Scholomance Academy

Input file: `standard input`
Output file: `standard output`
Time limit: 4 seconds
Memory limit: 1024 megabytes

As a student of the Scholomance Academy, you are studying a course called *Machine Learning*. You are currently working on your course project: training a binary classifier.

A binary classifier is an algorithm that predicts the classes of instances, which may be positive (+) or negative (-). A typical binary classifier consists of a scoring function S that gives a score for every instance and a threshold θ that determines the category. Specifically, if the score of an instance $S(x) \geq \theta$, then the instance x is classified as positive; otherwise, it is classified as negative. Clearly, choosing different thresholds may yield different classifiers.

Of course, a binary classifier may have misclassification: it could either classify a positive instance as negative (false negative) or classify a negative instance as positive (false positive).

Actual class	Predicted class	
	Positive	Negative
Positive	True positive (TP)	False negative (FN)
Negative	False positive (FP)	True negative (TN)

Таблица 1: Predicted classes and actual classes.

Given a dataset and a classifier, we may define the true positive rate (TPR) and the false positive rate (FPR) as follows:

$$\text{TPR} = \frac{\#TP}{\#TP + \#FN}, \quad \text{FPR} = \frac{\#FP}{\#TN + \#FP}$$

where $\#TP$ is the number of true positives in the dataset; $\#FP, \#TN, \#FN$ are defined likewise.

Now you have trained a scoring function, and you want to evaluate the performance of your classifier. The classifier may exhibit different TPR and FPR if we change the threshold θ. Let $\text{TPR}(\theta), \text{FPR}(\theta)$ be the TPR, FPR when the threshold is θ, define the *area under curve* (AUC) as

$$\text{AUC} = \int_0^1 \max_{\theta \in \mathbb{R}} \{\text{TPR}(\theta) | \text{FPR}(\theta) \leq r\} dr$$

where the integrand, called *receiver operating characteristic* (ROC), means the maximum possible of TPR given that $\text{FPR} \leq r$.

Given the actual classes and predicted scores of the instances in a dataset, can you compute the AUC of your classifier?

For example, consider the third test data. If we set threshold $\theta = 30$, there are 3 true positives, 2 false positives, 2 true negatives, and 1 false negative; hence, $\text{TPR}(30) = 0.75$ and $\text{FPR}(30) = 0.5$. Also, as θ varies, we may plot the ROC curve and compute the AUC accordingly, as shown in Figure 1.

Input

The first line contains a single integer n ($2 \leq n \leq 10^6$), the number of instances in the dataset. Then follow n lines, each line containing a character $c \in \{+, -\}$ and an integer s ($1 \leq s \leq 10^9$), denoting the actual class and the predicted score of an instance.

It is guaranteed that there is at least one instance of either class.

Output

Print the AUC of your classifier within an absolute error of no more than 10^{-9}.

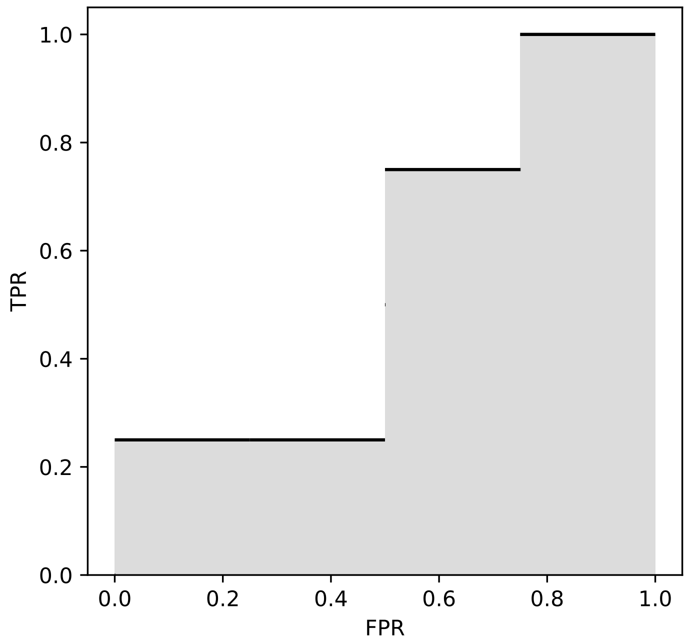

Рис. 1: ROC and AUC of the third sample data.

Examples

standard input	standard output
3 + 2 - 3 - 1	0.5
6 + 7 - 2 - 5 + 4 - 2 + 6	0.888888888888889
8 + 34 + 33 + 26 - 34 - 38 + 39 - 7 - 27	0.5625