

LINFO2275: project 2

Hand gesture recognition

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1 Introduction

We want to implement a hand gesture recognition system for a smart user interface. A 3D tracking of the position vector $\mathbf{r}(t) = (x(t), y(t), z(t))^T$ of the hand is recorded as a sequence of the 3 coordinates in function of the time t ¹. The user is executing a sketch that is recorded and recognized by the system.

In order to recognize two different kind of sketches, the system will be trained by two algorithms: a K-Nearest Neighbors classifier using dynamic time warping (dtw) as a distance function and a \$P\$-recognizer.

A first dataset contains the records of the numbers 0, 1, 2, 3, 4, 5, 6, 7, 8, 9 in three dimensions. We asked 10 users to draw 10 times each of these numbers. We have therefore a total of 1000 sequences. A second dataset contains the records of three-dimensional figures. As for the precedent dataset, 10 users have drawn each figure 10 times.

To analyse the results we will use two cross-validation scheme, the first one is *user-independent* which means that for each split, we use the data from 9 users to fit the model and the data from remaining user to test the model. The second one is *user-dependent* which means that for each split, we use 9 examples from each user to fit the model and the remaining example of each user to test the model.

2 Preprocessing

We first embedded the datas in a list of 1000 entries. Each entry consist in a matrix of dimension $(n_timepoints, vec_dimension)$ where $n_timepoints$ is the length of the time series and $vec_dimension$ is the dimension of the position vector which is 3 in our case. It's worth noticing that each time series can have different length. After that, we resampled each time series into $N = 64$ points for the dtw algorithm and into $N = 32$ points for the \$P\$-Recognizer algorithm by performing interpolation. Indeed, performing vector-quantization using a k-means algorithm gave us poor results so we chose to resample by interpolation as proposed in the following article (Wobbrock et al., 2007). This article claim that resampling time series into a number of points between 32 and 64 gives good results. We noticed it was also the case for the DTW algorithm and chose to limit ourself to 32 points for the \$P\$-Recognizer algorithm as resampling into more points implies too long computation time.

3 Dynamic time warping

3.1 Introduction

Given a time series of three-dimensional unknown vector data points, we would like to predict the sketch represented by these points. In order to do this, we used a K-Nearest Neighbors approach where we find the k most similar time series in the dataset and use the most represented target value among the k time series to use it as the prediction output.

To find the k most similar time series, we use a distance function as the similarity measure. However, we cannot use the often used euclidean distance as it produces pessimistic results when dealing with time series of different lengths (a typical example is two same time series with one shifted on the time axis).

Dynamic time warping — a often used technique in speech recognition problem — is a solution to this problem, it finds the optimum alignment between two time series by "warping" non-linearly a time series stretching or shrinking its time axis. Once we found the optimal alignment, we can determine the similarity between these twos.

¹Note that we will not consider the precise recorded time of the observations.

Let $s = (s_1, \dots, s_n)$ and $t = (t_1, \dots, t_m)$ be two time series of length n and m respectively where s_i, t_j are the position vector $\in \mathbb{R}^3$ for $i = 1, \dots, n$ and $j = 1, \dots, m$. We define a warping of order $n \times m$ as a sequence of k points $x = (x_1, \dots, x_k)$ where $x_l = (i_l, j_l) \in [1, n] \times [1, m]$. Each points x_l of the path aligns the vector s_{i_l} with the vector t_{j_l} .

The following constraints apply,

- **boundary conditions:** $x_1 = (1, 1)$ and $x_k = (n, m)$. This ensures that every index of the time series are used in the warp path.
- **locality:** $x_{l+1} - x_l \in \{(1, 0), (1, 1), (0, 1)\}, \quad \forall l \in [1, k - 1]$.

The locality condition implies a monotonicity condition: $s_1 \leq \dots \leq s_n$ and $t_1 \leq \dots \leq t_m$. This monotonicity implies that the lines representing the warp path do not overlap.

Among all the warping path we can construct, want to find the optimal warping path x^* that consists in the warping path that minimizes the square root of the following cost given for any warping path x ,

$$C_x(s, t) = \sum_{l=0}^k \|s_{i_l} - t_{j_l}\|_2^2 \quad (1)$$

We can then compute the dtw distance by computing the total cost of the warping path x^* .

In practice, to find the optimal path, we use a dynamic programming approach which consists in the following algorithm,

1. We define a distance matrix $D \in \mathbb{R}^{n \times m}$ where $D_{i,j}$ is the minimum-distance for the warping path between $s' = (s_1, \dots, s_i)$ and $t' = (t_1, \dots, t_j)$.
2. Each entry is computed by using the following recursion formula,

$$D_{i,j} = \|s_i - t_j\| - \min(D_{i-1,j}, D_{i-1,j-1}, D_{i,j-1}) \quad (2)$$

with the initial condition $D_{1,1} = 0$

3. The entry $D(n, m)$ contains the minimum-distance for the warping path between s and t .

This algorithm has $\mathcal{O}(nm)$ time complexity. We can however speed up the algorithm by applying **constraints** that consists in limiting the number of cells that are evaluated in the distance matrix (e.g. using a Sakoe-Chiba Band window²) and **data abstraction** that consists in performing the algorithm on a reduced representation of the data (Salvador and Chan, n.d.). Instead of running the algorithm on the full distance matrix, we reduce the size of the time series which implies that the number of cells in the distance matrix are reduced. Once the warping path is found on this low-resolution matrix, we map it back to a higher-resolution matrix. This projected path is used as an initial guess for a new warping path on this new distance matrix. In other words, the projected path is refined on the higher-resolution matrix by making **local adjustments**³ which implies that this matrix is only filled in the neighborhood of the projected path. This results in a algorithm with linear time complexity since the warping path grows linearly with the size of the time series.

Research have shown that using a single neighbor in the KNN algorithm gives the best results (Mitsa, 2010). Moreover, trying different combination of number of neighbors and radius hyperparameters, we notices that a good trade-off between efficiency and rapidity was not only obtained with a single neighbor but also with a radius of 1.

²In a nutshell, this window assumes that the best path will not stray too far away from the main diagonal of the distance matrix.

³These local adjustments can be controlled through a radius parameter that controls the number of cells that will be evaluated around the path.

3.2 Results

3.2.1 User-independent cross-validation

In the user-independent cross-validation, for the first domain, we get a mean accuracy of 0.743 with a large standard deviation of 0.146. Interestingly, looking at the confusion matrices for the different splits, we notice a lot of misclassifications for the last split. It could be that one user has a very poor handwriting compared to the others so that our system is not properly trained to recognize the shapes from this split.

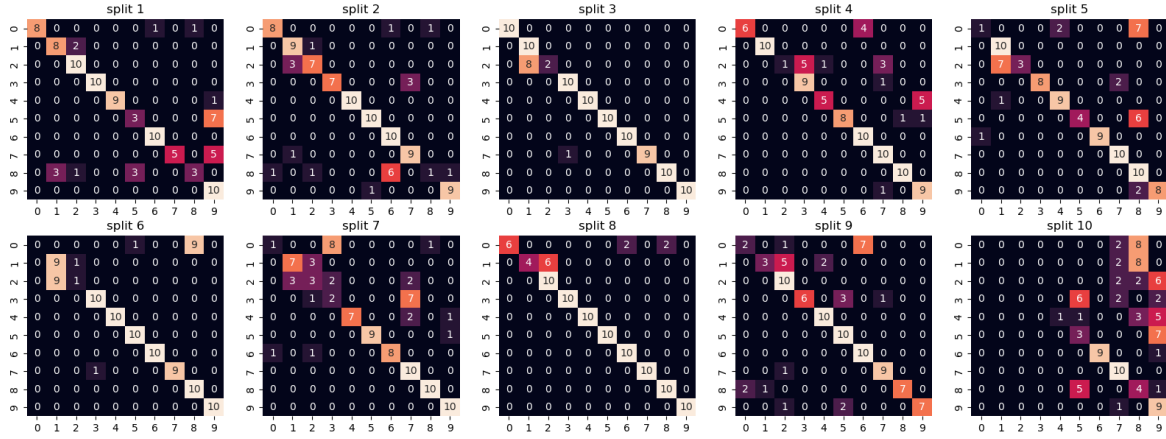


Figure 1: Confusion matrices of the different splits for the domain 1 using fast DTW algorithm (user independent cross-validation)

For the third domain however, we get a mean accuracy of 0.853 with still a large standard deviation of 0.117. It was pretty much unexcepted as this domain contains more complex sketches than simple numbers. Here it is the split nine that contains a lot of missclassifications. The same reason as above could explain it.

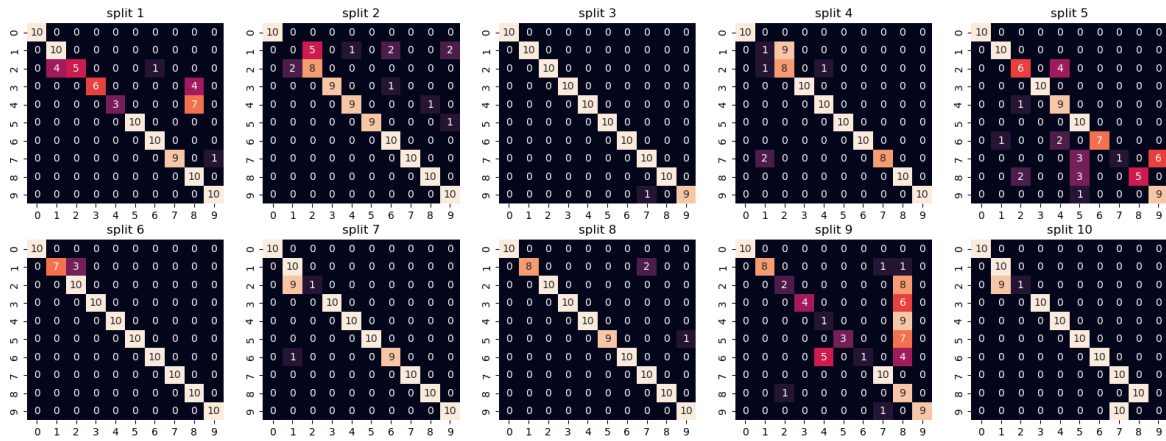


Figure 2: Confusion matrices of the different splits for the domain 3 using fast DTW algorithm (user independent cross-validation)

3.2.2 User-dependent cross-validation

In the user-dependent cross-validation, we get far more better results. For the first domain, our classifier is almost perfect with a mean accuracy of 0.99 and a standard deviation of 0.009. This makes

sense to get better results since the data from all the users are used to train the algorithm.

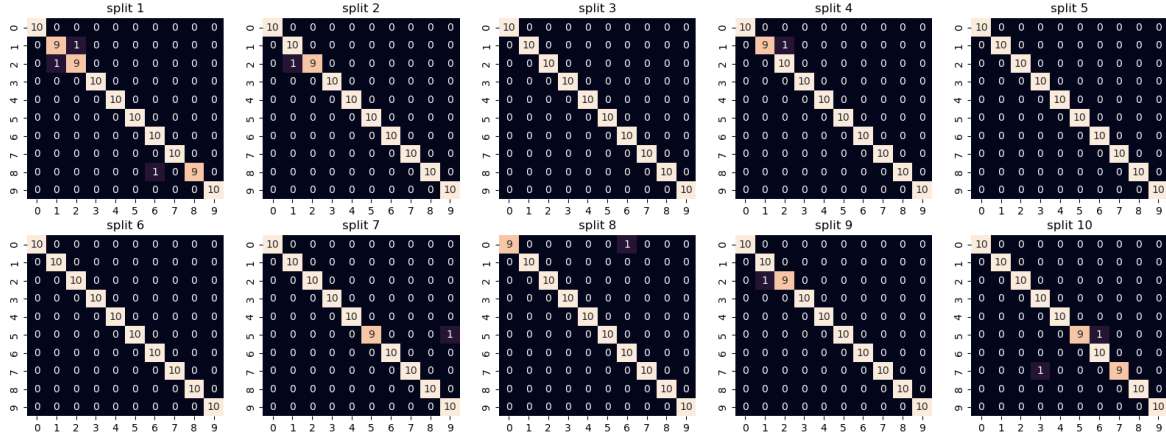


Figure 3: Confusion matrices of the different splits for the domain 1 using fast DTW algorithm (user dependent cross-validation)

For the third domain, we have a mean accuracy of 0.997 and a standard deviation of 0.005. This is still impressive.

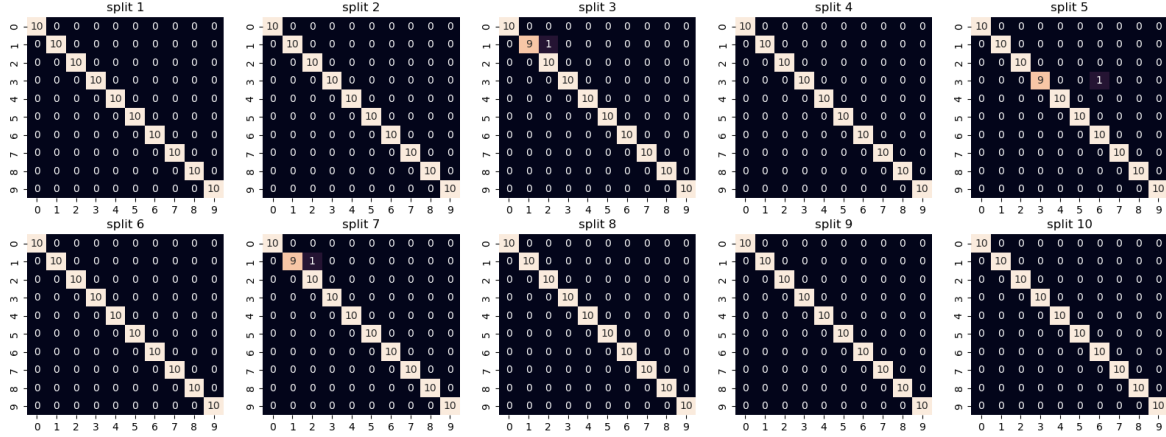


Figure 4: Confusion matrices of the different splits for the domain 3 using fast DTW algorithm (user dependent cross-validation)

4 \$P\$-recognizer

In this algorithm, we consider each gesture as a set of points: $\{p_i = (x_i, y_i) : i = 1, \dots, N\}$. In our case, because of the resampling made in the preprocessing step, each gesture is represented by a set of $N = 32$ points. It is worth noticing that gesture are seen as a cloud of points so that there does not need to have order in the set (i.g. p_1 does not have to be the starting point nor p_i has to follow p_{i-1}) even though it's the case for us.

Let C and T be clouds of points. The first one correspond to a gesture candidate whereas the second one is a template in the training set. The aim of this algorithm is to match C to T by the use of a nearest neighbor classifier (KNN) in the same idea as the precedent section. Here we obviously do not use a dtw algorithm to compute the distance but the sum of euclidean distances for all pairs of points

(C_i, T_j) where $C_i \in C$ is matched to $T_j \in T$ through some function $f : \mathbb{R}^2 \rightarrow \mathbb{R}^2$, $C_i \rightarrow f(T_j)$,

$$d(C, T) = \sum_{i=1}^N \|C_i - T_j\|_2 \quad (3)$$

However this algorithm requires to search for the minimum matching distance between C and T from $n!$ possible alignments. The library we used to run this algorithm uses a special heuristic called Greedy-5 (Vatavu et al., 2012). The idea is that for each point $C_i \in C$, we find the closest point in T that has not been matched yet. Once it is matched with C_i , we continue with C_{i+1} and so on until all the points of C are matched with a point of T . The closeness is computed through a weighted euclidean distance,

$$d(C, T) = \sum_{i=1}^N w_i \|C_i - T_j\|_2 \quad (4)$$

where w_i indicate the confidence in each pair (C_i, T_j) .

Basically, the first match has a weight of 1 since C_i has all the points of T to choose for the closest match. As long as the possibility of matching reduces, the confidence also. The formula for the weights translates a linearly decreasing weighting,

$$w_i = 1 - \frac{i-1}{N} \quad (5)$$

This heuristic allows us to have a time complexity of $\mathcal{O}(n^{2+\epsilon})$ which is comparable to the standard dtw algorithm without any optimization.

4.1 Results

4.1.1 User-independent cross-validation

For the first domain, we get a mean accuracy of 0.925 along with a standard deviation of 0.029 for the user-independent cross-validation. This is way better than with the dtw algorithm even though we had resample the datas with half the number of data points than for the precedent algorithm. Notice that we do not have anymore the problem of a split containing a lot of missclassifications as we had in dtw.

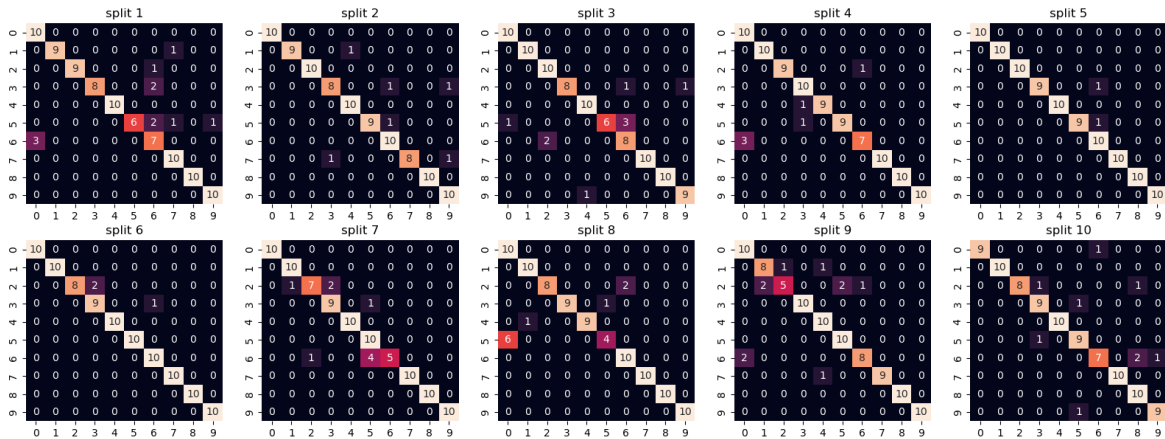


Figure 5: Confusion matrices of the different splits for the domain 1 using P -Recognizer algorithm (user independent cross-validation)

For the third domain, we get a mean accuracy of 0.971 along with a standard deviation of 0.021. This is slightly better than for the first domain despite this one has more complex shape to recognize.

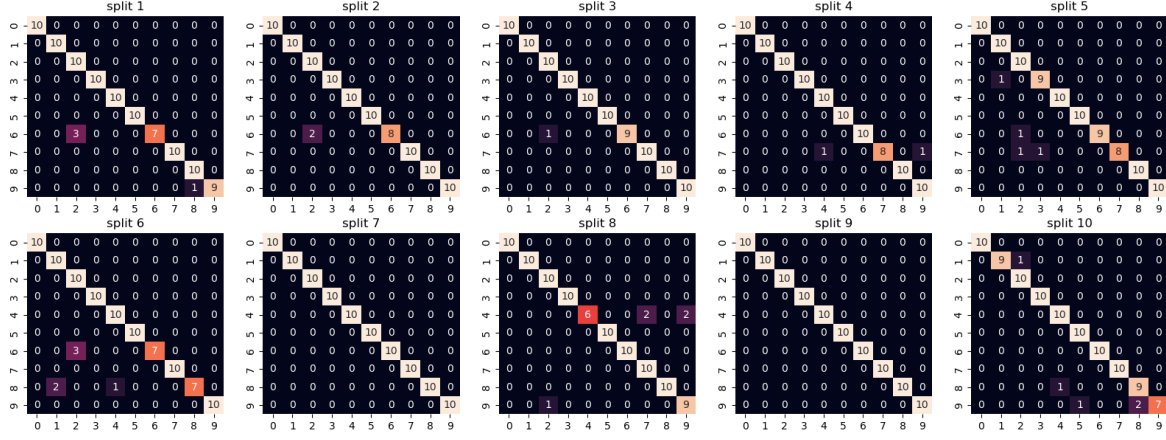


Figure 6: Confusion matrices of the different splits for the domain 3 using $\$P$ -Recognizer algorithm (user independent cross-validation)

4.1.2 User-dependent cross-validation

For the first domain, we get a mean accuracy of 0.967 with a standard deviation of 0.02 and for the third domain, we get a mean accuracy of 0.99 along with a standard deviation of 0.01. The results are somewhat comparable to those of dtw for the user-dependent setting.

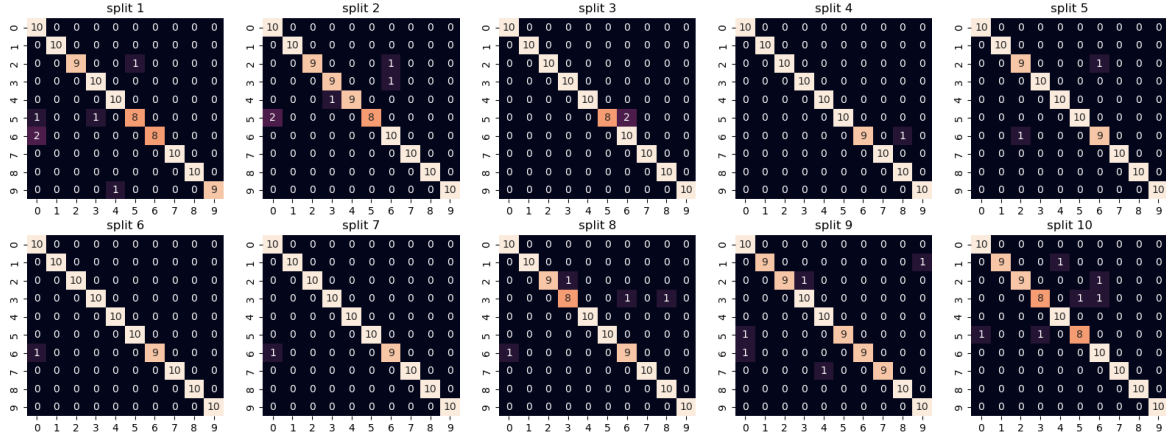


Figure 7: Confusion matrices of the different splits for the domain 1 using $\$P$ -Recognizer algorithm (user dependent cross-validation)

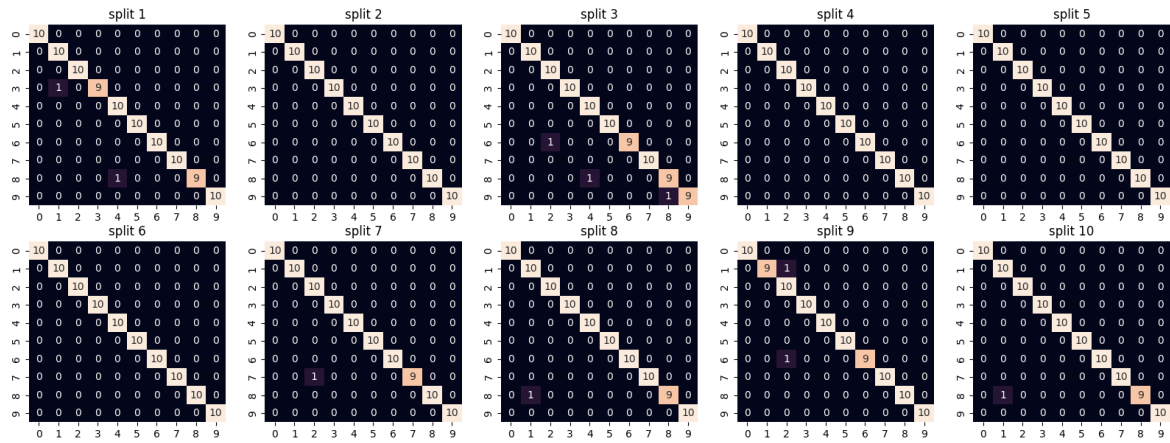


Figure 8: Confusion matrices of the different splits for the domain 3 using $\$P$ -Recognizer algorithm (user dependent cross-validation)

5 Conclusion

References

- Mitsa, T. (2010). *Temporal data mining*. CRC Press. <https://cds.cern.ch/record/1315223>
- Salvador, S., & Chan, P. (n.d.). Fastdtw: Toward accurate dynamic time warping in linear time and space.
- Vatavu, R.-D., Anthony, L., & Wobbrock, J. O. (2012). Gestures as point clouds: A \$p recognizer for user interface prototypes. *Proceedings of the 14th ACM international conference on Multimodal interaction*, 273–280. <https://doi.org/10.1145/2388676.2388732>
- Wobbrock, J. O., Wilson, A. D., & Li, Y. (2007). Gestures without libraries, toolkits or training: A \$1 recognizer for user interface prototypes. *Proceedings of the 20th annual ACM symposium on User interface software and technology*, 159–168. <https://doi.org/10.1145/1294211.1294238>