Keywords: support vector machine (SVM), machine learning, pressure pattern, classification

1 INTRODUCTION

Computers can be used to rapidly process large amounts of data. In natural science fields, scientists have started to use computerized techniques to analyze massive amount of data. In climatology, for example, statistical analysis of large-scale data sets and numerical simulations are now done by computer. In this study, we describe examinations of pressure patterns in climatology.

In climate research, the pressure pattern is often very important. There are 15 types of pressure patterns[1] (Yoshino, 2002). When a climatologist needs to know the days of a specific pressure pattern around Japan, for example, "low pressure in Western areas of Japan and high pressure in Eastern areas of Japan (Japanese winter-type)" or "high pressure in Southern areas of Japan and low pressure in Northern areas of Japan (Japanese summer type)," he or she has to visually check a huge number of surface weather charts, which is a laborious task.

To overcome this problem, we propose an automatic classification method using machine learning, which was developed in the computer science field. In this study, we used a support vector machine (SVM) and classified pressure patterns into two classes: "winter type" and "non-winter type." For training datasets and test datasets, we used the JRA-25 dataset from 1981 to 2000. We also used LIBSVM (Chang & Lin, 2000), an SVM library.

2 RESEARCH OBJECTIVE AND DATA USED

2.1 OBJECTIVE

In climatology, there are many pressure patterns and these have been classified into 15 types (Yoshino, 2002). In addition, some instances that do not belong to a single type are classified as transition or compound types. Both types are a combination of two of the 15 classified types.

This study investigated Japanese winter-type pressure patterns. Figure 1 shows a surface weather chart that illustrates a Japanese winter-type pattern, which is one of the most well-known Japanese pressure patterns. A feature of this type of pattern is low pressure in the West of Japan and high pressure in the East. When winter-type patterns occur, a cold wind

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[1] winter type, trough type (a to d), migratory anticyclone type (a to d), front type (a to b), summer type, typhoon type (a to c)

blows from the North and temperatures drop. It also often snows on the Sea of Japan side.

The aim of our study was to develop a system for automatically classifying a huge amount of meteorological data into two classes, winter type and non-winter type.

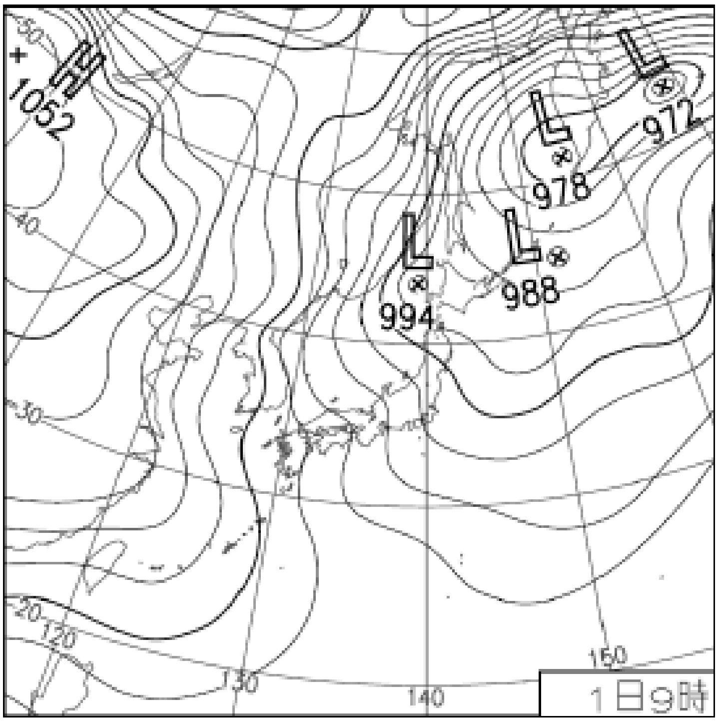


Figure 1. Surface weather chart (Japanese winter type)

2.2 Data

We used the JRA-25 (Japanese 25-year re-analysis) dataset for meteorological data. JRA-25 is from a reanalysis project from 1979 to 2004 conducted by the JMA (Japan Meteorological Agency) and CRIEPI (Central Research Institute of the Electric Power Industry) (Onogi et_al., 2005). This dataset is archived every six hours. Therefore we were able to use four datasets for each day. The format of the JRA-25 dataset is GRIB (GRIdded Binary). GRIB is a mathematically brief data format that is standardized by the WMO (World Meteorological Organization).

In this study, we used datasets gathered at 0900 JST, that is, one dataset for each day. In addition, we extracted only sea-level pressure (SLP) data from the JRA-25 dataset because the Japanese winter-type pattern is characterized by SLP. The JRA-25 dataset is divided into a number of data categories. To extract SLP data, we selected anl_p, which is one of the data categories. The dataset in the anl_p category has many different elements in addition to SLP; for example, it also includes temperature and humidity data. We transformed the dataset for the anl_p category from the GRIB format into a binary format and extracted numerical SLP data using a wgrib program. We needed to select the element "PRMSL" to extract SLP data.

Thus, we extracted numerical SLP data that had 145×288 = 41760 points. Since the field of this data is global, we used SLP data from latitude 15 to 60 degrees North and longitude 105 to 175 East, which indicates the field around Japan. One SLP data contained 37×57 = 2109 points.

3 STUDY METHOD

3.1 Support Vector Machine (SVM)

SVM is a machine-learning method that treats classification of two classes. It is widely used in many different fields, such as in text and speech recognition (Tsuda, 2000).

To use SVM, we needed a training dataset. A training dataset is expressed as $\{\mathbf{x}_i, y_i\}, i = 1, \cdots, l, y_i \in \{-1, 1\}$, where $\mathbf{x}_i$

describes a vector and y_i indicates a class. Based on training datasets, SVM constructs a hyperplane with a maximum margin, which is the distance between the hyperplane and support vectors (Tsuda, 2000). Figure 2 shows the concept of linear separation using SVM. Let us assume that in Figure 2, the symbols "○" indicate training data in class 1, and the symbols "☆" indicate training data in class 2. The shaded training symbols in each class are referred to as support vectors.

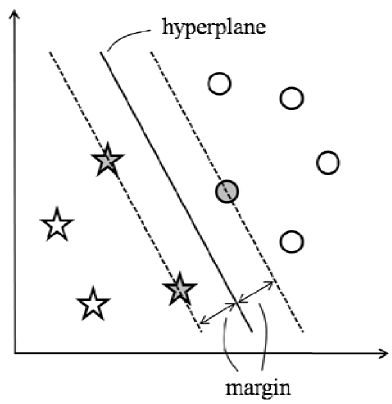


Figure 2. Concept of classification using SVM (○: training data in class 1, ☆: training data in class 2; shaded training symbols in each class, support vectors)

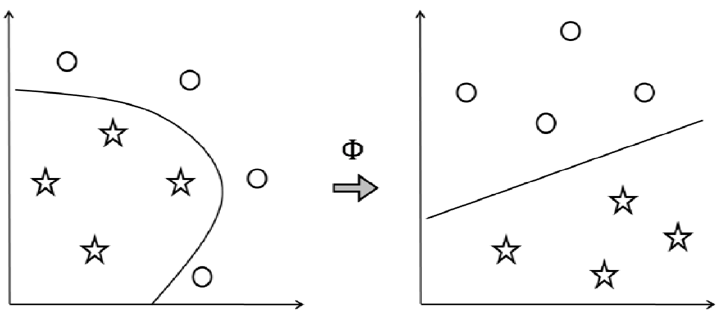


Figure 3. Concept of nonlinear separation (○: training data in class 1; ☆: training data in class 2)

When linear separation as in Figure 2 is impossible, nonlinear separation is applied. Figure 3 shows nonlinear separation. First, the training dataset is mapped into a high-dimensional space using nonlinear mapping. Then, in the high-dimensional space, the training dataset is separated into two classes by the hyperplane. To use nonlinear mapping, calculations of high-dimensional vectors, which are inner products of $\Phi(\mathbf{x}_i)$ and $\Phi(\mathbf{x}_j)$ for all combination of vectors, are required. However, a kernel function, $K(\mathbf{x}_i, \mathbf{x}_j)= \Phi(\mathbf{x}_i)\ \Phi(\mathbf{x}_j)$, provides an easy way of making the calculations (Tsuda, 2000). If we use a kernel function, we can make calculations in the original space. In our research, we used an RBF (Radial Basis Function) kernel, which is a major nonlinear kernel. The RBF kernel is expressed as follows:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\delta \cdot \left|\mathbf{x}_i - \mathbf{x}_j\right|^2) \tag{1}$$

where each of $\mathbf{x}_i$ and $\mathbf{x}_j$ denotes a vector of each training data and δ indicates a parameter. When we use an RBF kernel, parameter δ should be selected appropriately. The parameter values we selected in our study are described in section 4.4.

The SLP data has 37×57 = 2109 grid points. In both the training and testing phases of SVM, we regard this number as 1×2109 = 2109, and treat it as a 2109-dimensional vector. We then classify uncertain data as winter-type class or non-winter-type class using the 2109-dimensional vector. The process of SVM classification is as follows:

1. Make a training dataset comprising combinations of vector and class.

2. Generate a classifier from the training dataset using SVM.

3. Classify a test dataset using the constructed classifier.

3.2 Generation of Training Data

SVM conducts classification using a classifier produced from a training dataset. It can be assumed that different training datasets lead to different classification results. Therefore, we generated several training datasets and compared the results of each classification.

In generating a training dataset, it must be decided whether each piece of data belongs to a positive (winter type) or negative example (non-winter type). Accordingly, we used the classification described by Yoshino (2002) to decide positive and negative examples. As mentioned in section 2.1, Yoshino (2002) classifies pressure patterns into 15 types. In addition, some instances that do not belong to a single type are classified as transition or compound types, which are a combination of two types of the 15 types. Table 1 lists the classification proposed by Yoshino (2002).

Table 1. Definition of pressure pattern cases from Yoshino (2002)

case-A	Winter type
case-B	Transition type or compound type (winter type and another type)
case-C	June, July, August
case-D	Others

Table 2. Definition of training datasets based on Table 1

Training dataset ID	Positive example	Negative example
1	case-A, case-B	case-C, case-D
2	case-A, case-B	case-C
3	case-A, case-B	case-D
4	case-A	case-B, case-C, case-D
5	case-A	case-B, case-C
6	case-A	case-B, case-D
7	case-A	case-C, case-D
8	case-A	case-B
9	case-A	case-C
10	case-A	case-D

Case-A indicates data classified into winter type by Yoshino (2002). Case-B indicates data classified into transition or compound types with winter type and another type by Yoshino (2002). Case-C indicates data from June, July or August, which has no winter type. Case-D indicates data that does not belong to either case-A, case-B, or case-C.

Based on case-A to case-D, Table 2 describes the training dataset that we generated. We then inspected the influence of case-B, case-C, and case-D on the classification results.

4 EXPERIMENT

4.1 Experimental Data and Procedure

We conducted a classification experiment using SLP data from 1981 to 1990 for training datasets and SLP data from 1991 to 2000 for test datasets.

The classification test included two cases: the first used a linear kernel and the second an RBF (nonlinear) kernel. The RBF kernel parameter provided the most accurate classification in our experiment (in the rest of this paper, nonlinear kernel indicates an RBF kernel). In addition, we used LIBSVM (Chang & Lin, 2000), which is an SVM library. The

SVM procedure for classification was as follows:

1. Generate a classifier from a training dataset made using SLP data from 1981 to 1990.

2. Classify a test dataset from 1991 to 2000 using the generated classifier.

3. Compare and inspect the results of classification using Yoshino (2002).

4.2 Evaluation of Classification Results

We used two methods to evaluate the results of the classification. Table 3 shows the evaluation by weak winter type and Table 4 shows the evaluation by strong winter type.

1. Evaluation by weak winter type: performs evaluation treating case-A and case-B as winter type, and case-C and case-D as non-winter type. Normally, data belong to transition or compound type with a combination of winter type and another type is regarded as winter type. Here, we can evaluate weak winter type patterns because Case-B has features of winter type and another type.
2. Evaluation by strong winter type: performs evaluation treating case-A as winter type and case-B, case-C, and case-D as non-winter type. Normally, data assigned to winter type by Yoshino (2002) is regarded as winter type, and other data is regarded as non-winter type. Here, we can evaluate strong winter type patterns because case-B belongs to non-winter type.

Table 3. Evaluation by weak winter type

		Actual class	
		Winter type (case-A, case-B)	Non-winter type (case-C, case-D)
Classified class	Winter type	TP (True Positive)	FP (False Positive)
	Non-winter type	FN (False Negative)	TN (True Negative)

Table 4. Evaluation by strong winter type

		Actual class	
		Winter type (case-A)	Non-winter type (case-B, case-C, case-D)
Classified class	Winter type	TP (True Positive)	FP (False Positive)
	Non-winter type	FN (False Negative)	TN (True Negative)

This experiment used precision, recall and the F-measure as criteria for evaluating the classification results. The F-measure describes the harmonic mean of precision and recall (Witten & Frank, 2005). The formula for the precision, recall and F-measure for Tables 3 and 4 was as follows.

$$precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$F\text{–}measure = \frac{2 \cdot \mathrm{TP}}{(\mathrm{TP} + \mathrm{FP}) + (\mathrm{TP} + \mathrm{FN})} \tag{4}$$

4.3 Experiment: Comparison of Classification USING Multiple Training Data

Classification tests were as follows: classifiers were generated using the training datasets in Table 2.

- Experiment 1: evaluate classification results by Table 3 (evaluation by weak winter type)

- Experiment 2: evaluate classification results by Table 4 (evaluation by strong winter type)

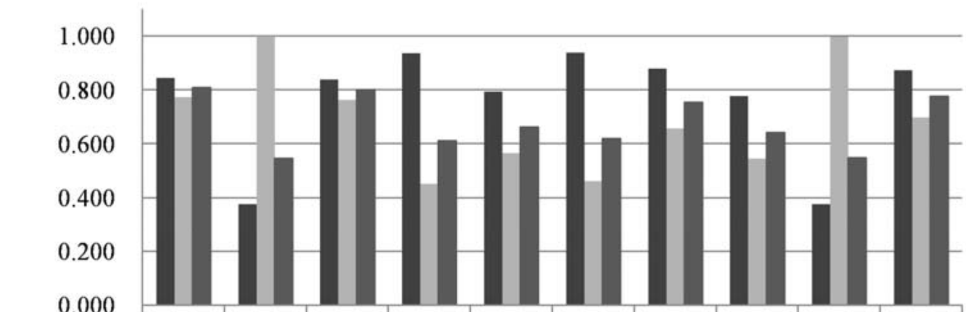
4.4 Results of Experiment

The nonlinear kernel parameter δ in this experiment was equal to 10×10^{-6}.

4.4.1 Results of Experiment 1

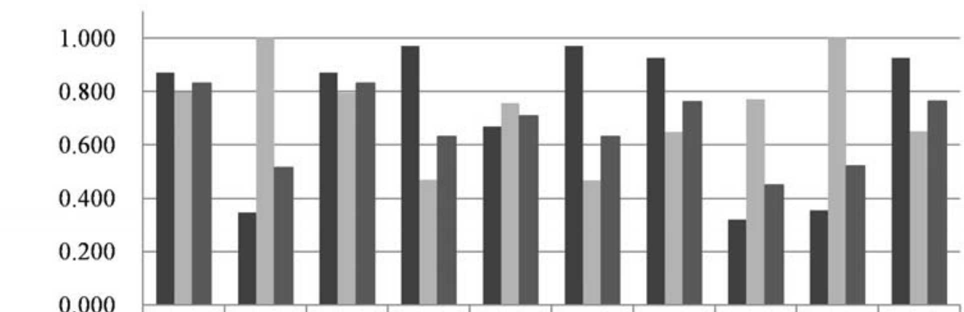
Figure 4 shows the classification results when using a linear kernel, and Figure 5 shows the results when using a nonlinear kernel. The results of experiment 1 are summarized as follows:

- Training dataset 1, 3: Precision and recall were high on the whole, and the highest F-measure was obtained.
- Training dataset 2, 9: Precision was low; however, recall was 1.0. Normally, this means that no false negatives occurred. Moreover, the lowest F-measure was obtained.
- Training dataset 4, 6: Compared with other training datasets, precision was high, while recall was low.
- Training dataset 5: Compared with other training datasets, average values were obtained.
- Training dataset 7, 10: Precision was high, while recall was a little low.
- Training dataset 8: When the linear kernel was compared with the nonlinear kernel, the positions of precision and recall were reversed. Moreover, the lowest F-measure was obtained using the nonlinear kernel.



	1	2	3	4	5	6	7	8	9	10
precision	0.846	0.376	0.838	0.937	0.795	0.939	0.880	0.777	0.378	0.873
recall	0.774	1.000	0.764	0.453	0.567	0.462	0.658	0.546	0.999	0.699
F-measure	0.808	0.547	0.800	0.610	0.662	0.619	0.753	0.641	0.548	0.776

Figure 4. Results of experiment 1 (linear kernel)



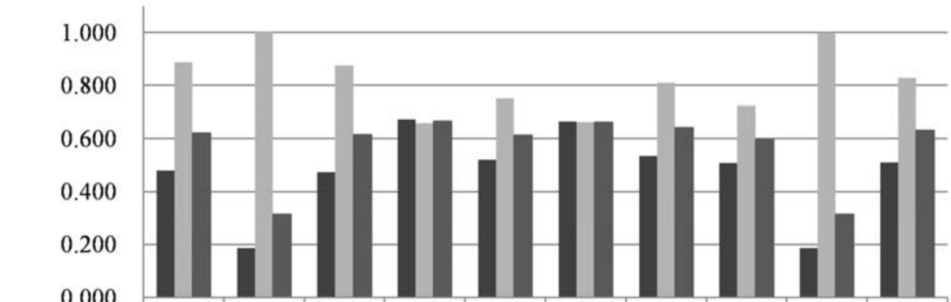
	1	2	3	4	5	6	7	8	9	10
precision	0.869	0.346	0.869	0.970	0.669	0.970	0.925	0.319	0.353	0.925
recall	0.796	1.000	0.795	0.468	0.757	0.467	0.649	0.770	1.000	0.650
F-measure	0.831	0.515	0.830	0.632	0.710	0.631	0.763	0.451	0.522	0.764

Figure 5. Results of experiment 1 (nonlinear kernel)

4.4.2 Results of Experiment 2

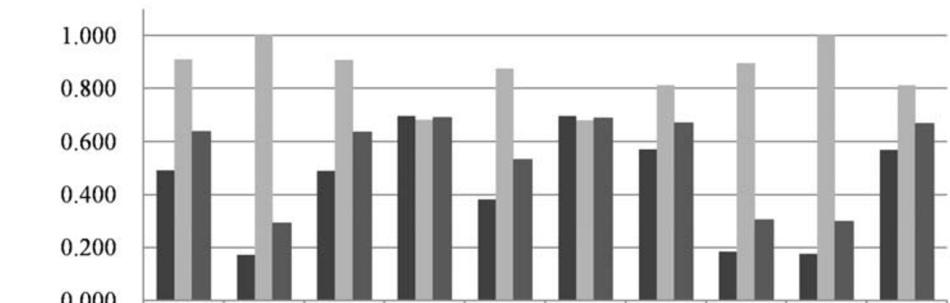
Figure 6 shows the classification results obtained using a linear kernel, and Figure 7 shows those obtained using a nonlinear kernel. The results of experiment 2 are summarized as follows:

- Training dataset 1, 3: Precision was low, while recall was high.
- Training dataset 2, 9: Precision was low, while recall was nearly 1.0. Moreover, the lowest F-measure was obtained.
- Training dataset 4, 6: Precision and recall were high on average. Moreover, the highest F-measure was obtained.
- Training dataset 5: Compared with other training datasets, results were average.
- Training dataset 7, 10: Precision was a little low, while recall was high.
- Training dataset 8: When using a linear kernel, average values were obtained. When using a nonlinear kernel, recall was high. However, the precision and F-measure were low.



	1	2	3	4	5	6	7	8	9	10
precision	0.478	0.186	0.473	0.673	0.518	0.663	0.533	0.507	0.186	0.510
recall	0.885	1.000	0.875	0.659	0.749	0.661	0.808	0.723	0.997	0.827
F-measure	0.621	0.313	0.614	0.666	0.613	0.662	0.643	0.596	0.314	0.631

Figure 6. Results of experiment 2 (linear kernel)



	1	2	3	4	5	6	7	8	9	10
precision	0.490	0.171	0.489	0.698	0.381	0.697	0.570	0.183	0.174	0.569
recall	0.909	1.000	0.907	0.683	0.875	0.680	0.811	0.893	1.000	0.811
F-measure	0.637	0.292	0.636	0.690	0.531	0.688	0.670	0.303	0.297	0.669

Figure 7. Results of experiment 2 (nonlinear kernel)

4.4.3 General Results of Experiments

Our results showed that the classification of winter-type patterns using an SVM produced a greater than 0.8 F-measure with evaluation by weak winter type, and a less than 0.7 F-measure with evaluation by strong winter type. Beyond that, there was little difference in the accuracy of classification when using linear and nonlinear kernels, except in the case of training dataset 8.

Our research used the classification by Yoshino (2002) to judge positive and negative examples and demonstrated that classification by computer is possible by selecting positive and negative examples based on a certain standard.

4.4 Consideration

The maximum value of the F-measure for the evaluation of weak winter-type patterns exceeded the maximum value for the strong winter-type evaluation by 0.1 or more. We therefore consider that the definitions for case-A to case-D, which were used in selecting positive and negative examples, were more suitable for evaluating weak rather than strong winter-type patterns.

In terms of precision, training datasets 4, 6, 7, and 10 obtained high precision when evaluated by weak winter type. With training datasets 4 and 6, case-B was treated as winter type in the evaluation, but as non-winter type (negative example) in the training phase. In other words, the training process was conducted under stricter conditions and the evaluation was conducted under relatively looser conditions. For training datasets 7 and 10, we consider that the incidence of false detection, caused by training from case-B, was restrained by not including case-B in the training datasets. However, the results for all training datasets showed low recall. Therefore, we consider that these are effective in emphasizing the truth of data classified into winter type rather than in covering winter-type data.

In terms of recall, some training datasets obtained high recall. In particular, training datasets with only case-C negative examples obtained a near 1.0 recall. This result indicates that this case represents a classification of two classes: winter and summer. The result was not surprising because it is difficult for winter data to be classified as summer-class data. However, precisions were low for individual training datasets. Thus, these are considered more effective in covering winter-type data than in emphasizing the truth of data classified into winter type.

There was little difference in accuracy between training datasets 1 and 3, 4 and 6, and 7 and 10. We thus assume that case-C, which consists of June, July and August, was not very important for the training datasets.

In the result for training dataset 8, which included comparison of linear and nonlinear kernels, and evaluation using weak winter-type patterns, the positions of precision and recall were reversed. Based on the results for training datasets 5 and 6 with case-C or case-D added to training dataset 8, we consider that the results for training dataset 8 occurred because there were no negative examples.

Several FPs belong to the typhoon type in Yoshino (2002). We consider that these were classified into winter type because of a mistake regarding the influence of a low pressure typhoon.

5 CONCLUSION AND FUTURE WORK

Using SVM, we automatically detected the winter-type pressure pattern, which is a specific pressure pattern around Japan. To select positive and negative examples, we used Yoshino (2002). We generated a number of classifiers using various training datasets, and compared the results of classification.

In experiments, our method obtained a greater than 0.8 F-measure. We also demonstrated that computer classification is possible by selecting positive and negative examples based on a certain standard. Classification accuracy depended on the training dataset used for generating classifiers.

In future research, we will focus on improving classification accuracy and classifying other pressure patterns. We will investigate whether accuracy is improved by changing the latitude and longitude when using grid data around Japan, or by using more useful elements other than pressure. In classifying other pressure patterns, appropriate elements will have to be selected carefully because elements that characterize individual pressure patterns differ.

6 ACKNOWLEDGEMENTS

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