NEURAL NETWORK RETRIEVAL OF UPPER LEVEL WINDS FROM GROUND BASED PROFILER MEASUREMENTS

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Abstract

In artillery meteorology, measurements of upper level winds are important to the accuracy of calculated ballistic trajectories. One of the objectives of the MMS-Profiler POC (Meteorological Measurement Set – Profiler Proof of Concept) is to monitor the wind fields continuously so that meteorological data can be timely and accurate during artillery operations. Previous work involved experimentation with neural network methods to retrieve temperature profiles from ground based microwave radiometers and to retrieve winds from satellite sounder data. Those experiments have yielded errors comparable to those achieved by other sounder based methods. Current studies involve the fusion of varied measurement sources to improve the upper level wind retrievals using neural network techniques. Neural networks are ideally suited for processing diverse data measurements and allowing analysis of large data sets. The MMS-Profiler POC comprises a suite of remote sensing instruments combined with surface measuring systems. The wind profiling radar, an integral part of the MMS-Profiler POC, is capable of measuring wind velocities from the near surface up to 7 kilometers depending on atmospheric conditions. A neural network has been developed to estimate upper level winds from these lower wind measurements. To demonstrate the feasibility of this method, a large training and testing set was extracted from the NCDC archived radiosonde data of North America (1946-1994) for El Paso, Texas. The 700mb level winds were used as input into the neural network to derive the 400mb level winds in the preliminary test runs. The results show U wind component RMS errors of 9.01 m/s and V wind component RMS errors of 8.03 m/s. Future studies are discussed.

Introduction

In artillery meteorology, measurements of upper level winds are important to the accuracy of calculated ballistic trajectories. One goal of the MMS-Profiler POC (Meteorological Measurement Set – Profiler Proof of Concept) (Cogan et al, 1998a) is to monitor the wind fields continuously so that meteorological data can be timely and accurate during artillery operations. The wind profiling radar is one of the primary remote measurement instruments of the MMS-Profiler POC system. Previous work involved experimentation with neural network methods to retrieve temperature profiles from ground based microwave radiometers (Measure et al, 1998) (Bustamante et al, 1994) and to retrieve winds from satellite sounder data (Cogan et al, 1998b). Those experiments have yielded errors comparable to those achieved by other sounder based methods (Butler et al, 1996).

Current studies involve the fusion of varied measurement sources to improve the upper level wind retrievals using neural network techniques. Neural networks are ideally suited for processing diverse data elements and allowing analysis of large data sets. The MMS-Profiler POC comprises a suite of remote sensing instruments combined with surface measuring systems. The wind profiling radar, an integral part of the MMS-Profiler POC, is capable of measuring wind velocities from the near surface up to 7 kilometers depending on atmospheric conditions.

An initial neural network has been developed to estimate upper level winds from these lower wind measurements. Archived radiosonde data from the NCDC (National Climatic Data Center) covering the period 1946-1994 was used to train and test out the neural network. To demonstrate the feasibility of this method, a large training and testing set was extracted from the NCDC archived radiosonde data of North America (1946-1994) for El Paso, Texas. The 700mb level winds were used as input into the neural network to derive the 400mb level winds in the preliminary test runs.

Background

Upper level winds can have a significant effect on the trajectory of artillery rounds. Unfortunately, collecting timely and accurate upper level winds has been one of the shortcomings of all wind measuring instruments. Current methods to obtain wind velocity profiles include satellite-based data, thermal wind approximations, cloud tracking (Nieman et al, 1997), moisture field tracking (Velden et al, 1997), and radar. Each of these methods can provide useful information for some synoptic scale applications but each one has certain limitations.

The wind radar systems provide accurate and timely wind velocities but these measurements usually do not extend beyond 5-7 kilometers in height. Satellite measurements can collect wind information at higher atmospheric levels but the accuracy is not sufficiently adequate for precise artillery operations. Figure 1 depicts the ideal scenario in which satellite based measurements are coincident with ground based wind profiling measurements. The ultimate goal would be to combine both measurements to produce an optimal wind profile.

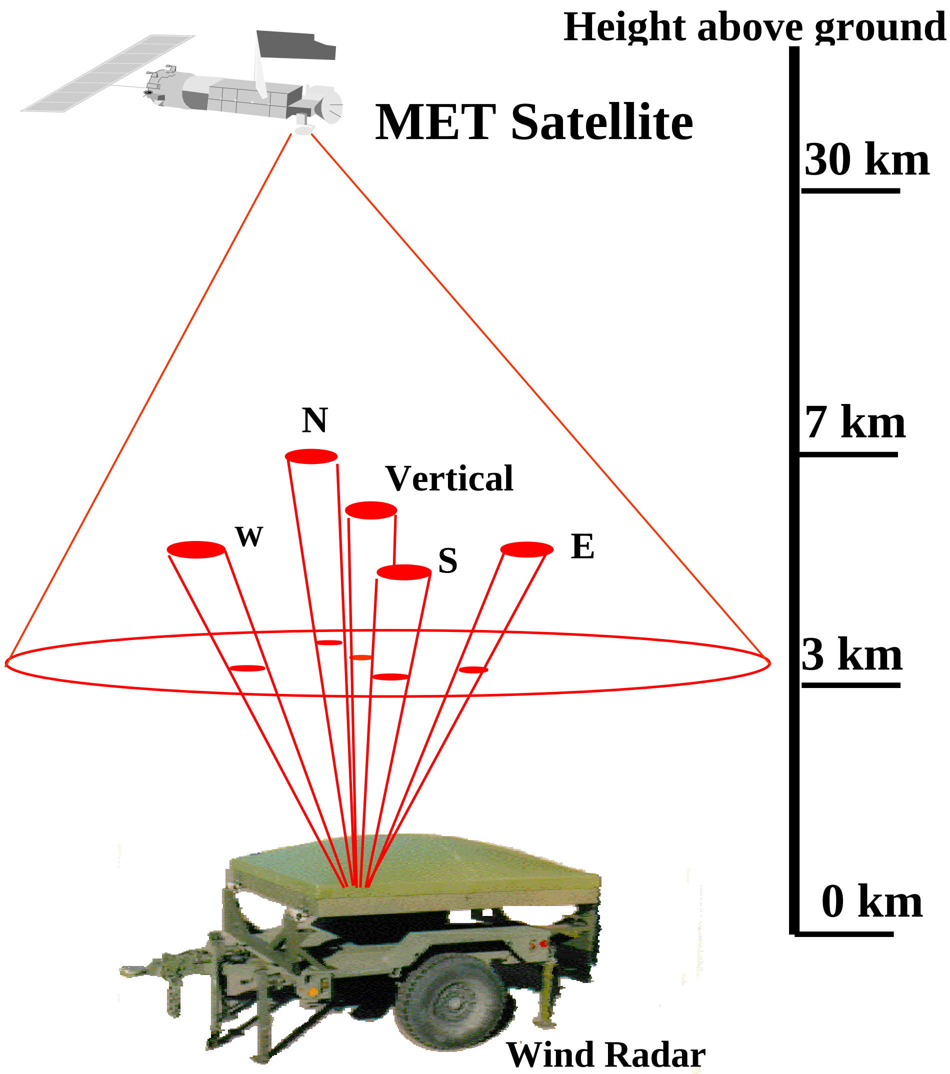

Figure 1. Idealized measurement of the wind field using combined ground based wind radar and satellite based derived winds.

Wind Profiling Radar System

The wind profiling radar system is one of the key components of the MMS-P(POC). The instrument is capable of collecting accurate wind vectors from near the surface to a height of 4 to 7 kilometers depending on the atmospheric conditions. Figure 2 is a photograph of the 924MHz wind profiling radar antenna built onto a High Mobility Trailer (HMT). The processing hardware and software is installed inside a shelter on a High Mobility Multi-Wheeled Vehicle (HMMWV). There are different radar signal processing methodologies to extract wind direction and speed. One technique is the Advanced Signal Processing (ASP) method and another one is the more traditional consensus method. A comparison of the two methods is given by Creegan (2000).

Figure 2. Photograph of the 924 MHz wind profiling radar antenna towed by HMMWV. Processing hardware and software are housed inside the HMMWV's shelter.

Figures 3 and 4, wind speed and wind direction respectively, represent a derived wind profile from the wind radar using the consensus processing method. The data was taken at the White Sands Missile Range, New Mexico on August 10, 1999. The data was taken within several miles of a mountain range which may account for the variability in the vertical profile. When comparing wind profiling measurements with rawinsonde measured winds, past field data show reasonable agreement even though the wind profiler is a volumetric measurement versus a point by point displacement measurement used by the rawinsonde.

Neural Network Methodology for Winds

An overview of the neural network procedure is shown in figure 5. Training the neural network would involve the collection of coincident wind radar data and rawinsonde data. These data would be filtered via algorithms that screen the data for missing fields and defective data records. If a data field is missing in any of the input sets, the case for that wind profile was rejected for the purpose of training or testing. After extracting the wind direction and wind speed for selected height levels of interest, the wind parameters were converted to U (East-West) and V (North-South) wind

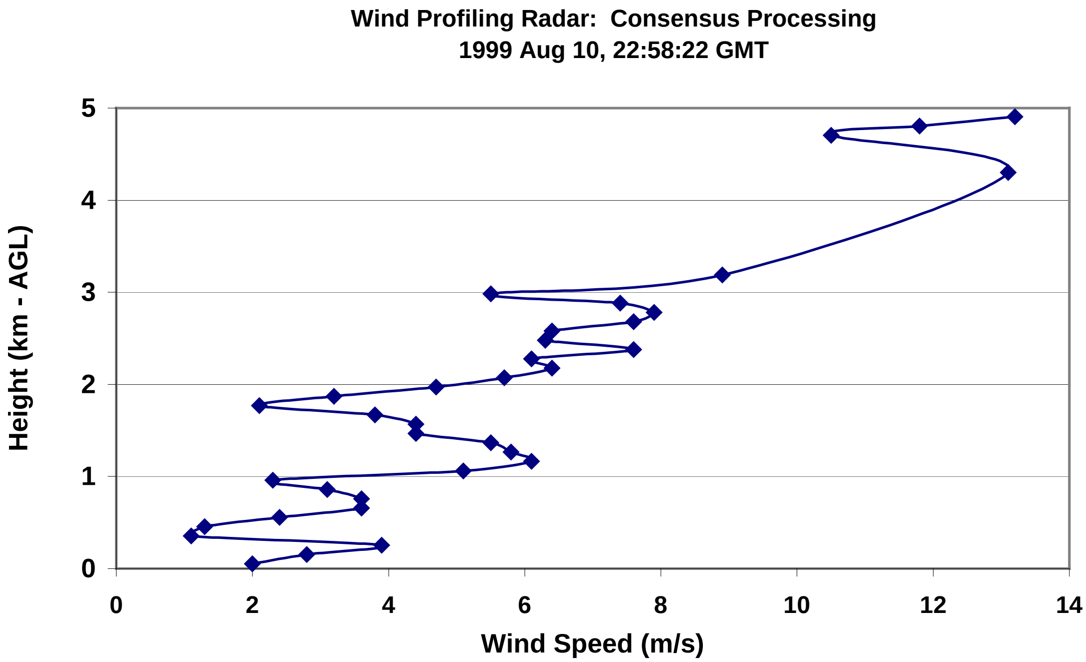

Figure 3. Wind profiling radar sample measurement showing Wind Speed from the near surface to 5 kilometers.

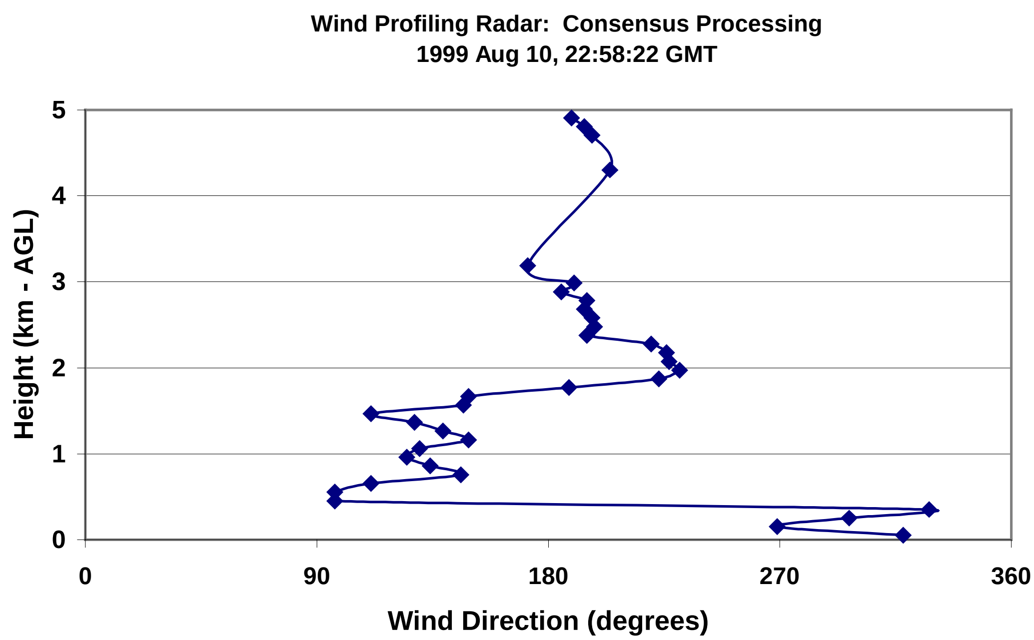

Figure 4. Wind profiling radar sample measurement showing Wind Direction from the near surface to 5 kilometers. Corresponds with the same profile shown in Figure 3.

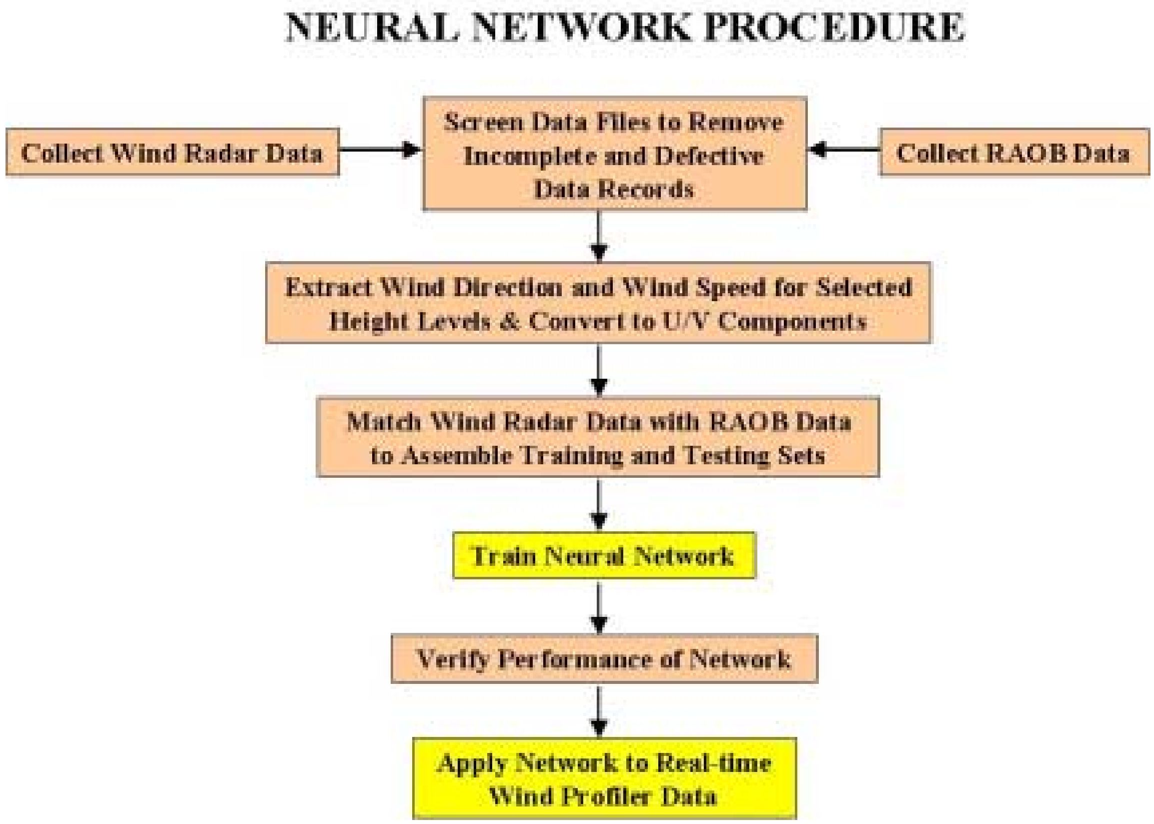

Figure 5. Flowchart of the neural network procedure for deriving upper level winds. The training set is used to train the neural network and the testing set is used to verify the performance of the network.

components. To assemble the training and testing sets for the neural network, wind radar data would then be matched with the appropriate rawinsonde data. The wind radar measurements can be taken continuously but the rawinsonde wind data may take over an hour to complete its profile. Thus exact matching is not possible.

Previous work by Bustamante et al (1999) and Gutman (1998) have shown that a back propagation, feed forward, neural network is appropriate for these types of physical measurements. Using a commercially available neural network development package, the following parameters were defined for the existing neural network (Table 1).

Table 1. Neural Network Parameters

Learning Rule	Delta-Rule
Transfer Function	Sigmoid
Summation	Sum
Noise	Uniform

Network Training Data Sets

The first step in the neural network development was to obtain archived National Climatic Data Center (NCDC) meteorological data, "Rawinsonde Data of North America" (Vols 1-4, 1946-1994), with enough cases to adequately train the network. Since there was only a small data set of coincident wind radar profiles and rawinsonde wind profiles to train the neural network, the rawinsonde measurements in the lower atmosphere were used in lieu of actual wind radar data for this study. The number of cases or rawinsonde profiles used for the training testing sets are shown in Table 2.

Table 2. Training and Testing Sets

Number of Training Cases	20,223
Number of Testing Cases	3,999

Simulated Tests to Derive Upper Level Winds

For these studies, archived rawinsonde soundings from the National Climatic Data Center for El Paso, Texas (1957-1994) was used. El Paso is approximately 60 miles from the White Sands Missile Range, NM and the latitude is 31.84N with a longitude of 1.06.40W. Data for both the 0000 UTC and the 1200 UTC cases were included in the assembled data sets.

To show the feasibility of the methodology, preliminary neural network runs were made to derive 400mb upper level winds from the corresponding 700mb winds. Figure 6 is a scatter diagram showing the results of the derived (predicted) U component winds at 400mb versus the corresponding "true" rawinsonde U component wind at the same height level. Figure 7 is a scatter diagram showing the corresponding comparisons for the V component of the winds at 400mb level. The RMS error for the U component of the wind in the testing set was 9.1 m/s and the RMS error for the V component of the wind was 8.3 m/s. Comparing the ground-based derived winds at 400mb with previous derived winds from satellite radiances at the same height level, the RMS errors are comparable for the U component but there appears to be better correlation for the ground-based derived V component winds over the satellite derived V components.

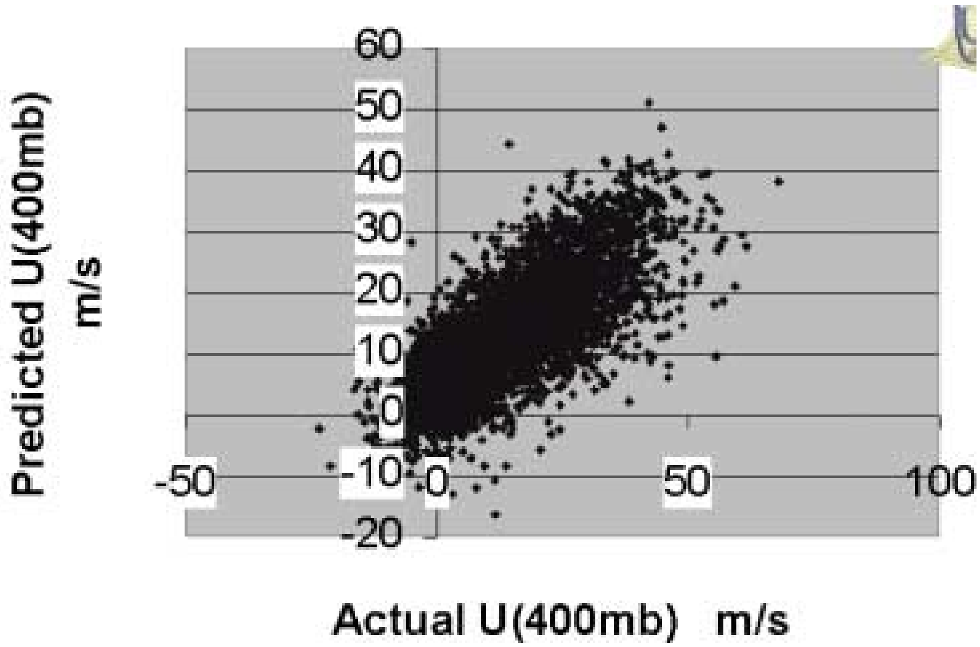

Figure 6. Scatter diagram comparing neural network derived (predicted) U(400mb) component winds using 700mb winds as input versus "true" rawinsonde U component winds at 400mb.

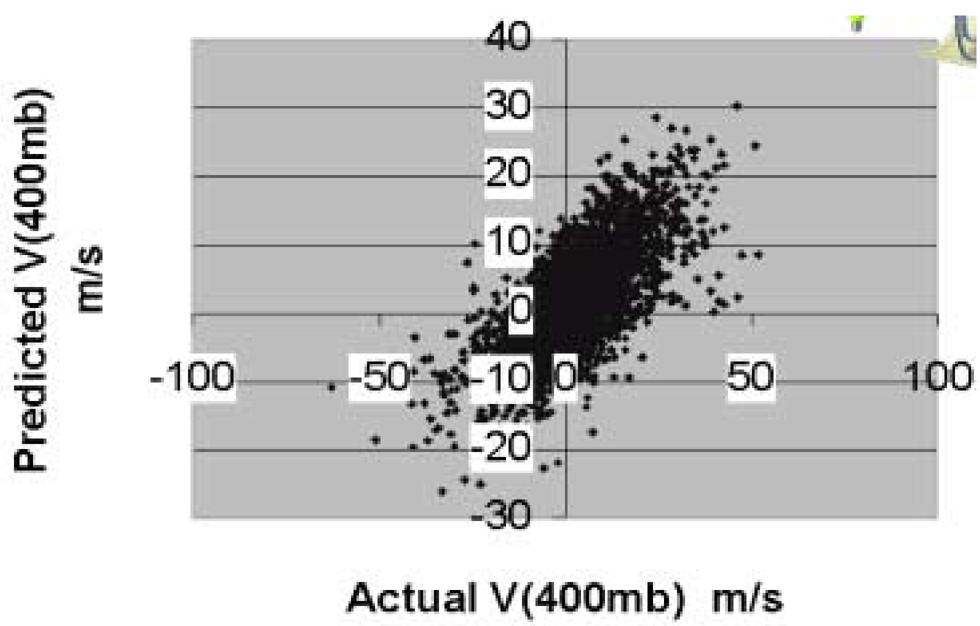

Figure 7. Scatter diagram comparing neural network derived (predicted) V(400mb) component winds using 700mb winds as input versus "true" rawinsonde V component winds at 400mb.

Recommendations

From these preliminary studies, future work will center on the following directions:

- Collect more real measurements of coincident wind radar and rawinsonde profiles to provide a large enough data set to train the neural network.
- Incorporate more lower level winds at different heights as input into the neural network for upper level wind inference.
- Combine satellite radiance fields and lower level winds based on wind radar capabilities to produce a multi-sensor training set
- Investigate other sites
- Train on data sets that covers a range of geographical locations to increase the robustness of the neural network

Conclusions

Initial trial runs using near surface winds as input to a neural network to derive upper level winds at 400mb showed poor correlation with the "true" rawinsonde winds at the same height level. This suggests that lower boundary layer effects are important. The wind profiling radar is capable of measuring winds above the boundary layer where correlation to upper level winds should be reasonably better.

A neural network was developed to derive upper level winds at 400mb using winds at 700mb as input into the network. At the test site of El Paso, the 700mb height above sea level is approximately 3100 to 3200 meters and the 400mb height above sea level is approximately 7400-7500 meters. The results show U wind component RMS errors of 9.1 m/s and V wind component RMS errors of 8.3 m/s.

The next step will be to use real wind radar measurement as input into the trained neural network and compare the predicted upper level winds with the actual rawinsonde measured winds. Future work will be to develop a network that uses information from both the satellite and ground-based wind profiler to produce an optimal wind profile. The results are encouraging but much work needs to be done to provide the optimal wind profile from the near surface up to 30 kilometers as required by the future artillery met.

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