

Severity Classification of a Seismic Event based on the Magnitude-Distance Ratio Using Only One Seismological Station

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ABSTRACT

Seismic event characterization is often accomplished using algorithms based only on information received at seismological stations located closest to the particular event, while ignoring historical data received at those stations. These historical data are stored and unseen at this stage. This characterization process can delay the emergency response, costing valuable time in the mitigation of the adverse effects on the affected population. Seismological stations have recorded data during many events that have been characterized by classical methods, and these data can be used as previous “knowledge” to train such stations to recognize patterns. This knowledge can be used to make faster characterizations using only one three-component broadband station by applying bio-inspired algorithms or recently developed stochastic methods, such as kernel methods. We trained a Support Vector Machine (SVM) algorithm with seismograph data recorded by INGEOMINAS’s National Seismological Network at a three-component station located near Bogota, Colombia. As input model descriptors, we used the following: (1) the integral of the Fourier transform/power spectrum for each component, divided into 7 windows of 2 seconds and beginning at the P onset time, and (2) the ratio between the calculated logarithm of magnitude (Mb) and epicentral distance. We used 986 events with magnitudes greater than 3 recorded from late 2003 to 2008.

The algorithm classifies events with magnitude-distance ratios (a measure of the severity of possible damage caused by an earthquake) greater than a background value. This value can be used to estimate the magnitude based on a known epicentral distance, which is calculated from the difference between P and S onset times. This rapid (< 20 seconds) magnitude estimate can be used for rapid response strategies.

The results obtained in this work confirm that many hypocentral parameters and a rapid location of a seismic event can be obtained using a few seconds of signal registered at a single station. A cascade scheme of SVMs or other appropriate algorithms can be used to completely classify an event in a very short time with acceptable accuracy using data from only one station.

RESUMEN

Los algoritmos de determinación de parámetros hipocentrales empleados en la actualidad, se basan específicamente en la información recibida en las estaciones de monitoreo mas cercanas al epicentro y no tienen en cuenta la valiosa información histórica registrada a lo largo del tiempo en dichas estaciones. Es por esto que los procesos de caracterización toman varios minutos, tiempo precioso que podría ser de gran utilidad en la generación de alertas tempranas que permitan una oportuna reacción ante el evento. El registro de información, a lo largo el tiempo, de sismos ocurridos en los alrededores de la estación, puede ser empleada para dotarla de algún grado de experiencia que le permita, mediante detección y clasificación de patrones, realizar una caracterización previa mucho mas rápida, mediante el empleo de técnicas modernas las cuales pueden ser algoritmos bio-inspirados o métodos estocásticos mas recientes conocidos como métodos Kernel. En el presente trabajo se emplea un método conocido como Maquinas de Soporte Vectorial (MSV), entrenando dicho algoritmo con información de la relación del área bajo la curva de la potencia de la transformada de Fourier de las componentes N-S, E-W y Vertical, calculada para 5 ventanas de 2 segundos, desde la onda p, de 123 sismos de magnitud superior a 3, desde 2004 hasta 2008, alrededor de la estación El Rosal, de la Red Sismológica Nacional de Ingeominas. El Algoritmo clasifica sismos que superen un umbral predeterminado de la relación entre el Logaritmo de la magnitud y la distancia, que refleja, de alguna manera, la intensidad del sismo. Con la obtención de este parámetro será posible conocer la magnitud del evento, debido a que la distancia puede ser calculada, con base en picado de la onda S, y de esta manera establecer una aproximación rápida de la magnitud en un tiempo aproximado de 20 segundos después del evento. Los resultados obtenidos permiten confirmar que con poco tiempo se señal en una sola estación sismológica es posible obtener información confiable para ser empleada en alertas tempranas.

Key words: Machine learning, seismology, single station, magnitude, distance.

Palabras clave: Aprendizaje de máquina, sismología, una estación, magnitud, distancia.

Record

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1 Introduction

Seismic activity is a natural phenomenon with enormous and uncontrollable power, and damage in populated areas can impede appropriate responses when earthquakes occur.

Recent developments have allowed efficient and alternative solutions inspired by natural and biological processes that have been converted to stochastic models and have been used in seismology with acceptable results.

When an earthquake is detected, seismologists determine its main features, such as magnitude, hypocenter coordinates, fault mechanisms, etc., to help authorities respond appropriately and allow scientists to study the Earth internal structures. Seismometers are distributed across an area of interest, many with three-component broadband sensors that detect, at the same point, movement in three mutual, orthogonal directions (North-South, East-West and up-down). These stations transmit information in near real time to seismological centers.

The traditional characterization of earthquakes takes a few minutes, depending on the degree of automatization, network density and the number of stations involved in the process. Earthquakes usually must be detected by at least five stations, and features such as compressive (P) and shear (S) wave arrival times are determined by expert analysis or an automatic algorithm. Subsequently, the hypocenter coordinates can be calculated. In Colombia, an institute called INGEOMINAS can obtain seismic event localization in approximately 8 minutes due largely to the low-density network. In some seismological centers with many stations, this time can be reduced by half because earthquake energy requires additional time to arrive at stations farther away from the hypocenter. However, we are mostly interested in earthquakes occurring near population centers, where seismic energy can arrive in tenths of a second, making warning impossible.

Long processing times are associated with conventional methods that are based on information related only to the particular event and that ignore valuable previously collected historical information.

Therefore, new alternatives must be explored to reduce the processing time and allow rapid generation of warnings. The main purpose of this study is to use historical information from only one station to detect patterns correlated with known event features available from very accurate, traditional processing.

2 Problem definition

Colombia has a central seismological network, managed by INGEOMINAS, and local networks located in certain cities, such as Armenia (Quindío) and Cali (Valle). It is important to develop a system based on these valuable resources to discover patterns that will allow more rapid seismic early warnings. Recent developments in Computational Intelligence (CI) techniques allow this goal to be achieved by solving certain seismological problems in near real time.

The automatic detection and discrimination of different events recorded with a seismometer, including seismic and non-seismic signals, using CI have been achieved using Artificial Neural Networks (ANNs) in many cases around the world. ANNs use a probe that is an excellent pattern recognition tool. ANNs were created to reproduce the mechanisms of human reasoning and allow discrimination of signals to simulate the brain processing of the operator. It is an efficient processing strategy for solving seismic signal discrimination problems, in which multiple hypotheses must be controlled in parallel, the number of input parameters is large and a well-defined solution is not always well known.

The onset time determination is usually the first step to locating the hypocenter of an event. The first arrival of a P wave can be compressive or tensile, which is key to determining the focal mechanism. Interactions between body waves and changes in the mechanical properties of rocks at strata interfaces generate diffraction and reflection phenomena, generating new body waves. These new onsets can provide clues to the distribution of strata in the subsurface, and these clues can then be used as seismic tomography data to determine the Earth's internal structure. The automatic detection of P waves can be accomplished using comparison algorithms, such as the one reported by Allen 1978, who developed an application to determine P wave onset by

comparing discrete signal parameters. The P onset is present where the short-term average (STA) of the signal increases abruptly with respect to the long-term average (LTA). Later, Allen 1982 established that technological development will lead to more efficient S wave detection through the use of a signal-in-frequency domain. Baer and Kradolfer, 1987, developed an improved methodology based on signal processing. The complexity of the S wave onset requires alternative methods to achieve better solutions. Cichowicz, 1993, developed an algorithm that identifies the S wave onset using three-component seismometers in local networks.

Recently, a neural network approach has been proposed to solve this problem because many simultaneous parameters can be included and the approach is easy to implement and flexible. It is also not necessary to be proficient with the interactions of the analyzed variables. Wang and Teng, 1997, applied a Back Propagation Neural Network (BPNN). Dai and McBeth, 1997, implemented a BPNN to identify and detect P and S waves from three-component recordings of local earthquake data. Two years later, Zhao and Takano, 1999, used BPNNs for P wave detection by combining three BPNN detectors (long, mid and short term). Aldersons, 2004, developed a system (MannekenPix) that automatically detects the phase of a wave. This program is based on a weighting mechanism calibrated with reference detections and weights provided by the user; in other words, it is a learning process that uses examples and statistical techniques to separate groups by criteria similitude. This approach is a linear combination of predictors to maximize differences among groups, while minimizing differences within groups. Di Stefano et al. 2005 applied this algorithm to achieve precise phase detection using Pg, Pn and their polarities. These authors demonstrate that such data are suitable for high-precision earthquake location, focal mechanism determination and high-resolution seismic tomography.

Once signal spectral characterization is complete and arrival times for P and S signals are determined, it is possible to generate the subsurface structure. This issue has been resolved using Computational Intelligence techniques, such as Genetic Algorithms (GAs) and Simulated Annealing (SA). A good subsurface structural model is an important step for calculating the focal parameters of seismic events. The high model combination rates obtained with GA can perform a very wide exploration of the solution's space, and this computation alternative is preferred when solving this kind of problem.

Bhattacharyya et al. 1999, analyzed regional seismograms using a GA to determine crustal structure in a four-layered crustal model of the eastern Great Basin and western Colorado plateau, in which the optimizing variables were thickness and P-wave velocity. The resulting model agreed well with results reported in several geological publications.

Chang et al. 2004, implemented a GA and modeled crustal structure in southern Korea using teleseismic P-wave receiver function data and Rayleigh-wave phase velocity measurements. The genotype describes the distribution of wave velocities and is determined using 40 1-km-thick layers. Lawrence and Wiens, 2004, combined the inversion of body wave receiver functions and Rayleigh wave phase velocities using a Niching Genetic Algorithm (NGA). Using non-unique inversion models, it is possible to explore many solutions to problems associated with the determination of focal parameters. Pezeshk and Zarrabi, 2005, developed an inversion procedure for spectral analysis of surface waves (SASW) using a Genetic Algorithm.

Kim et al. 2006, proposed a method for determining hypocentral parameters for local earthquakes in 1-D using Genetic Algorithms and two-point ray tracing, which calculates seismic ray trajectories that cross a known velocity structure. In this case, the velocity structure is not known, but the arrival times at different stations are available. With GA, it is possible to explore many subsurface velocity distributions, and a comparison between the calculated and observed arrival times can be a useful fitness selection function. Assimaki and Steidl, 2007, used a hybrid algorithm that combined a genetic algorithm with a local least-squares fit operator for inversion of weak and strong motion among an array of data obtained during the Mw 7.0 Sanriku-Minami earthquake. This combination accelerates the convergence of the GA by improving the parental population with the local hill-climbing operator.

Many of the processes mentioned above can be described by Computational Intelligence tools, which must be designed, or trained, for

particular geological, environmental and structural settings. Additionally, these techniques can be applied to function in near real time by processing information at the seismological center or directly in the sensor using electronic devices with embedded models. These devices are faster and can transmit processed information via parallel link, requiring fewer resources for transmission.

However, these processing tasks only use information transmitted from current seismic activity registered by the nearest stations. The processing takes approximately 5 to 10 minutes, which does not allow for early warnings and alerts. More stations can be used to determine seismic source magnitude and location, but more time is needed for processing; thus, less time is available for reaction.

The generation of early warnings depends on extracting the most accurate and reliable magnitude and location values using the fastest signal time. New data-driven pattern analysis models (e.g., kernel methods) with solid statistical foundations have been applied to classification and regression issues. These pattern analysis models apply historical data available in seismological databases to determine signal features (descriptors) and relationships between signal features and previously processed results. The descriptors and their relationships with previously processed results can be used to “train” certain simple algorithms, which can be used to process new data more rapidly.

Here, we present the first results obtained from a single three-component seismic station with our rapid and accurate characterization of a seismic event using only a few seconds of signal following the P wave onset. This station is near the source, where energy does not saturate the data, and uses Support Vector Machine models to obtain a Magnitude-Distance ratio from 14 seconds of signal.

3 Data set description

The data set used in this research was obtained from INGEOMINAS’s National Seismological Network. We have waveform files and calculated data from approximately 45,000 registered seismic events from 1993 to mid-2008. We selected 130 of the events registered at the “EL ROSAL” station that had magnitudes (Mb) greater than 2.1 and epicentral distances less than 120 kilometers. This station has digital, three-component broadband seismometers and is located near Bogota, which is vulnerable to medium- or high-magnitude events. This research is proposed as a first step to developing a reliable early warning system for the city. Only events registered after late 2003 were used because the three-component station data were not available prior to this time. The location of selected events is presented in Fig. 1, in which symbol size is proportional to event magnitude.

4 Methodology

One of the most important steps in Kernel Method Processing is to determine the best “descriptors” to be used as input variables for the model. These descriptors are the key to obtaining good correlations with desired output, and the selection of descriptors depends on the type of information available for processing. In this case, we have time signals, which have certain characteristic features that can be described by signal transformations, such as Fourier transform and others.

- Fourier transform was applied to each of the three components of the signal, starting at the P wave onset.
- This transform was divided into 2-second windows (80 samples).
- The integral of the squared frequency spectrum was calculated for each window, which generated one value for a given two-second partition.
- Finally, the ratios between the values of each component calculated in the step above are the input descriptors of the model and are calculated as follows:

$$xy = \frac{x}{y} \quad (1)$$

$$xz = \frac{x}{z} \quad (2)$$

$$yz = \frac{y}{z} \quad (3)$$

where x, y and z are the values of the squared Fourier Transform integral at each x, y, and z component registered at the seismological station.

These descriptors are used in our classification model as input variables.

An output value is needed to separate the two classes that represent, in some way, the severity of a given earthquake’s effects at the station site. The effects of an earthquake at any place depend directly on magnitude and inversely on epicentral distance. A ratio between the logarithm of magnitude and epicentral distance is proposed here as a classifier based upon the following equation:

$$C = \begin{cases} A, & \text{si } \frac{\log(M)}{D} > 0,5 \\ B, & \text{si } \frac{\log(M)}{D} < 0,5 \end{cases}$$

where M is body wave magnitude and D is epicentral distance, based on reports processed by INGEOMINAS for each seismic event. The physical context of this classifier variable is related to the energy that an earthquake has when it reaches the seismic station; very near events with low magnitudes are perceived to be similar to distant events with high magnitudes. Higher classifier values are obtained for high-magnitude earthquakes occurring close to the station. To achieve a balance between the number of events over and under a background limit, a value of 0.5 was determined to be the classification limit.

With calculated descriptors and the information available for the classification variable, an SVM was trained to find the optimal separator hyperplane that discriminates the events corresponding to classes A and B.

Appendix I includes the events used in the model and the calculated severity values from known magnitudes and distances, as well as the predicted SVM model.

5 Classifier evaluation

A machine learning classifier performance depends entirely on the data used for training, validation and testing. Therefore, the method’s evaluation must consider answers to certain questions about the data, such as ‘Do we have enough training data to represent the model?’; ‘Do we have balanced training data for each considered class?’; ‘What is the effect of re-using data in the training sets?’; etc.

To answer these questions, the algorithms and data used in this research were evaluated using 10-Fold Cross Validation techniques, and the results are summarized below.

[Complexity C=0.1]

	<i>Predicted</i>	
<i>Real</i>	A	B
A	9	32
B	0	98

[Complexity C=1]

	<i>Predicted</i>	
<i>Real</i>	A	B
A	20	12
B	4	94

[Complexity C=10]

	<i>Predicted</i>	
<i>Real</i>	A	B
A	22	10
B	3	95

Table 1: Confusion matrix.

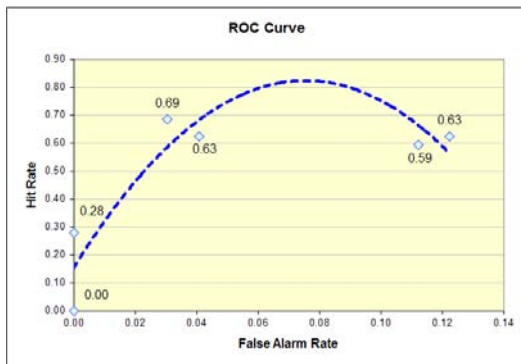
% correctly classified instances	87.69%
% incorrectly classified instances	12.31%
Mean Absolute Error	0.12
Mean Square Root Error	0.35
Relative Mean Absolute Error	32.95
Relative Mean Square Root Error	81.39

Table 2: SVM Classifier with Quadratic Kernel results.

	A	B
True Positives	62.5%	95.9%
False Negatives	4.0%	37.5%
Precision	0.830	0.887
Recall	0.625	0.959
Mean-F	0.714	0.922
ROC Curve Area	0.792	0.792

Table 3: Estimated error of the SVM Quadratic Kernel Classifier.

Table 1 shows the results from the determination algorithm of the meta parameters, which determine the curve ROC that was used to evaluate the value of C for which the classification model has the best results. Figure 2 shows the curve ROC for multiple values of C , achieving the best value as a compromise between hits and false alarms. Similar curves were generated to locate other parameters, such as the degree of polynomial function used for mapping vectors in the feature space. Using this approach, the quadratic kernel was selected as the best mapping function for this problem and dataset. Figure 2 shows the relationship between the numbers of hits and false alarms, which are determined using the following equations:

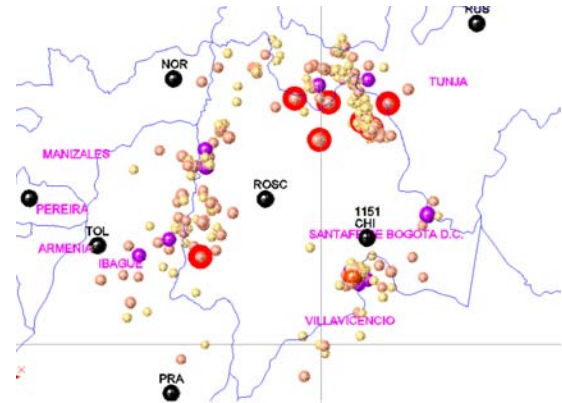
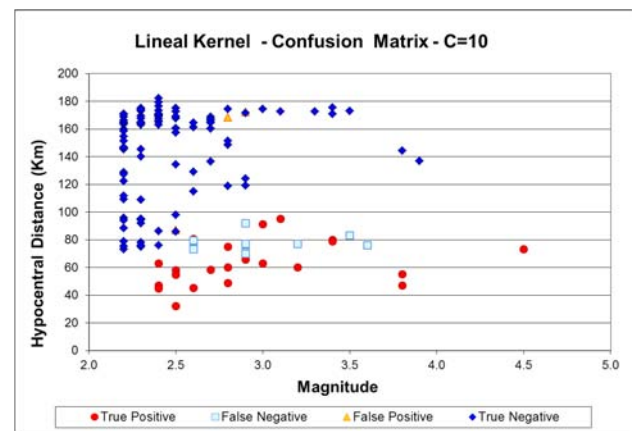
**Figure 2:** ROC curve for C estimation.

$$\text{HitRate} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalseNegative}}$$

$$\text{FlaseAlarmRate} = \frac{\text{FalsePositive}}{\text{FalsePositive} + \text{TrueNegative}}$$

Wrongly classified events that exceeded the background limit of C , known as “false negatives”, are cases where no alarm was generated but a moderate event was imminent. This unique situation indicates that there is a local condition that must be analyzed carefully to determine the area’s unique pattern (Figure 3). To increase accuracy and obtain better results, it is necessary to explore other descriptors.

Figure 4 plots the values of the confusion matrix. There is a very good correlation for a severity threshold of 0.5. This result can be used as an initial early warning parameter.

**Figure 3:** Wrongly classified events (red points).**Figure 4:** Plotted confusion matrix.

6 Results

Results obtained in this study using the classification methods described above are presented in Tables 2 and 3. Class B events were classified with high accuracy, but Class A events were wrongly classified in 31% of the cases.

Future work will focus on the identification of new descriptors to better characterize the input signal using a priori knowledge. It is possible to implement new strategies using *Bagging*, which combines many algorithms.

The described algorithm proposes a new classification method for early warning purposes only.

7 Conclusions

- The structure of the input data is important for classifier behavior and determining relationships within the model. One of main challenges in this work was selecting the best signal descriptors and determining the relationships between them.
- With a small signal interval processing from only one seismological station, it will be possible to estimate parameters such as *magnitude* and *distance*, which will allow the rapid classification of a seismic event based only on the effects at this station.
- Previous determinations of hypocentral parameters ignore historical data from previous seismic events and instead use only information recorded during current earthquakes. The proposed method uses historical data to calculate a relationship between *magnitude* and *distance* and allows rapid warning generation times.
- The results suggest that it is possible to use the proposed method to calculate other hypocentral parameters, such as hypocenter location, azimuth, distance and others.

- Improvements to the technique can be accomplished by including a priori information in descriptors calculated from signals and spectral characteristics. These techniques have been used previously as input in some artificial intelligence approaches and resulted in better accuracy and faster processing times.

- The adjustment results obtained using this approach cannot be compared with conventional strategies because they do not use the same information. This approach is based on a single station, whereas others are based on multiple stations (no fewer than 5).

- Early detection systems must consider combined strategies to optimize the identification of descriptors that can be used more efficiently in these types of approaches.

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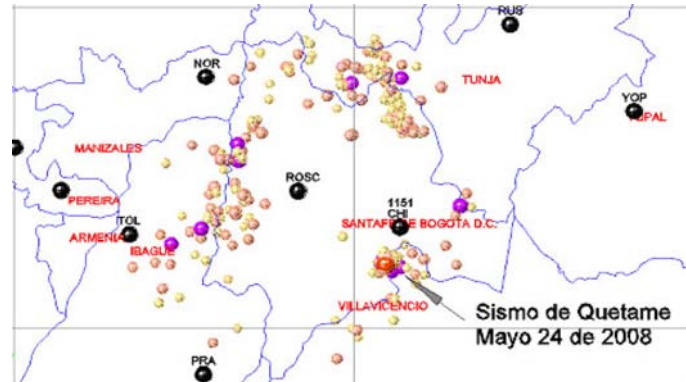


Figure 1: Selected earthquakes.

Appendix I: List of used events and parameters.

DATE	TIME	LAT	LON	DIST	MAG	DEPTH	HYPO DIST	Log Mag Dist Hipo	CLASSIFICATION	
									REAL (0.5)	PREDICTED
07/11/2002	22:22	4.008	-74.15	96	2.2	0	96.0	0.36	B	B
13/11/2002	23:23	5.775	-73.906	112	2.5	115	160.5	0.25	B	B
08/01/2003	09:09	4.492	-74.898	75	2.2	6	75.2	0.46	B	B
14/04/2003	22:22	4.658	-74.535	32	2.5	3.1	32.1	1.24	A	A
29/04/2003	01:01	4.05	-74.11	92	2.9	2.6	92.0	0.50	A	B
08/06/2003	10:10	5.258	-73.649	88	2.4	156.2	179.3	0.21	B	B
12/06/2003	11:11	4.636	-74.647	43	2.8	22.9	48.7	0.92	A	A
20/06/2003	01:01	4.684	-74.785	54	2.7	21.9	58.3	0.74	A	A
28/06/2003	23:23	5.59	-74.352	81	2.2	100.3	128.9	0.27	B	B
01/07/2003	21:21	4.159	-75.146	119	2.8	0	119.0	0.38	B	B
20/08/2003	23:23	5.519	-73.858	90	2.4	136	163.1	0.23	B	B
01/09/2003	11:11	5.543	-74.389	76	2.6	104.3	129.1	0.32	B	B
19/10/2003	02:02	5.618	-73.915	96	2.8	117.3	151.6	0.30	B	B
20/10/2003	11:11	5.778	-74.675	109	2.2	6.8	109.2	0.31	B	B
31/10/2003	00:00	5.213	-73.714	79	2.8	155.5	174.4	0.26	B	B
03/11/2003	20:20	5.704	-74.413	94	2.2	0	94.0	0.36	B	B
09/11/2003	14:14	5.375	-74.927	88	2.2	8.2	88.4	0.39	B	B
20/12/2003	19:19	5.219	-74.546	47	3.8	2.2	47.1	1.23	A	A
26/12/2003	12:12	5.779	-73.873	114	2.9	129.4	172.5	0.27	B	A
02/01/2004	09:09	5.74	-74.311	98	2.5	1	98.0	0.41	B	B
12/01/2004	17:17	5.589	-73.874	96	2.3	134	164.8	0.22	B	B
24/01/2004	07:07	5.805	-73.878	116	2.8	122	168.3	0.27	B	A
01/02/2004	10:10	5.431	-73.741	91	2.7	142.3	168.9	0.26	B	B

10/03/2004	07:07	4.54	-75.06	88	2.3	26	91.8	0.39	B	B
24/03/2004	01:01	5.868	-74.003	118	2.4	138.8	182.2	0.21	B	B
01/04/2004	15:15	5.443	-73.781	89	2.2	140.6	166.4	0.21	B	B
04/04/2004	16:16	4.347	-73.853	77	3.2	4	77.1	0.66	A	B
17/04/2004	20:20	5.577	-73.884	94	2.6	135.2	164.7	0.25	B	B
19/04/2004	00:00	4.579	-74.776	58	2.5	0	58.0	0.69	A	A
24/04/2004	13:13	5.315	-73.774	80	2.6	140	161.2	0.26	B	B
16/05/2004	01:01	5.629	-73.893	98	2.4	135.7	167.4	0.23	B	B
25/05/2004	17:17	4.678	-74.679	43	2.6	14	45.2	0.92	A	A
24/06/2004	23:23	4.686	-74.807	56	3.2	21.7	60.1	0.84	A	A
28/06/2004	12:12	5.435	-73.769	89	2.7	140.7	166.5	0.26	B	B
24/07/2004	22:22	5.215	-74.552	47	2.4	3.2	47.1	0.81	A	A
22/08/2004	02:02	5.067	-74.761	53	2.5	13.6	54.7	0.73	A	A
22/08/2004	17:17	5.596	-73.856	97	2.5	124	157.4	0.25	B	B
26/08/2004	04:04	5.628	-73.986	93	2.3	111.9	145.5	0.25	B	B
27/09/2004	14:14	5.785	-73.924	112	2.2	102	151.5	0.23	B	B
07/10/2004	23:23	5.605	-74.381	83	2.2	96.4	127.2	0.27	B	B
21/11/2004	14:14	5.361	-73.725	87	2.9	147.8	171.5	0.27	B	B
22/11/2004	10:10	4.583	-75.138	95	3.1	0	95.0	0.52	A	A
19/12/2004	14:14	4.053	-74.039	95	2.3	0	95.0	0.38	B	B
01/01/2005	15:15	5.013	-74.844	60	2.4	18.3	62.7	0.61	A	A
21/01/2005	07:07	5.419	-73.742	90	2.3	148	173.2	0.21	B	B
23/01/2005	07:07	5.241	-73.686	83	2.3	153.1	174.2	0.21	B	B
08/02/2005	09:09	5.367	-74.91	86	2.4	7.8	86.4	0.44	B	B
11/02/2005	22:22	5.278	-73.777	77	2.4	155.4	173.4	0.22	B	B
06/04/2005	19:19	5.791	-74.028	109	2.3	1.8	109.0	0.33	B	B
16/04/2005	05:05	5.453	-73.817	87	2.2	134.4	160.1	0.21	B	B
04/05/2005	12:12	5.291	-73.736	82	2.7	146	167.5	0.26	B	B
26/05/2005	09:09	4.681	-74.863	62	2.9	22.2	65.9	0.70	A	A
30/06/2005	03:03	5.326	-73.756	82	2.4	143.5	165.3	0.23	B	B
10/07/2005	03:03	4.415	-75.05	94	2.3	8.7	94.4	0.38	B	B
16/07/2005	12:12	5.594	-73.891	95	2.2	122	154.6	0.22	B	B
16/07/2005	02:02	5.92	-74.499	119	2.2	28.7	122.4	0.28	B	B
29/07/2005	22:22	5.632	-74.61	91	3	4	91.1	0.52	A	A
05/08/2005	01:01	5.716	-74.38	95	2.2	58.7	111.7	0.31	B	B
15/08/2005	18:18	5.608	-73.867	98	2.3	131.7	164.2	0.22	B	B
19/08/2005	23:23	5.304	-73.751	81	2.4	150.5	170.9	0.22	B	B
09/10/2005	04:04	5.325	-73.721	85	2.3	146.8	169.6	0.21	B	B
15/10/2005	01:01	5.749	-73.973	106	2.2	101.5	146.8	0.23	B	B
23/10/2005	13:13	5.744	-73.906	109	2.8	100.9	148.5	0.30	B	B
12/11/2005	09:09	5.289	-73.751	80	2.2	144	164.7	0.21	B	B
17/11/2005	03:03	4.728	-74.708	44	2.4	8.7	44.9	0.85	A	A
21/11/2005	00:00	5.325	-73.761	82	2.2	150.1	171.0	0.20	B	B
02/01/2006	00:00	5.45	-74.159	68	3.5	48	83.2	0.65	A	B
07/02/2006	03:03	5.321	-73.76	81	2.7	143.6	164.9	0.26	B	B
27/03/2006	02:02	5.286	-73.813	74	2.2	151.6	168.7	0.20	B	B
04/06/2006	06:06	5.6	-73.869	97	2.2	131.5	163.4	0.21	B	B
17/06/2006	05:05	5.287	-73.724	82	2.4	148.3	169.5	0.22	B	B
20/06/2006	18:18	4.177	-74.54	79	2.6	0	79.0	0.53	A	B

21/06/2006	03:03	5.435	-73.802	87	2.3	138	163.1	0.22	B	B
10/07/2006	07:07	5.284	-73.738	81	3.4	155.7	175.5	0.30	B	B
06/08/2006	04:04	5.615	-74.045	90	2.3	107.3	140.0	0.26	B	B
16/08/2006	04:04	5.301	-73.754	81	2.3	155.2	175.1	0.21	B	B
06/09/2006	00:00	5.641	-73.88	100	2.4	132	165.6	0.23	B	B
06/09/2006	09:09	5.299	-73.735	82	2.4	149.5	170.5	0.22	B	B
18/09/2006	17:17	5.312	-73.745	82	2.5	154.9	175.3	0.23	B	B
06/10/2006	03:03	5.281	-73.713	83	2.5	151.4	172.7	0.23	B	B
23/10/2006	22:22	5.289	-73.709	84	3.4	148.9	171.0	0.31	B	B
01/11/2006	12:12	5.206	-74.013	52	3.9	126.5	136.8	0.43	B	B
07/11/2006	07:07	5.274	-73.708	83	3.5	151.8	173.0	0.31	B	B
12/12/2006	07:07	5.09	-74.781	56	2.8	22	60.2	0.74	A	A
18/01/2007	19:19	5.591	-74.086	86	2.5	103.3	134.4	0.30	B	B
27/01/2007	05:05	5.515	-74.078	78	2.7	112.2	136.6	0.32	B	B
31/03/2007	01:01	5.69	-73.865	106	2.4	131.7	169.1	0.22	B	B
12/04/2007	16:16	5.485	-73.82	90	2.4	144.5	170.2	0.22	B	B
16/04/2007	07:07	4.582	-74.754	56	3	28.3	62.7	0.76	A	A
03/05/2007	07:07	5.737	-73.902	108	2.2	98.5	146.2	0.23	B	B
19/05/2007	07:07	4.526	-75.309	115	2.6	0	115.0	0.36	B	B
29/06/2007	17:17	5.303	-73.705	85	2.2	148.3	170.9	0.20	B	B
10/07/2007	17:17	5.272	-73.664	87	2.4	153.6	176.5	0.22	B	B
14/07/2007	10:10	5.238	-73.701	82	2.3	143.2	165.0	0.22	B	B
16/10/2007	10:10	5.293	-73.669	88	2.5	142.7	167.7	0.24	B	B
12/11/2007	09:09	5.459	-73.803	89	2.7	133.4	160.4	0.27	B	B
17/11/2007	21:21	5.771	-74.26	102	2.9	62	119.4	0.39	B	B
02/12/2007	11:11	4.696	-73.647	77.8	2.6	15.7	79.4	0.52	A	B
17/12/2007	09:09	5.263	-73.673	85.7	3.1	150	172.8	0.28	B	B
29/12/2007	06:06	5.265	-73.717	81.6	3.3	152	172.5	0.30	B	B
11/01/2008	02:02	5.305	-73.739	82	2.3	146.3	167.7	0.22	B	B
13/01/2008	04:04	5.244	-73.649	87	3	151.4	174.6	0.27	B	B
14/03/2008	16:16	4.88	-74.821	55	3.8	4	55.1	1.05	A	A
07/04/2008	04:04	5.345	-73.785	81	2.2	136.3	158.6	0.22	B	B
13/04/2008	02:02	5.622	-73.941	95	2.2	110.2	145.5	0.24	B	B
24/05/2008	19:19	4.422	-73.83	73	4.5	6.3	73.3	0.89	A	A
24/05/2008	21:21	4.409	-73.762	80	3.4	2.9	80.1	0.66	A	A
24/05/2008	19:19	4.395	-73.82	76	3.6	4	76.1	0.73	A	B
24/05/2008	21:21	4.452	-73.766	77	2.9	0	77.0	0.60	A	B
24/05/2008	17:17	4.453	-73.83	71	2.9	0	71.0	0.65	A	B
24/05/2008	21:21	4.512	-73.657	84	2.5	22.8	87.0	0.46	B	A
24/05/2008	23:23	4.58	-73.726	74	2.4	17.6	76.1	0.50	B	B
24/05/2008	19:19	4.431	-73.797	76	2.3	4	76.1	0.48	B	B
25/05/2008	11:11	4.452	-73.799	74	2.8	12	75.0	0.60	A	A
25/05/2008	17:17	4.475	-73.729	79	2.6	15.9	80.6	0.51	A	A
25/05/2008	00:00	4.483	-73.825	70	2.9	0	70.0	0.66	A	B
25/05/2008	02:02	4.406	-73.698	86	2.5	0	86.0	0.46	B	B
25/05/2008	06:06	4.439	-73.76	78	2.2	10.8	78.7	0.43	B	B
26/05/2008	01:01	4.461	-73.775	75	2.3	3.4	75.1	0.48	B	B
30/05/2008	19:19	4.439	-73.767	78	2.3	0	78.0	0.46	B	B