

Machine Learning

Offensive Tweet Detection

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Problem

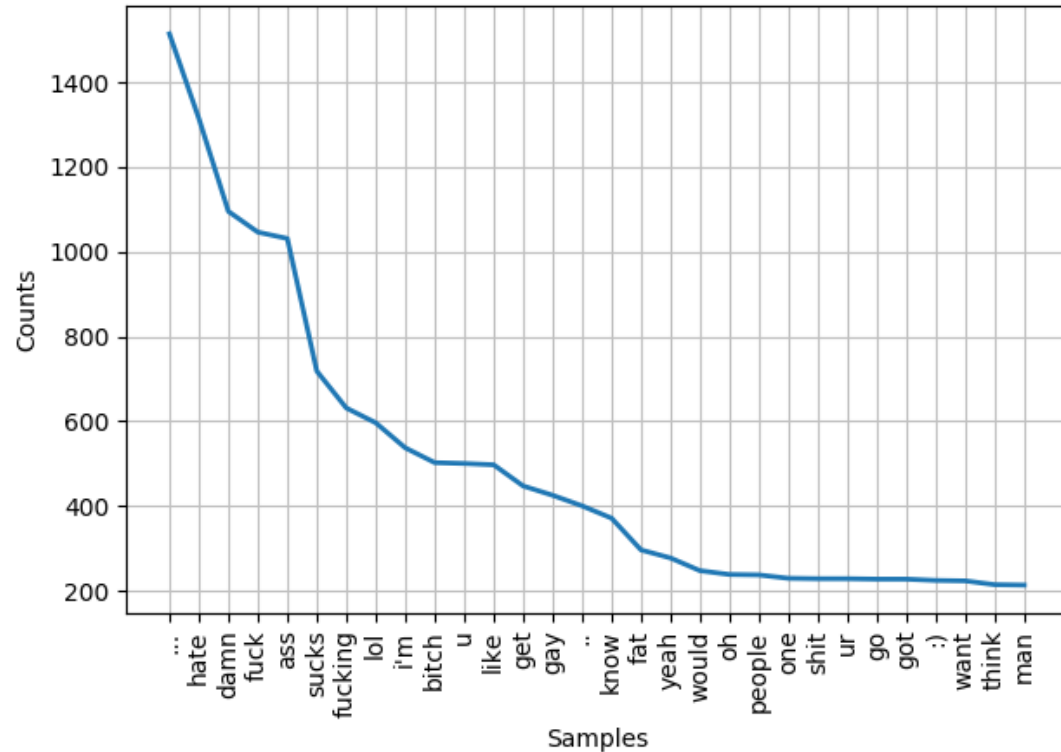
- Improve the Twitter implementation of “Safe Search”
- Don't show offensive tweets from users with “safe search” on
- Also useful when large websites use Twitter widget to show tweets related with a topic
- Twitter can suspend or delete accounts with successive violations of safe tweets

Dataset

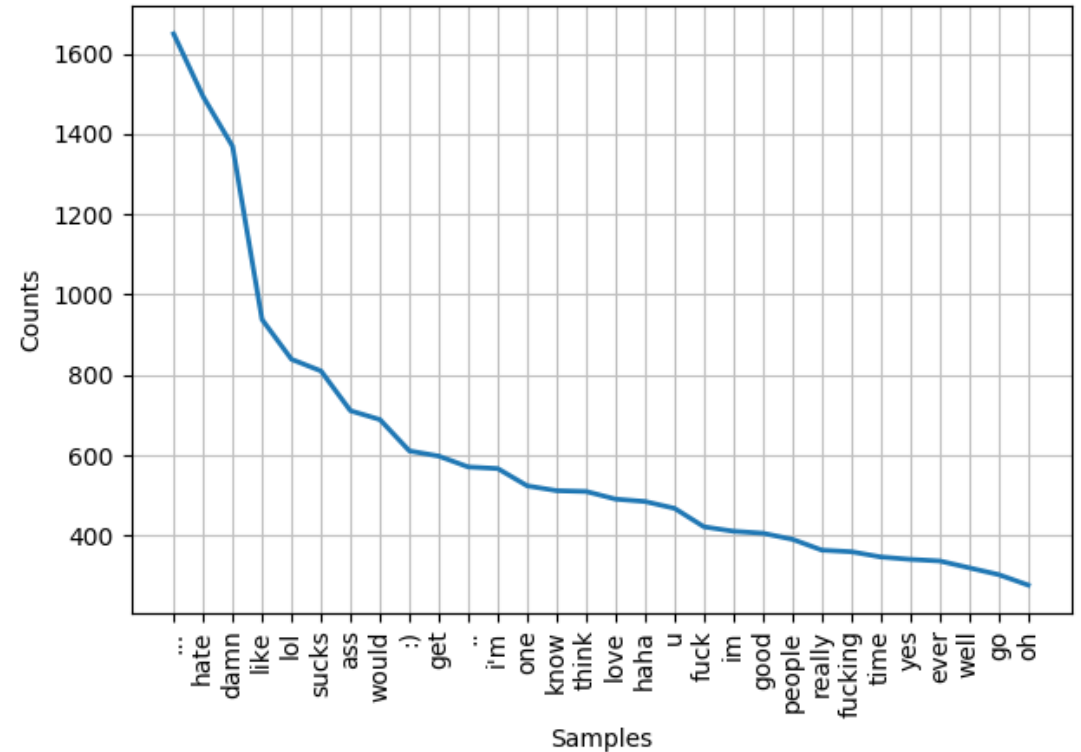
- 20001 tweets
- Human-labelled data in two categories:
 - 1 (offensive)
 - 0 (non offensive)
- 7822 labelled as offensive tweets and 12179 labelled as non offensive tweets
- Source: <https://www.kaggle.com/dataturks/dataset-for-detection-of-cybertrolls/>

Dataset statistics

Offensive tweets frequency

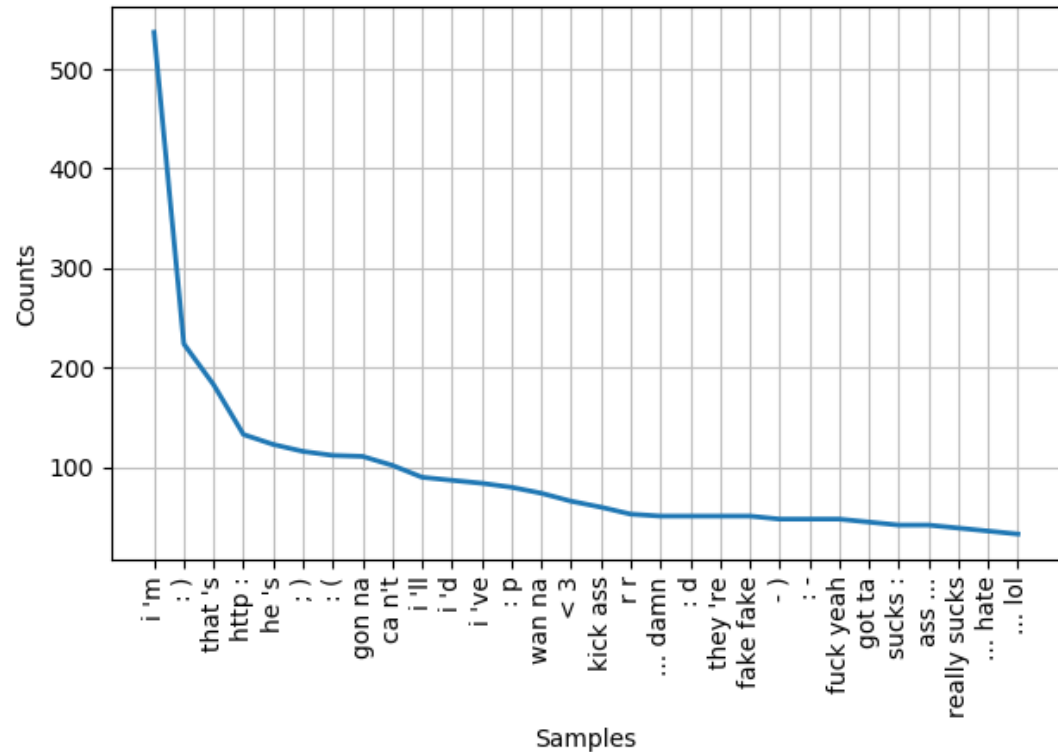


Non-offensive tweets frequency

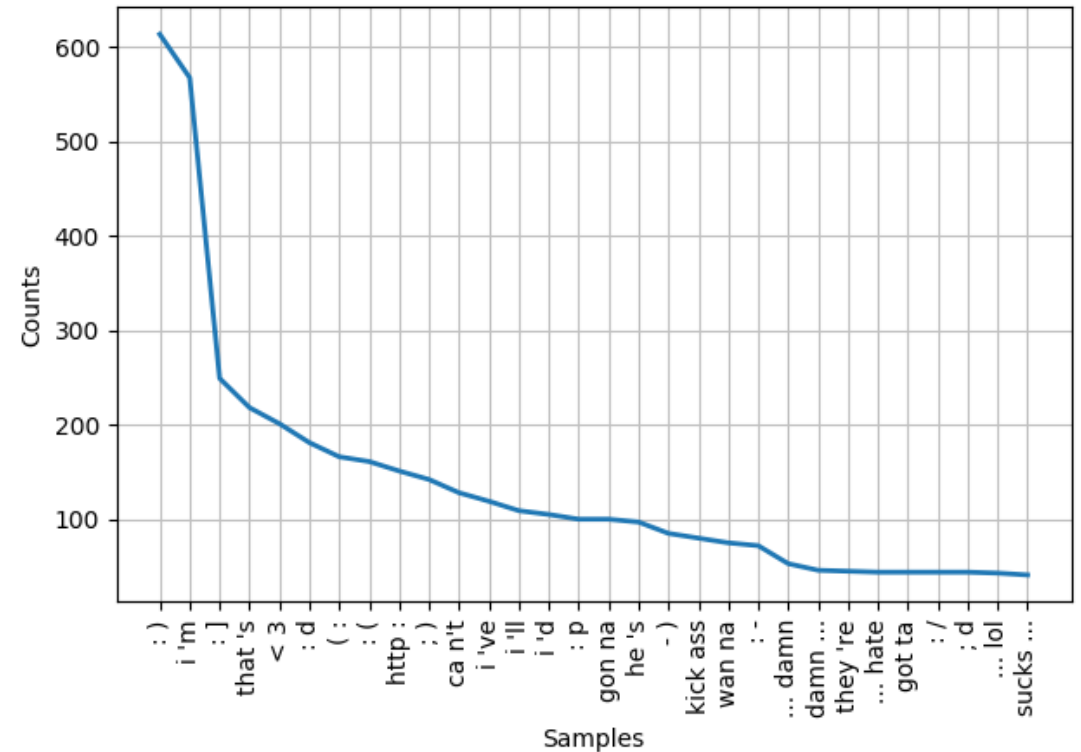


Dataset statistics

Offensive tweets frequency with bi-gram



Non-offensive tweets frequency with bi-gram



Data pre-processing

- Convert all words into lowercase
- Apply tokenizer
- Remove punctuation
- Remove stop words (the, and, or, ...)
- Lemmatize

Feature extraction

Tokens counting

- Select the N most used tokens and transform them into features
- Count the number of feature tokens that each tweet has
- Normalize the counting

The pre-processed tokens can be grouped in a contiguous sequence: n-gram

We have chosen to treat each one as a word. Example:

- 1-gram: ["We", "Love", "AI"]
- 2-gram: ["We Love", "Love AI"]

Feature extraction

TF-IDF weighting

- Select the N most used tokens and transform them into features
- Calculate the TF-IDF for the feature tokens that each tweet has
 - TF-IDF is a numerical statistic that reflects the importance of a token in a tweet
 - TF – term frequency
 - IDF – inverse document frequency

Classifiers

Initially, 11 classifiers were put to test:

- Logistic Regression
- SGD Classifier
- Linear SVC
- NuSVC
- SVC
- Gaussian Naive Bayes
- Decision Tree
- Random Forest
- AdaBoost
- XGBoost
- Multi-layer Perceptrons

Training & Testing approach

Dataset division: 80% train and cross-validation (5-fold cross-validation), 20% test

Parameters to be taken into consideration:

- Maximum number of tokens to create features
- Different N-gram parameters (for the tokens counting)
- Token counting and TF-IDF weighting combination
- Classifiers hyperparameters

Too many combinations!

Training & Testing approach

First phase:

- Test all classifiers with the default hyperparameters
- Test with tokens counting, TF-IDF and both combined
- Test with the following number of most used tokens:
 - 100, 1000, 5000, 10000, 25000
- Test with 1-gram, 2-gram and both combined (only applied to tokens counting)
- Perform 5-fold validation and store the confusion matrix

Training & Testing approach

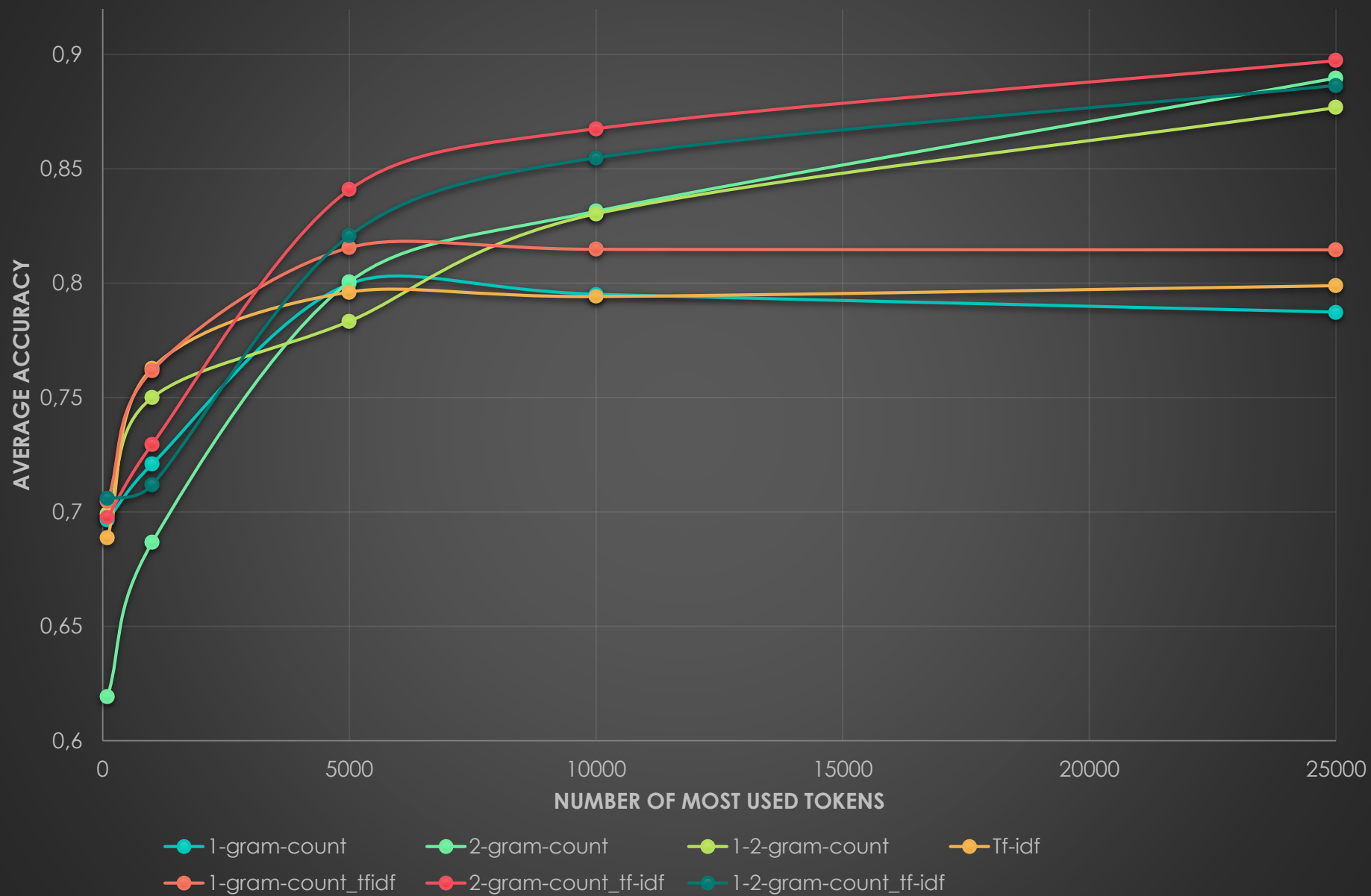
Second phase:

- Use the four best classifiers from the first phase
- Perform 5-fold cross validation on those four classifiers with different hyperparameters
- Select the best hyperparameters for each one of them and get the confusion matrix on the test data

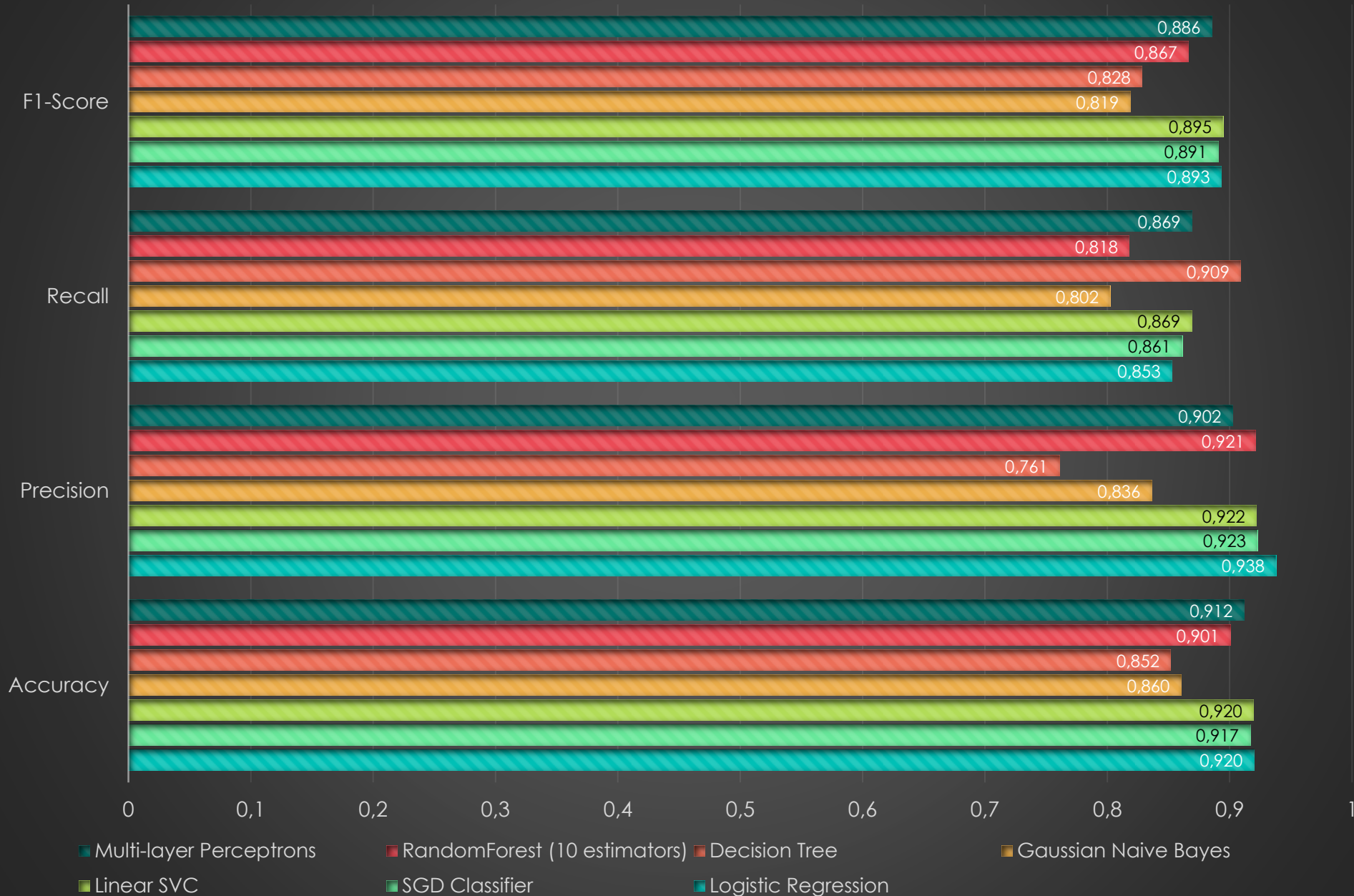
Third phase:

- Test the four best classifiers with the best hyperparameters from the second phase

Average accuracy with different number of most used tokens



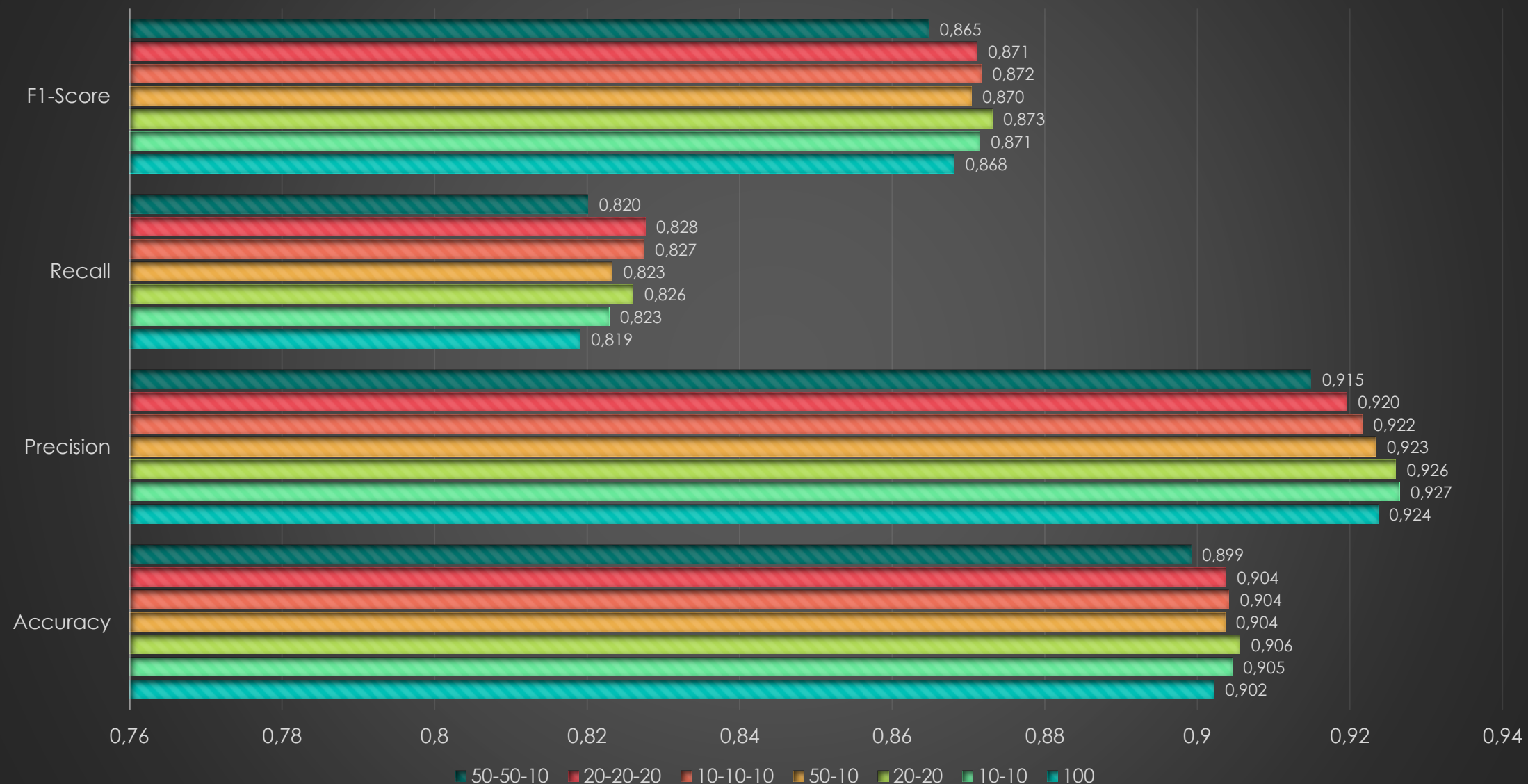
Results with 2-gram count and tf-idf features



Multi-layer Perceptrons (MLP)

- Activation function: ReLU
- Solver: Adam
- 500 epochs
- Early Stopping activated
- Different network configurations tested:
 - 100, 10-10, 20-20, 50-10, 10-10-10, 20-20-20, 50-50-10
- Different lambda values tested:
 - 0, 0.0001, 0.001, 0.01, 0.1, 1

Results with different network configurations



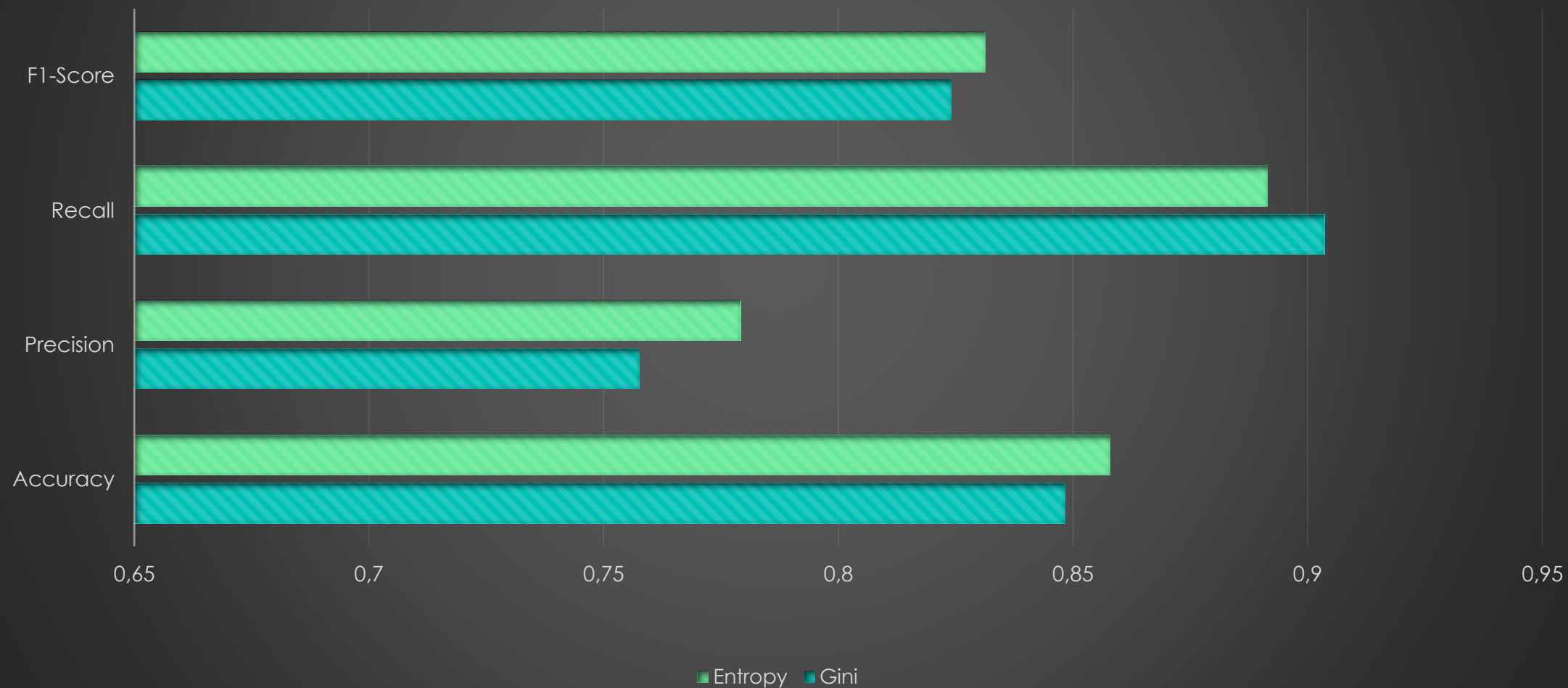
Recall with different network configurations and lambda values



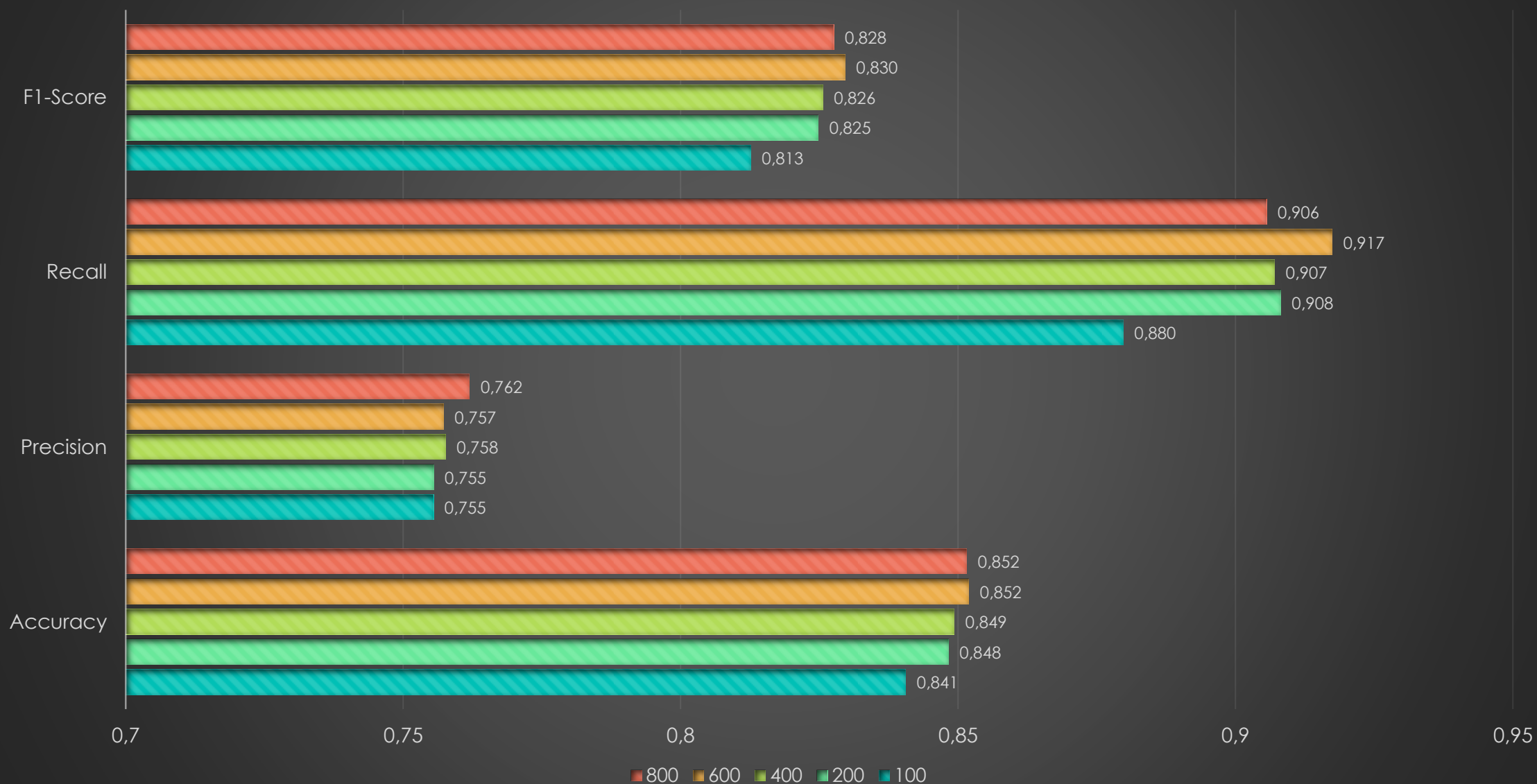
Decision Tree

- Criterion: measures the quality of a split
 - Gini
 - Entropy
- Maximum depth of decision tree
 - 100
 - 200
 - 400
 - 600
 - No maximum depth (~800)

Results score when using different criterion for splitting nodes in tree



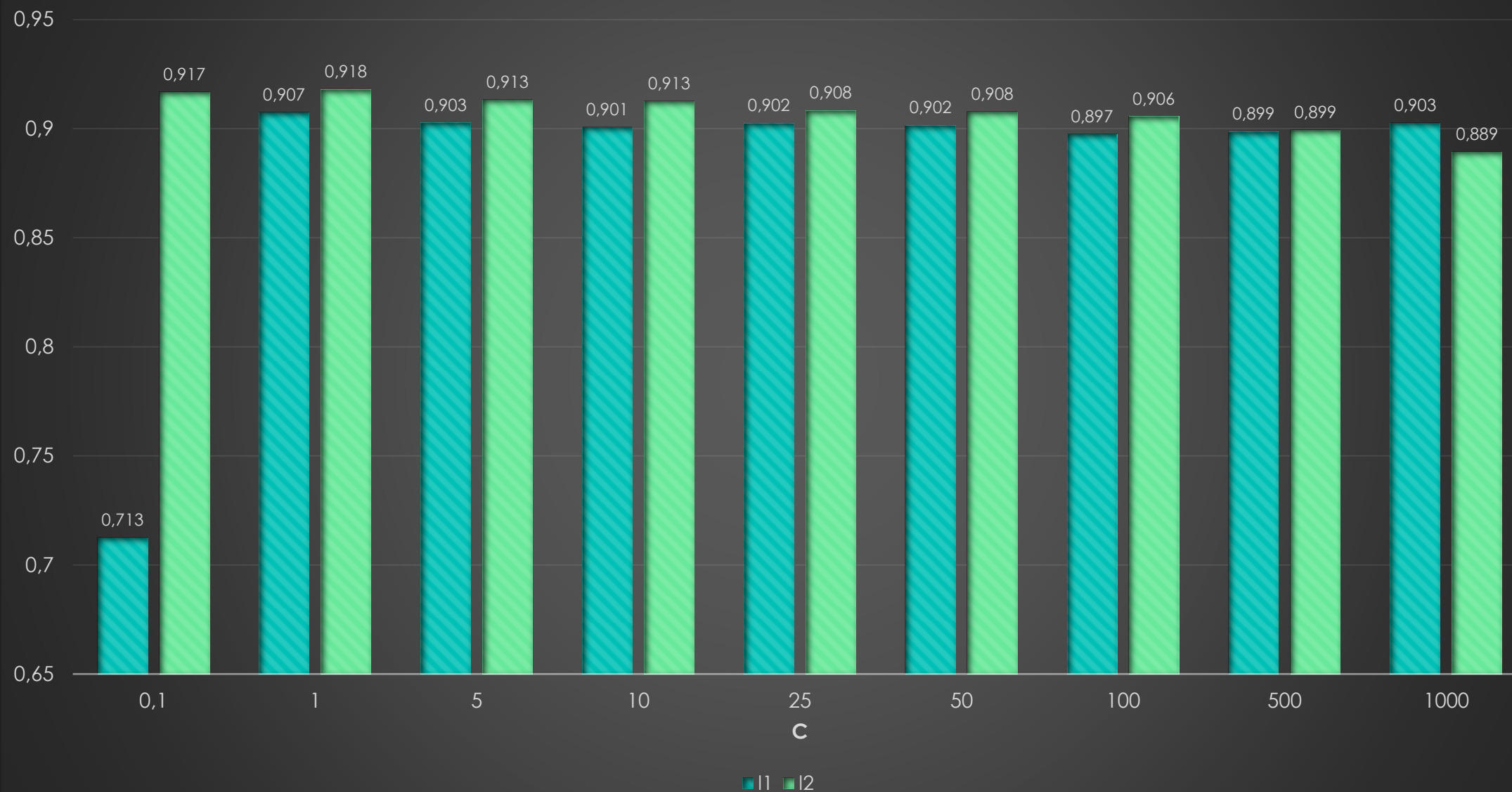
Classifier score for Gini Entropy



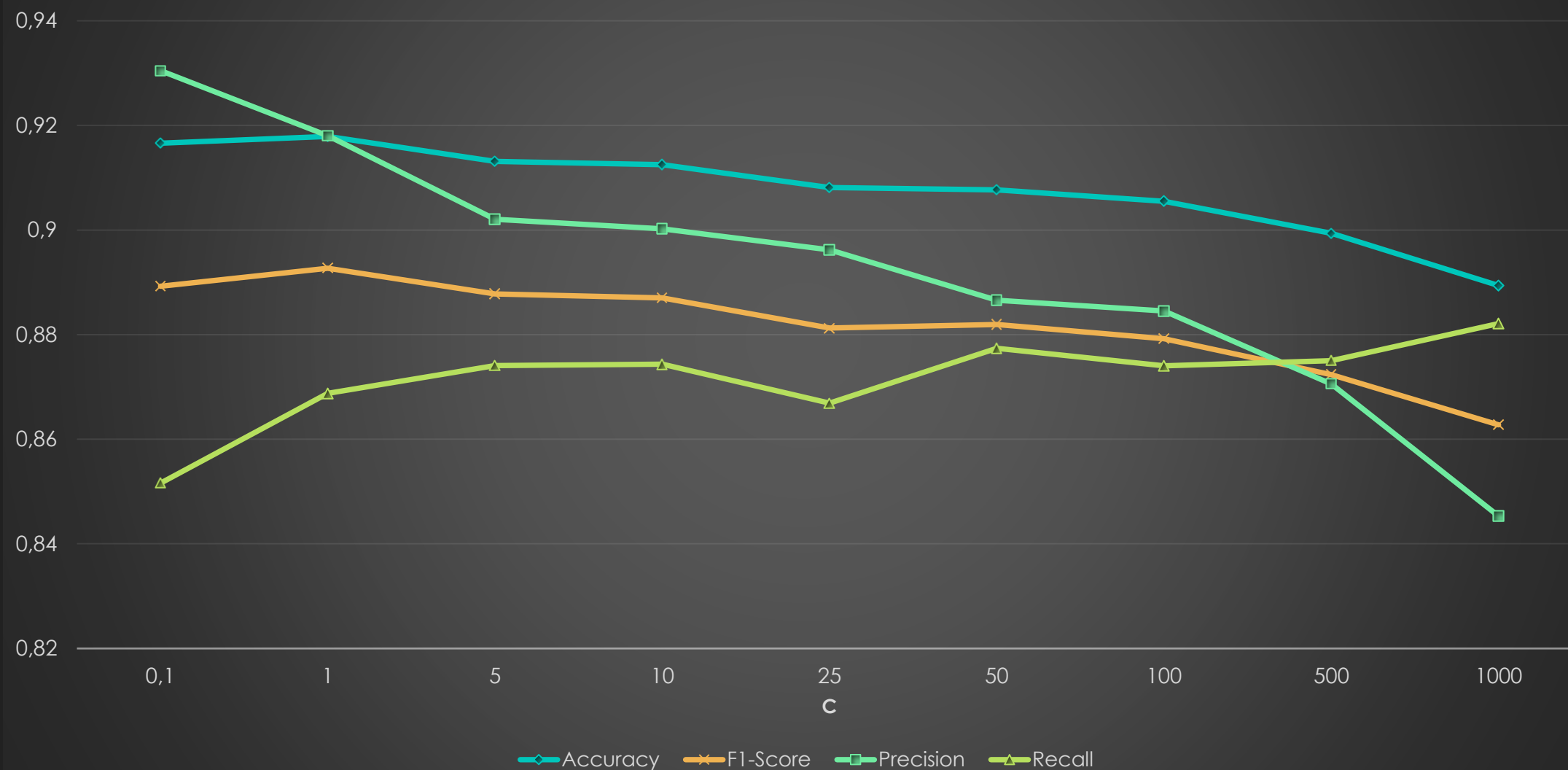
Linear SVC

- Penalty: norm used in the penalization
 - l_1
 - l_2
- C: penalty parameter C of the error term
 - 0.1
 - 1
 - 5
 - ...
 - 1000

Accuracy between l1 and l2 penalty with different C values

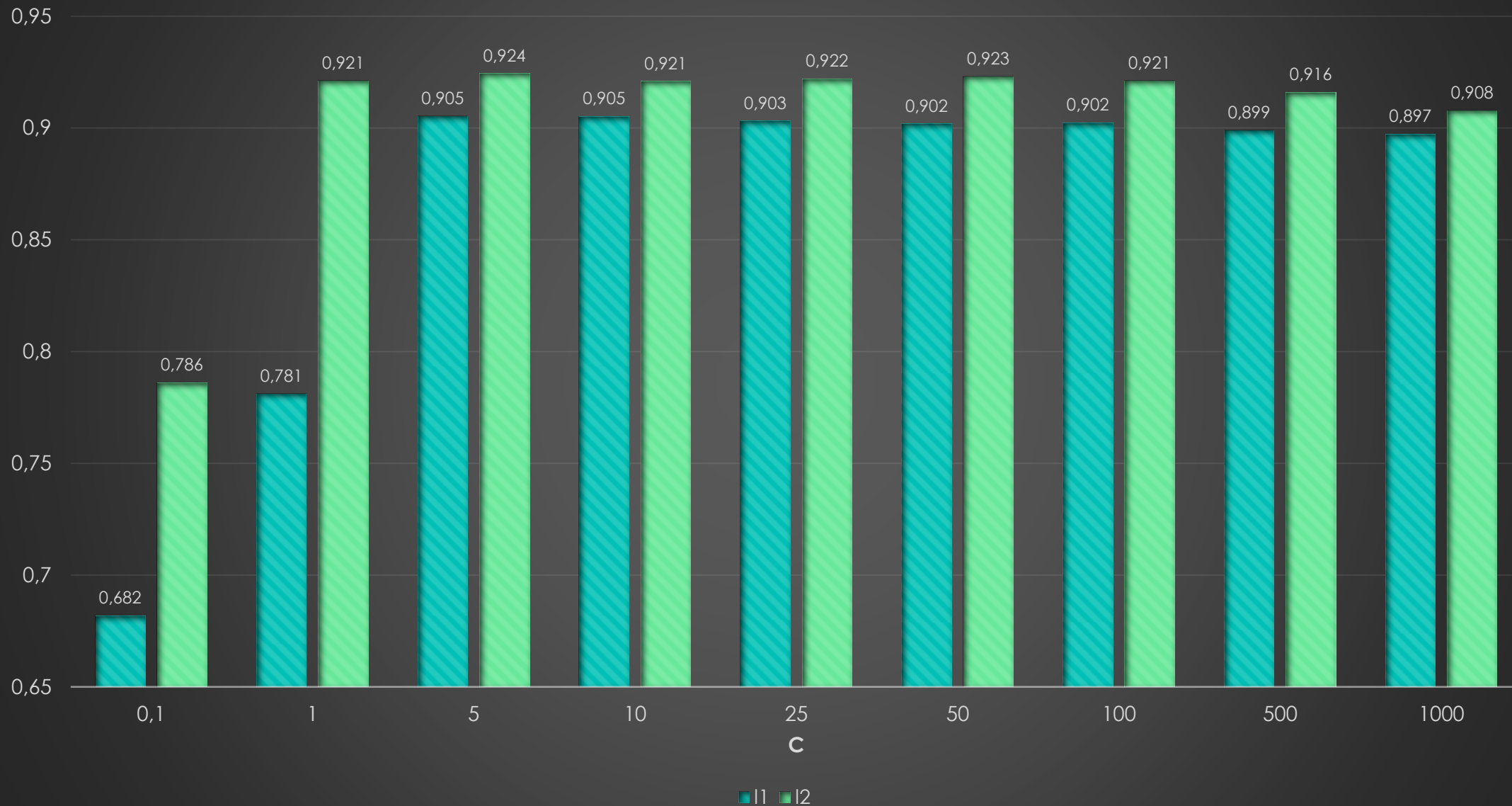


l2 penalty results with different C values

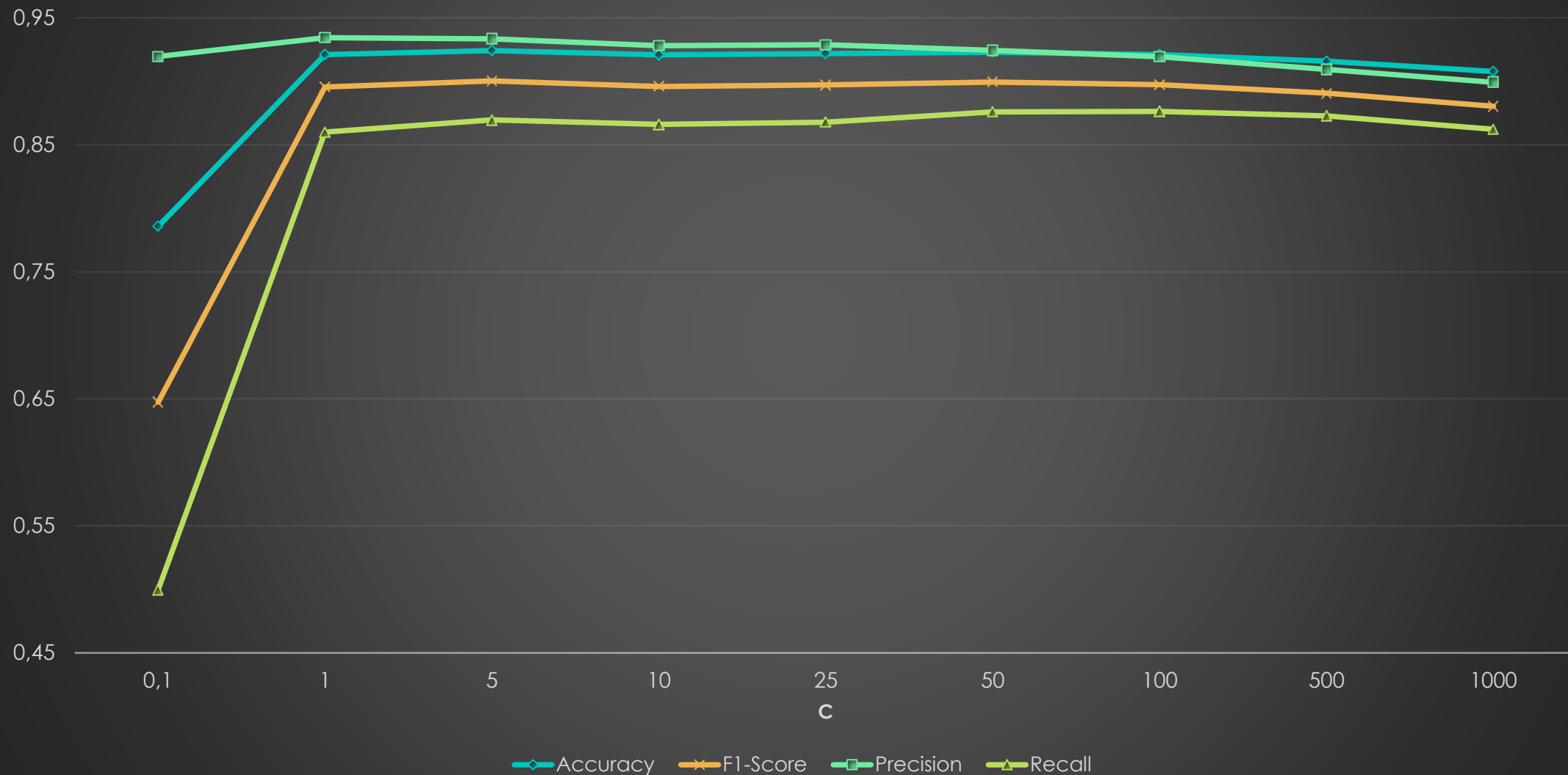


Logistic Regression

- Penalty: norm used in the penalization
 - l_1
 - l_2
- C: penalty parameter C of the error term
 - 0.1
 - 1
 - 5
 - ...
 - 1000

Accuracy between l1 and l2 penalty with different C values

l2 penalty results with different C values



Final results

Classifier	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.956	0.940	0.946	0.943
Linear SVC	0.952	0.924	0.952	0.938
Decision Tree	0.871	0.764	0.959	0.850
Multi-layer Perceptrons	0.944	0.943	0.907	0.925

Data division: 80% train and 20% test