Recurrent Convolutional Neural Networks help to predict location of Earthquakes

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Abstract—We examine the applicability of modern neural network architectures to the mid-term prediction of earthquakes. Our data-based classification model aims to predict if an earthquake with the magnitude above a threshold takes place at a given area of size $10 \times 10$ kilometers in 30-180 days from a given moment. Our deep neural network model has a recurrent part (LSTM) that accounts for time dependencies between earthquakes and a convolutional part that accounts for spatial dependencies. Obtained results show that neural networks-based models beat baseline feature-based models that also account for spatio-temporal dependencies between different earthquakes. For historical data on Japan earthquakes 1990-2016 our best model predicts earthquakes with magnitude $M_c > 5$ with quality metrics ROC AUC 0.975 and PR AUC 0.0890, making $1.18 \cdot 10^3$ correct predictions, while missing $2.09 \cdot 10^3$ earthquakes and making $192 \cdot 10^3$ false alarms. The baseline approach has similar ROC AUC 0.992, number of correct predictions $1.19 \cdot 10^3$, and missing $2.07 \cdot 10^3$ earthquakes, but significantly worse PR AUC 0.00911, and number of false alarms $1004 \cdot 10^3$.

I. INTRODUCTION

The earthquake prediction is a substantial while challenging problem [9]. The goal is to predict the time and location of a future earthquake. The two common ways to solve this problem are physical modeling and machine learning based on data on past observations.

While physical modeling is a well-established approach, it covers only part of the full picture due to high uncertainties in observed data and complex nonlinear behavior of seismicity. An alternative approach is the construction of machine learning models based on data to replace expensive and sometimes imprecise physical modeling. The machine learning modeling [12] appears to work in various areas including drilling [19], aerospace engineering [31] and high energy physics engineering [6]. Usage of machine learning as an alternative or a complement to physical modeling is also an area of active research in earthquake prediction [22] [23].

A typical machine learning model takes information about past measurements and outputs prediction of an earthquake probability [25] [26] [10] [15] [32]. Different models use different available data sources as inputs such as soil radon data [32] or history of past earthquakes itself.

For example, in [5], the authors considered the prediction of earthquakes as a binary classification problem. The authors generated eight seismic indicators used as input features based on well-known seismic characteristics such as the frequency of foreshocks and the released energy. As machine learning models, they used fully-connected and recurrent neural networks, random forest, and boosting of decision trees. The authors of [4] proceed similarly but identify that the set of useful seismic features for different regions can be different.

Other inputs inspired by physics are RTL features introduced in [30]. RTL features are aggregations of the past seismic activity into a single index by weighting recent earthquakes that occur near the region, where we predict an earthquake. The RTL feature generation has several hyperparameters that crucially affect the performance of the whole model. So, we need to solve a separate problem of selection of hyperparameters [27] to get the right input features for the earthquake prediction.

Another approach for machine learning models based on features generated from signals on earthquake monitoring was proposed in [10]. The authors used 6 expert-generated features based on observation from seismic stations as inputs to machine learning model for short-term detection of earthquakes.

The generation of precursors for earthquakes dates back to at least 1994 [2]; the presented approach uses a simple neural network to predict future earthquakes, the authors validate their approach using a sample of moderate size 142. Moreover, in [1] the authors conclude that Radial Basis Functions Neural Networks are also useful while prediction large earthquakes occurrence. The number of events in [1] is 313068. However, only 21 of them have magnitude greater or equal to 6, so the authors adopt specific methods for training of neural networks using small samples.

Convolutional neural networks (CNN) also serve as machine learning models for earthquake prediction [26]: the authors predict earthquakes in Oklahoma caused by wastewater injection into the soil. They apply a convolutional neural network on data from waveform records from two stations. The article [24] considers another application of CNN in the context of earthquakes. The authors combine convolutional and recurrent neural networks (RNN) to solve an earthquake signal detection problem and achieve high accuracy. So, CNNs and RNNs work well in problems connected with earthquakes.

Another recent application of LSTM is in [Wang2017convolutional&LSTM]. The authors predict earthquakes taking into account temporal and spatial correlations among earthquakes. They divide China into $N_{\text{regions}} = 9$ rectangle sub-regions and make predictions of earthquakes in each of them. To utilize spatial correlations between earthquakes, the authors use neural networks with fully connected layers from $N_{\text{regions}}$ number of features to $N_{\text{regions}}$ number of features. However, the authors solve the problem at a global level with too large selected sub-regions, so predictions of earthquakes in each of them are not dense.
enough to make local decisions.

An approach [Huang2018convolutional] uses convolutional neural networks with poolings to predict earthquakes. The model predicts the probability of an earthquake with a magnitude larger than 6 happening anywhere in Taiwan in the next 30 days. The authors create a binary map of earthquakes in Taiwan $256 \times 256$ with each pixel is an indicator of the occurrence of an earthquake in the given region. These maps serve as inputs to a machine learning model. To solve the problem, the authors use a convolutional neural network. Training of the model proceeds with a relatively small training sample size. The model outputs a single number for the whole region, making it impossible to predict earthquakes locally.

However, there is a gap in approach on earthquakes prediction. According to our knowledge nobody considers local predictions of earthquakes at small areas. Also there is a limited usage of modern Neural Networks for earthquake prediction. These observations lead us to the following problem statement.

II. PROBLEM STATEMENT

We consider a history of records on Japan earthquakes over 26 years. Each earthquake has four parameters: location $(x, y)$, time $t$ and magnitude $M$.

To define the problem of earthquake location prediction we split the whole map of Japan into the grid of size $200 \times 250$. So, each cell is about 10 km long and 10 km wide. Thus, if we can identify that there will be an earthquake in a cell, the location will be precise enough for most of applications.

Our goal is to construct a model that predicts if there is an earthquake in the time cylinder $[T + T_{\text{min}}, T + T_{\text{max}}]$ for each cell in our grid for some $T$ using historical information about all earthquakes up to time $T$. We consider middle time range for earthquake prediction with $T_{\text{min}}$ being 10 days and $T_{\text{max}}$ being 50 days. To identify limits of applicability of our model we consider different thresholds $M_c = 3.5$ and $M_c = 5$ for the earthquake magnitude: we predict only earthquakes with $M \geq M_c$.

Thus, the considered problem is a machine learning classification problem, where we want to predict for a particular cell, if there will be an earthquake of a given magnitude or higher. While smaller thresholds $M_c$ are better from the machine learning point of view, as we have less severe class imbalance in our training and test samples, bigger values of $M_c$ are more interesting from the applied point of view.

We have pairs $(x_i, y_i)$, where $y_i$ is the indicator of an earthquake with a magnitude higher or equal to the threshold $M_c$, and $x_i$ is vector of features characterizing moments of times (in days) and specific locations of past earthquakes. All these pairs form a sample $D = \{(x_1, y_1)\}_{i=1}^n$ of size $n$. Our goal is to create a model predicting $\hat{y}(x)$ that is as close as possible to the true value $y(x)$.

III. DATA

We study the prediction of strong earthquakes in the middle-term horizon. Strong earthquake is an earthquake with the magnitude higher than $M_c = 5$. Prediction of earthquakes is difficult not only because the process itself is difficult, but also due to challenging characteristics of the dataset. In our work we consider a dataset from a typical seismic-active region — Japan. The dataset contains 247204 earthquakes that occurred from 1990 to 2016. The sample is unbalanced.
Fig. 2: Histogram of magnitudes: the total sample size is about 250000. Only earthquakes with magnitude smaller or equal to 6 are presented. There are only 350 earthquakes with a magnitude greater or equal to 6 and only 2387 earthquakes with magnitude greater or equal to 5. Also we see a local maximum at 3, as our grid of observational stations are not dense enough, and we miss some earthquakes with smaller magnitudes.

Figure 2 demonstrates the histogram of number of earthquakes with respect to the magnitude. Most of classifiers and their accuracy metrics are tailored to balanced samples with uniform distribution of examples among classes. Thus in our case we have to tune a classifier to make it more sensitive to the target class.

Also the sample is non-homogeneous as the network of seismic stations changes over time and is nonuniform. So we should take these into account when generating features and assessing the results provided by predictive models. An overview of the sample is in Figure 3. We see that we can capture earthquakes with small magnitude only at regions with high density of observational stations and that the network of stations evolves over time as well as typical patterns of earthquakes.

IV. METHODS

A. Naive baseline

A rather strong baseline for prediction of an earthquake probability at a given location is usage of a historical mean occurrence value at this subarea.

B. RTL features

Another approach for the midterm prediction of earthquakes is usage of RTL features to identify the probability of an earthquake in a given region [30]. RTL features try to capture spatial and temporal dependencies between earthquakes. Thus the model based on RTL features is an adequate baseline to compare with the results based on Recurrent-Convolutional Neural Networks that also take into account these spatial and temporal dependencies between earthquake events.

According to the general theory RTL is composed of weighted quantities associated with three parameters: time, location and magnitude of earthquakes. As a result, RTL feature is the product of three functions:

\[ \text{RTL}(x, y, t, M) = R(x, y, t, M) \cdot T(x, y, t, M) \cdot L(x, y, t, M). \]

Here \( R(x, y, t, M) \) is an epicentral distance, \( T(x, y, t, M) \) is a time distance and \( L(x, y, t, M) \) is a rupture length. They depend on the size of the space-time cylinder \( \mathcal{E}_{r_0, t_0} \), defined by radius \( r_0 \) and time length \( t_0 \):
which deals with time series pretty well, but has some
we use recurrent neural networks. It is a classical approach
D. Our approach
(with values equal to the optimal ones from \[27\]) or binary
use either RTL features with varying hyperparameters
proach is suitable for imbalanced classification problems \[20\].
the practical problems \[8\] and with some modifications the ap-
measure.
objects to decrease their contribution to the total model error
that are poorly classified using the current ensemble, so while
construct successively each basic classifier in the ensemble.
functional gradient in the space of decision tree classifiers to
Boosting \[13\]. In this approach we take into account the
of Decision Trees, the most used nowadays is Gradient
over-fitting and handling of various problems in data including
The advantages of this approach include a decent performance
missings, and outliers.
Among various approaches for construction of Ensembles
of Decision Trees, the most used nowadays is Gradient
Boosting \[13\]. In this approach we take into account the
functional gradient in the space of decision tree classifiers to
construct successively each basic classifier in the ensemble.
During model construction we increase weights of objects
that are poorly classified using the current ensemble, so while
constructing a new basic classifier we concentrate on these
objects to decrease their contribution to the total model error
measure.
Modern implementations have better properties in most of
the practical problems \[8\] and with some modifications the ap-
proach is suitable for imbalanced classification problems \[20\].
As inputs to Gradient Boosting classifiers in this article we
use either RTL features with varying hyperparameters \(r_0, t_0\)
(with values equal to the optimal ones from \[27\]) or binary
indicators of earthquakes for previous days.

C. Ensembles of decision trees

Typical nonlinear baseline in classification problems is
Ensemble of Decision Trees. It consists of a number of basic
decision tree classifiers. The ensemble of decision tree works
in the following way during inference:
- For each object and for each decision tree in ensemble we
proceed through the decision tree according to the input
variables for this object until it reaches a leaf of a tree.
- If we reach a leaf, a basic classifier returns probabilities to
belong to classes according to the distribution of objects
in a training sample.
- Final probabilities for the ensemble is a weighted sum of
probabilities from each basic decision tree classifier.

The advantages of this approach include a decent performance
with default settings \[11\], fast model construction, almost no
over-fitting and handling of various problems in data including
missing values and outliers.

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(with values equal to the optimal ones from \[27\]) or binary
indicators of earthquakes for previous days.

D. Our approach

1) RNNs: As we want to benefit from temporal correlations
we use recurrent neural networks. It is a classical approach
which deals with time series pretty well, but has some
problems with catching long-term correlations. As long-term
dependencies are important for us we use LSTM, a type of
RNN which uses one more hidden state to store information
for long periods of time \[14\]. Classical LSTMs which work
with series of vectors use linear layers for vector-to-vector
transformations inside an LSTM cell. In our case we work
with a series of two-dimensional feature maps so we need
some map-to-map transformations.

2) CNNs: We process a distribution of earthquakes on the
map of 200 × 250 cells. To benefit from spatial dependencies
between earthquakes we use convolution neural networks \[21\],
which efficiently work with images or other two-dimensional
signals like remote-sensing data.

Our approach combines RNN and CNN architectures, as we
pass information through RNN in a form of a feature map,
obtained using CNN, see paragraph \[IV-F\].

E. Residuals normalization for neural networks

First we made preliminary experiments with a naive classi-
fier, which predicts the probability of an earthquake as a share
of time moments \(y_{\text{mean}}\) with earthquakes observations in a
considered cell. We noticed that the naive classifier performs
quite well. It means that instead of predicting probability of an
earthquake we can make our classifier to predict corrections
to the mean earthquake rate in the cell.

In this case, a direct usage of a softmax activation function
(softmax) at a final layer of the network is flawed, as the
prediction should belong to the segment \(\Delta p \in (-y_{\text{mean}}, 1 -
y_{\text{mean}})\), but an output of the softmax activation function
belongs to \((0, 1)\). So, we modify the neural network loss
function to take into account that we predict residuals.

Our modification is to make an inverse softmax transfor-
mation of mean earthquake rate in each cell. Then add the
residual, which is the output of the last layer of the neural
network model before the softmax layer, and then apply the
softmax transformation back.

We use the following correction procedure (we assume that
we have a \(k\) class classification problem, so \(i \in \{1, 2, \ldots, k\}\)):
- We denote an output of our network model by \(\delta o_i\). The
naive prediction before softmax is equal to \(o_i = \log p_i + c\),
where \(p_i\) is the prior probability of the earthquake at a
given location, and \(c\) is a hyperparameter that scales the
power of this prior.
- Before softmax we calculate \(o_i + \delta o_i\).
- After softmax we obtain the probability of an earthquake
as the prediction of the neural network defined as \(\hat{y}_i =
\text{softmax}(o_i + \delta o_i)\).
- In our case \(k = 2\), so we use a threshold \(t = 0.5\): if
\(\hat{y}_2 > t\), then we report that there will be an earthquake.
To train the neural network model we optimize a standard log
loss function by comparing \(\hat{y}_i\) to the true labels \(y_i\).

F. Full pipeline

The architecture is in Figure 4. The detailed pipeline is the
following:

1) We represent data as a sequence of heat maps: for each
cell we specify a magnitude of an earthquake on this

\[
R(x, y, t, M) = \sum_{e_i \in E_{x, y, t}} \exp \left( -\frac{r_i}{r_0} \right),
\]

\[
T(x, y, t, M) = \sum_{e_i \in E_{x, y, t}} \exp \left( -\frac{t - t_i}{t_0} \right),
\]

\[
L(x, y, t, M) = \sum_{e_i \in E_{x, y, t}} \exp \left( -\frac{l_i}{r_1} \right),
\]

where \(e_i\) is a description of an earthquake \((x_i, y_i, t_i, M_i)\), \(r_i =
\sqrt{(x - x_i)^2 + (y - y_i)^2}\). Value \(l_i\) is an empirical parameter.
For Japan it is equal to:
\[
l_i = \exp(0.5M_i - 1.8).
\]

For generation of RTL features we consider earthquakes with
magnitude at least \(M_i \geq M_c\).
We set it to zero if no earthquake happened. The input heat map at each time moment has size $200 \times 250$.

2) We pass the input heat map through a convolutional network to create an embedding of size $200 \times 250$ with 16 channels. As an output of LSTM at each time moment we have a hidden representation (short term memory) of size $32 \times 200 \times 250$, cell (long term memory) representation of a similar size, and the output of size $32 \times 200 \times 250$.

3) We use a series of convolutions to transform the output to the size $2 \times 200 \times 250$ with two channels of size $200 \times 250$ corresponding to differences between the probabilities of earthquakes with prior probabilities in the cells.

4) We add the result to reversed mean values, see description in paragraph IV-E, feed to the softmax layer and then get predictions of earthquake probabilities in all cells locations.

We also tried U-net architecture [28], often used for image segmentation, instead of the convolutional architecture, but results were worse.

V. RESULTS

The code for the conducted experiments is available at [github](https://github.com/romakail/Earthquake_prediction_DNN).

A. Quality metrics

There are many quality metrics for comparing classifiers. Accuracy metric alone is not representative due to significant class imbalance: even a constant prediction "there-is-no-earthquake" already provides a very high accuracy. Instead we calculate different types of errors. Also we used two standard machine learning metrics: the area under the Receiver Operating Characteristic (ROC) curve (ROC AUC) and the area under the Precision-Recall (PR) curve (PR AUC). The rest of this subsection is devoted to the definition of these metrics.

Let us consider a test sample $D = \{(x_i, y_i)\}_{i=1}^{n}$, $x_i$ is an input vector, $y_i$ is a true class label, either 0 (no earthquake) or 1 (earthquake of a magnitude higher than a threshold). We have predictions of a classifier at each location $\hat{y}_i \in \{0, 1\}$.

For a particular classification there are four numbers that represent its quality: number of True Positive (TP) — correctly classified objects of the first class, False Negative (FN) — objects of the first class attributed by the classification to the second class, False Positive (FP) — objects of the second class attributed by the classification to the first class, and True Negative (TN) — correctly classified objects of the second class:

$$TP = \frac{1}{n} \sum_{i=1}^{n} [y_i = 1][\hat{y}_i = 1], \quad TN = \frac{1}{n} \sum_{i=1}^{n} [y_i = 0][\hat{y}_i = 0],$$

$$FP = \frac{1}{n} \sum_{i=1}^{n} [y_i = 0][\hat{y}_i = 1], \quad FN = \frac{1}{n} \sum_{i=1}^{n} [y_i = 1][\hat{y}_i = 0].$$

By dividing the number of TP objects by the total number of positive objects (sum of TP and FN) we get True Positive Rate (TPR), by dividing the number of False Positive objects by the total number of negative objects (sum of False Positive and True Negative objects) we get False Positive Rate (FPR):

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}.$$
outputs a probability \( p_i \) of an object to belong to a class \( i \). To obtain the final classification with labels we apply a threshold \( t \) to the probabilities \( \hat{y}_i = |p_i > t| \): the objects with probabilities below the threshold are classified as the first class objects, and the objects with probabilities above the threshold are classified as the second class objects.

By varying the threshold, we get a trajectory in the space of TPR and FPR that starts at the point (0, 0) when all objects are classified as the negative class, and ends at (1, 1) where all objects are classified as the positive class. This trajectory is a ROC curve. In a similar way we define precision as \( \frac{TP}{TP + FP} \) and recall as \( \frac{TP}{TP + FN} \) and plot the trajectory in the space of precision and recall values. This trajectory is a PR curve.

By calculating areas under ROC and PR curves, we get measures of the quality of classifiers. Higher values of ROC AUC and PR AUC suggest that the classifier is better. ROC AUC and PR AUC values for a random classifier are 0.5 and the share of the positive class respectively, ROC AUC and PR AUC values for the perfect classifier are 1. For imbalanced classification problems, PR AUC suits better.\(^7\)\(^20\).

### B. Compared algorithms

We use the following methods from Section \(^IV\):

- Baseline — outputs mean earthquake probability at a given location obtained from historical data.
- Grad. boosting, indicator — Gradient boosting with earthquake indicator input features.
- Grad. boosting, RTL — Gradient boosting with earthquake RTL input features, see paragraph \(^IV-E\).
- CNN — series of stacked one by one convolution layers, trained on given amount of previous days.
- CNN+LSTM — Recurrent neural network, which passes data as a feature map, obtained by CNN.
- CNN, resid. (residuals) — same as CNN, but it predicts a residual to \( o_i \), see paragraph \(^IV-E\).
- CNN+LSTM, resid. (residuals) — same as CNN+LSTM, but it predicts a residual to \( o_i \), see paragraph \(^IV-E\).

We note that actually there are no efficient ways to improve accuracy of Naive approach and Gradient Boosting based models significantly. Therefore, we provide an ablation study only for our neural network approach in subsections \(^IV-D\) and \(^IV-E\) Then we compare all considered approaches in subsection \(^IV-E\).

### C. Fighting class imbalance

To deal with the class imbalance we use an oversampling technique increasing weights for the less populated minor class objects during training, while keeping weights for the major class objects 1. The dependence of model quality on the weight of the minor class objects is in Table \(^I\). In other experiments we use weight 1000 providing performance close to optimal.

\[ \text{Weight} \times \text{Minor class objects} \]

| Weight | \( M_c = 3.5 \) | \( M_c = 5 \) |
|--------|---------------|---------------|
| \( 1 \) | 0.643 | 0.517 |
| 10 | 0.909 | 0.705 |
| \( 10^2 \) | 0.943 | 0.705 |
| \( 10^3 \) | 0.952 | 0.890 |
| \( 10^4 \) | 0.956 | 0.936 |
| \( 10^5 \) | 0.948 | 0.935 |
| \( 10^7 \) | 0.961 | 0.911 |

TABLE I: Dependence of CNN+LSTM model quality on the weights of the minor class objects during training. Optimal weights are significantly better than 1, while the usage of too large weights for the case of \( M_c = 5 \) leads to decrease in performance

### D. Analysis of the best model: selecting hyperparameters

Selection of an architecture and hyperparameters of a neural network can significantly affect the performance of the constructed model.

We vary two important hyperparameters of a neural network: number of intermediate layers for the LSTM architecture and a learning rate for an optimization algorithm, see values of the metrics in Table \(^II\). The default values seem to be a safe choice for all models.

| Learning rate | \( M_c = 3.5 \) | \( M_c = 5 \) |
|---------------|---------------|---------------|
| \( 0.03 \) | 0.944 | 0.924 |
| \( 0.003 \) | 0.954 | 0.924 |
| \( 0.003^* \) | 0.952 | 0.937 |
| \( 0.00003^* \) | 0.960 | 0.917 |

TABLE II: Dependence of LSTM model quality on the learning rate and the number of intermediate layers. Smaller number of intermediate layers is better. Default values are with \(*\) sign

### E. Comparison of proposed models

In Table \(^III\) we compare our methods based on neural networks with general Gradient boosting approach and Naive baseline. Both PR AUC and ROC AUC scores suggest that performance of our models is better. Moreover, taking into account residuals during the prediction further improves the model. The improvement is significant for both cases of earthquakes with the magnitudes greater or equal to the thresholds \( M_c = 3.5 \) and \( M_c = 5 \).

Number of errors of different kind for our best classifier for a varying threshold is in Table \(^IV\). We see, that we can select a trade-off between the number of False alarms (FP) and the number of missed earthquakes given by our model.

### VI. Conclusions

Modern neural network architectures are good for the midterm prediction of earthquakes. Our machine learning...
model predicts if an earthquake with a magnitude above a given threshold takes place at a given location in a time range of 30-180 days from a selected moment.

LSTM (Recurrent Neural Network) and Deep Convolutional Neural Network account for time and spatial dependencies correspondingly. A machine learning model based on these architectures provides a decent quality. Thus, we are able to replace hand-crafted features (e.g. RTL based on time and location) by features automatically extracted by neural networks, avoiding manual feature generation.

For historical data on Japan earthquakes 1990-2016, our best model has the quality metrics ROC AUC 0.975 and PR AUC 0.0890 compared to ROC AUC 0.992 and 0.00911 for the baseline approach. More intuitive quality metrics are amount of undetected earthquakes \( (2.09 \cdot 10^3 \text{ vs } 2.07 \cdot 10^3) \) and number of false alarms \( (192 \cdot 10^3 \text{ vs } 1004 \cdot 10^3) \) with the same amount of properly detected earthquakes on the test dataset. The proposed model significantly decreases number of false alarms and increases the most important quality metric PR AUC.

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TABLE IV: Values (in thousands) of True positive (TP, detected earthquakes), False Negative (FN, undetected earthquakes), False Positive (FP, false alarms about earthquakes), True Negative (TN, correct no alarm about earthquake) for different values of probability threshold $t$ for the best method CNN + LSTM, $M_c = 3.5$ and $M_c = 5$.

| Threshold | $M_c = 3.5$ | Baseline | $M_c = 5$ |
|----------|-------------|-----------|-----------|
|          | TP  | FN  | FP  | TN  | TP  | FN  | FP  | TN  |
| 0.0001   | 1440| 34510| 10.85| 69.71| 42948|
| 0.1      | 1210| 47800| 36.55| 1006| 48913|
| 0.99     | 1210| 47800| 36.55| 1006| 48913|

| Threshold | $M_c = 3.5$ | Baseline | $M_c = 5$ |
|----------|-------------|-----------|-----------|
|          | TP  | FN  | FP  | TN  | TP  | FN  | FP  | TN  |
| 0.0001   | 192 | 49805| 2.09 | 192 | 49805| 0.3  | 1.19 | 2.07 | 1004 | 48993|
| 0.1      | 0.53 | 49904| 2.74 | 92  | 49804| 0.9  | 0.213 | 3.05 | 29.79 | 49967|
| 0.99     | 0.53 | 49904| 2.74 | 92  | 49804| 0.9  | 0.213 | 3.05 | 29.79 | 49967|

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