A Stopping Criterion for Active Learning

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A Stopping Criterion

- Manual annotation takes time and human effort
- Could stop when some performance is achieved
- A better solution would consider how much can be learnt by labelling unlabelled instances
- Proposed approach examines classifier confidence

Reuters Document Classification

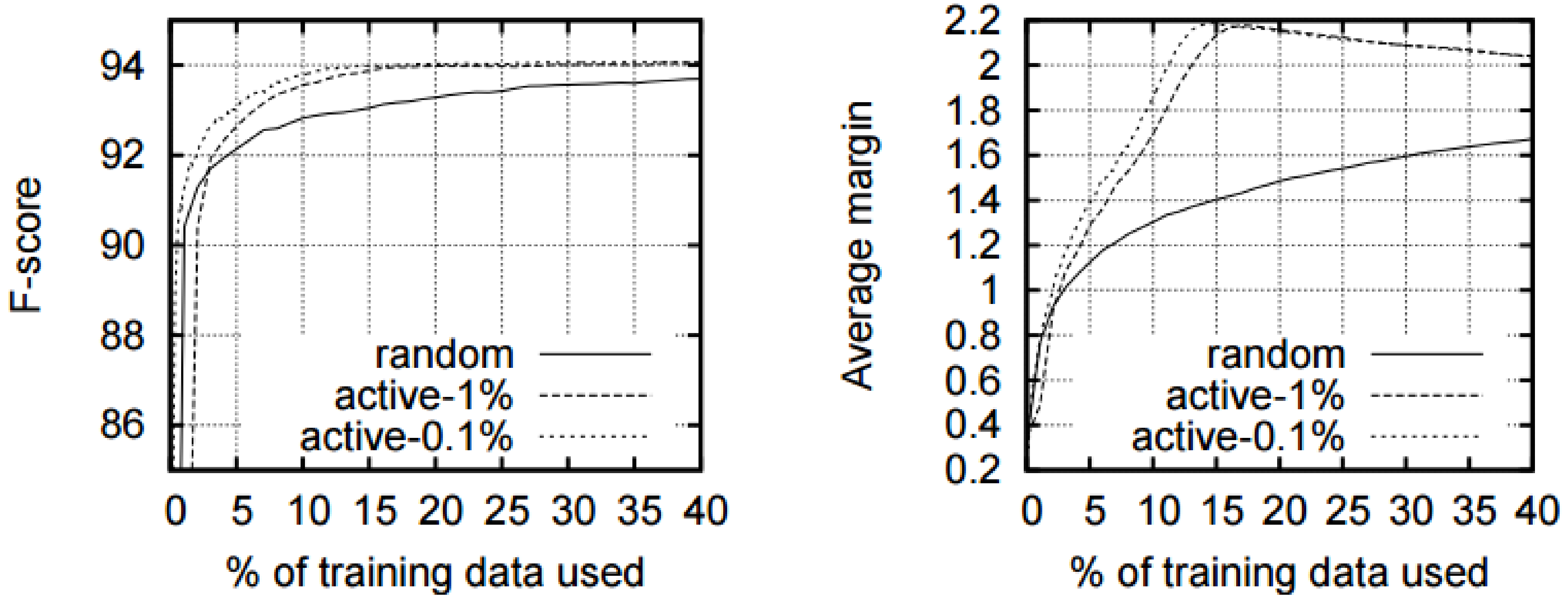
Support Vector Machines (SVM)

- Typically used as a binary classifier
- Kernel functions (such as linear, $K(x_i, x_j) = x_i \cdot x_j$)
  - Compare instances
  - Effectively map to higher dimensions
- Classify by finding hyperplane with maximal margin

Training a Reuters SVM Classifier with AL

- SVMs trained on most popular topic in Reuters
- Margin used as measure of uncertainty
- Average margin of test set data used as a measure of the confidence of the classifier
- Three SVMs compared:
  - Random test data sampling
  - AL, adding 1% of pool to the training data each time
  - AL, adding 0.1% of pool to the training data each time

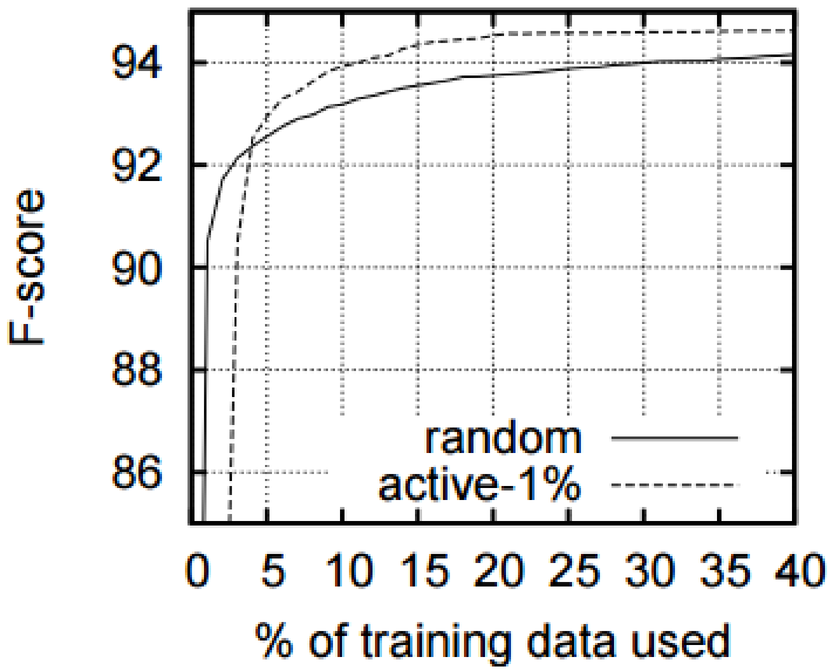
Linear SVM Training on Reuters

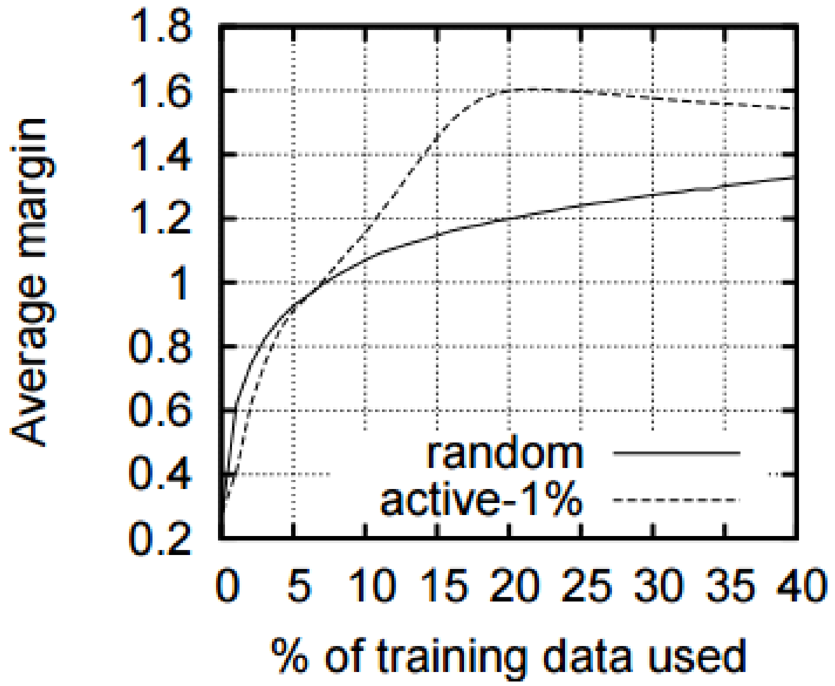


The Rise-Peak-Fall Pattern

- The confidence follows a rise-peak-fall pattern
- Rise to a peak as training data with novel information is used (performance changes little after this)
- Falls as contradictory instances selected:
  - The classifier is confident, but incorrect, about these
  - Presumably, these are due to limitations of the feature set (eg a bag-of-words model ignoring word order)

Gaussian SVM Training on Reuters



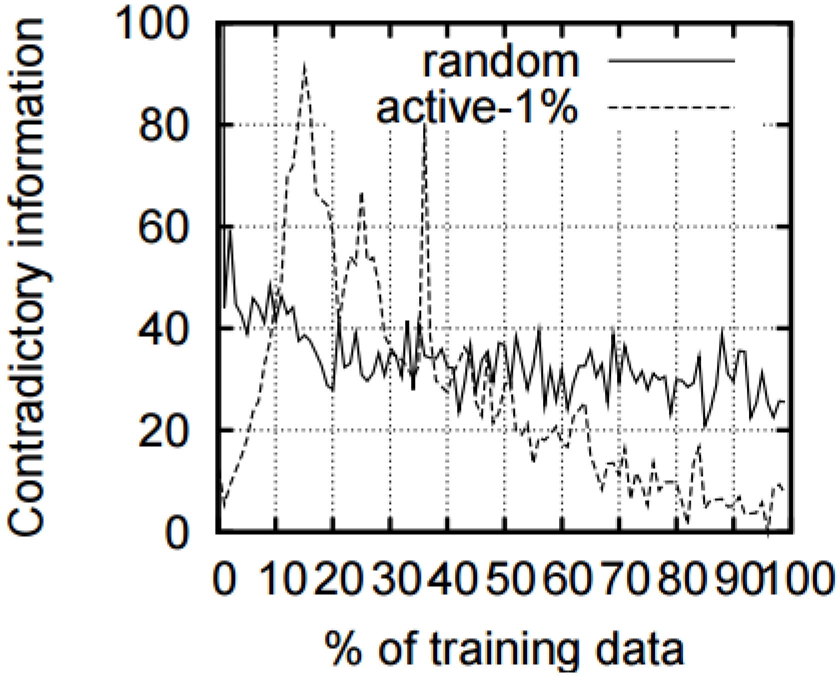


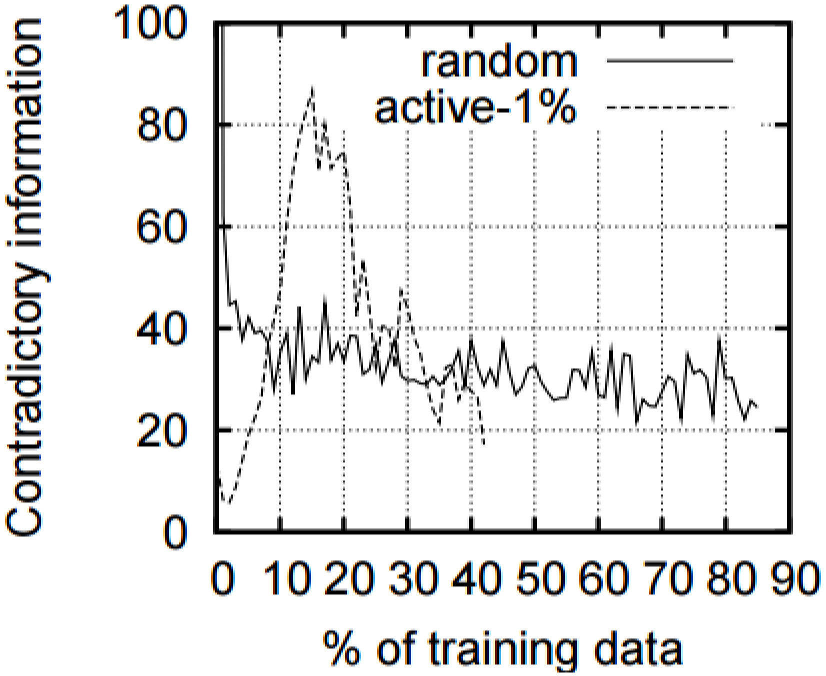
Contradictory Information

- Contradictory information is added when
  - An instance whose label is incorrectly predicted
  - Is added to the training data
- For round *t* this is computed as:

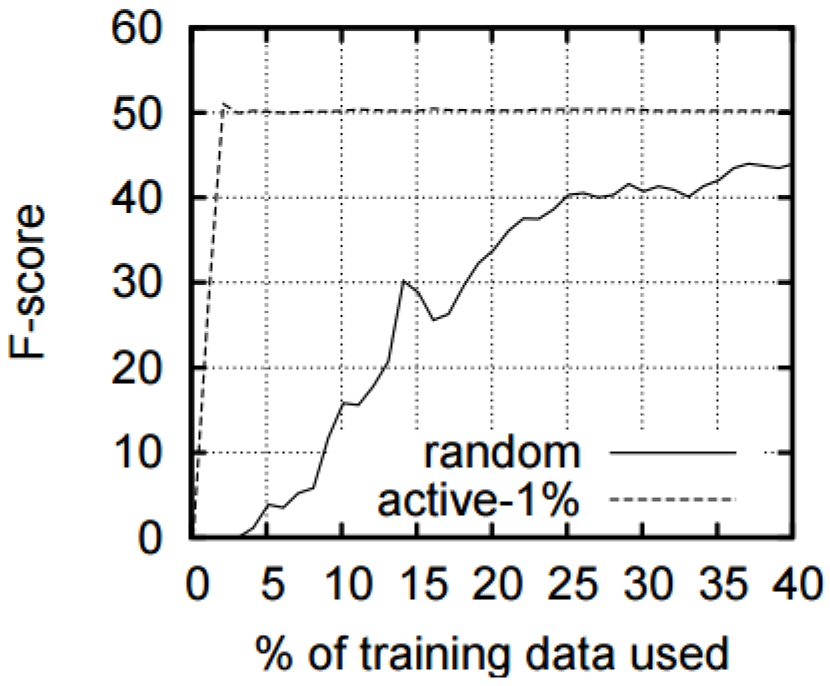
$$Contradictory\_information(t) = \sum_{i \in i^t} \frac{| f^t(x_i) |}{| f^t(x) |}$$

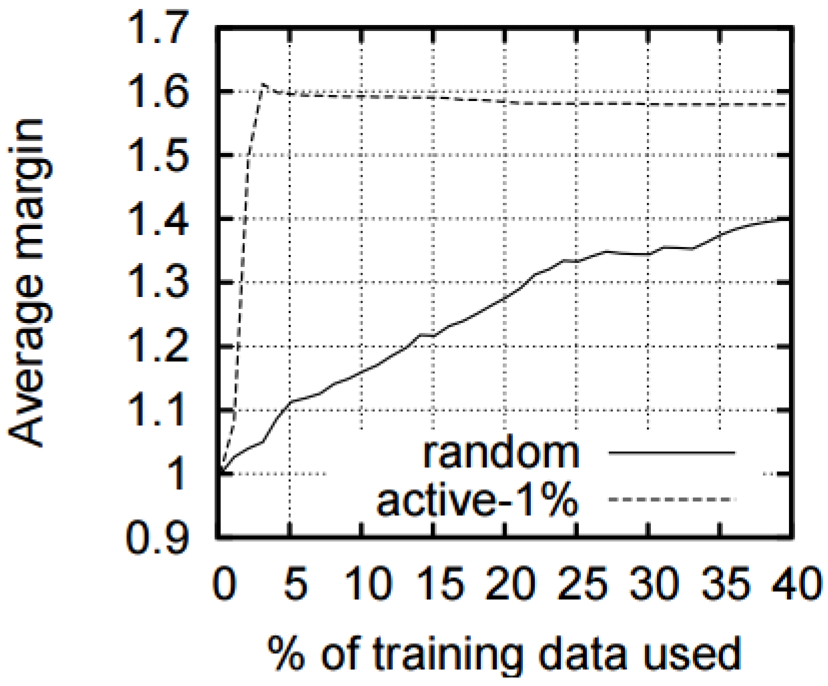
SVM Contradictory Information



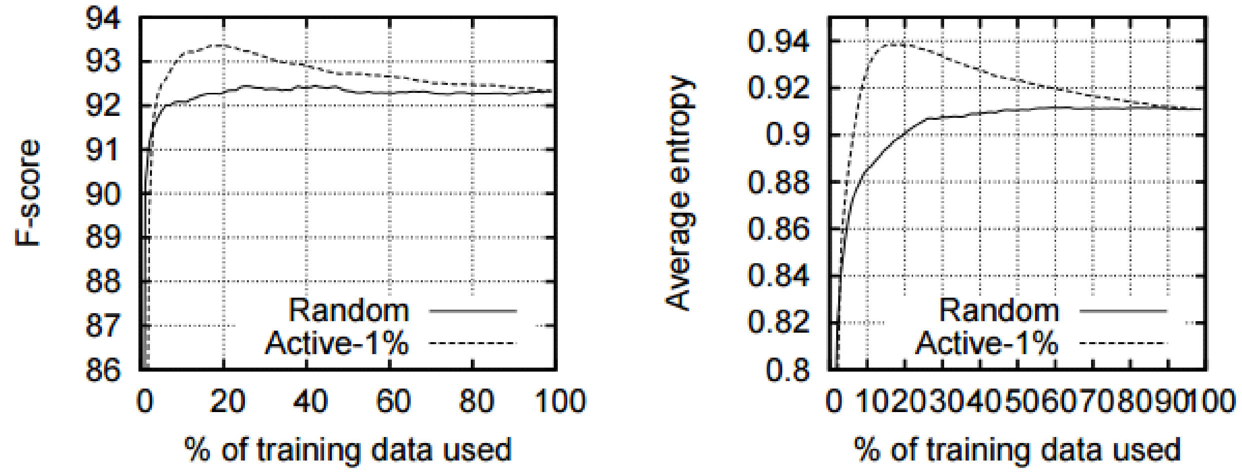


Linear SVM for an Infrequent Class

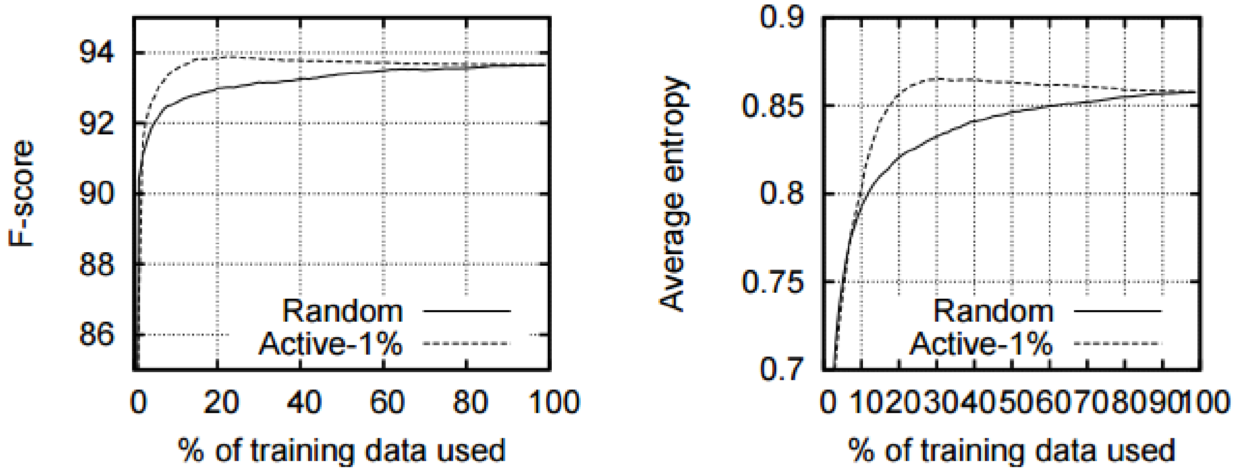




Experiments With Other Classifiers



Bayesian Logistic Regression Classifier



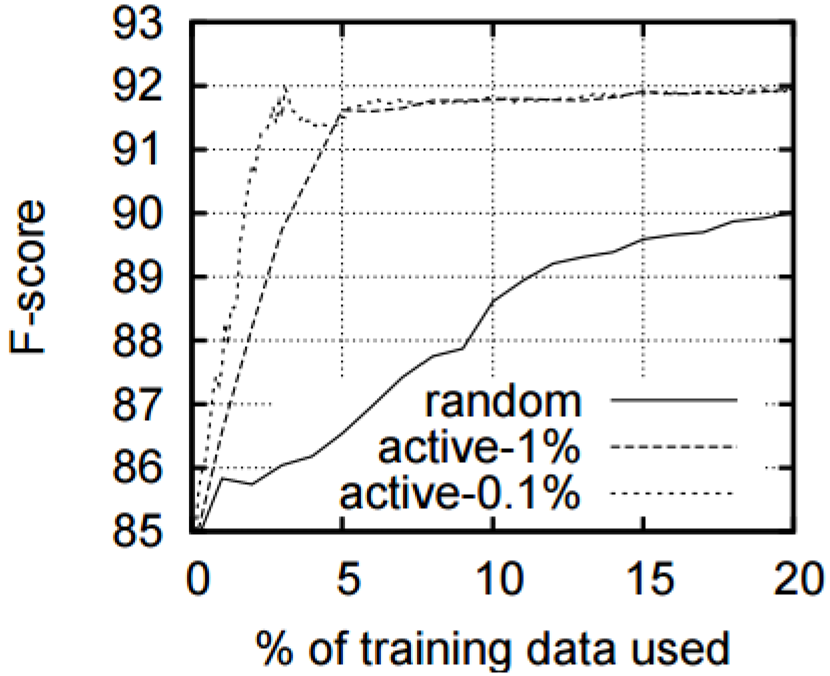
Maximum Entropy Classifier

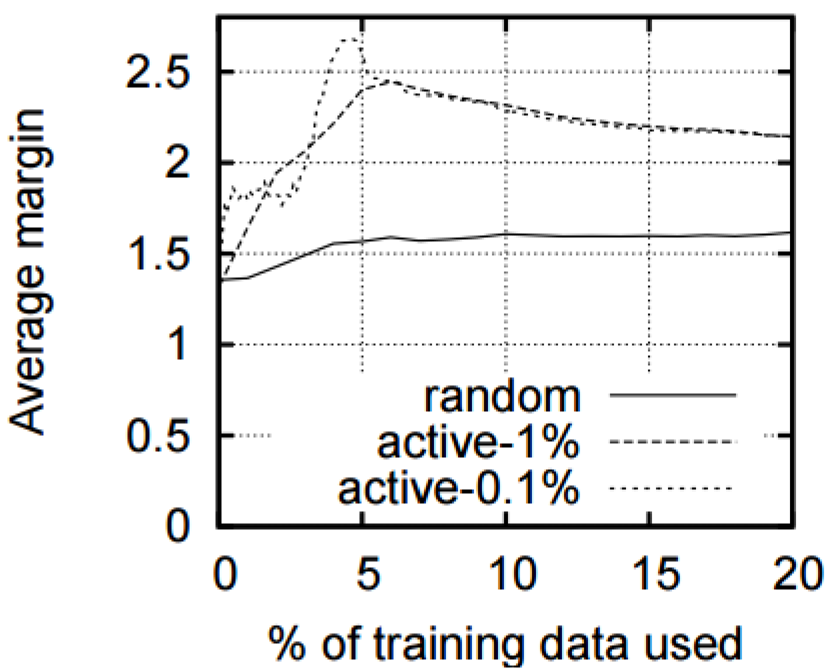
Binary NER Classification

Set-up

- The dataset has four entity types to be recognised
- Reduce this to a binary task by just identifying if there is a named entity or not
- Train a linear kernel SVM using AL
  - Randomly choose 1% of data as seed data
  - Use 1% and 0.1% batches
- Classifier uses simple lexical features

Linear SVM for NER





Tricking the Stopping Criterion

- The criterion detects a rise-peak-fall pattern
- The criterion can be satisfied non-optimally with
  - A noisy or misleading seed
  - Bad early selections
- Instead, require a consistent drop in the confidence

Multiclass SVM

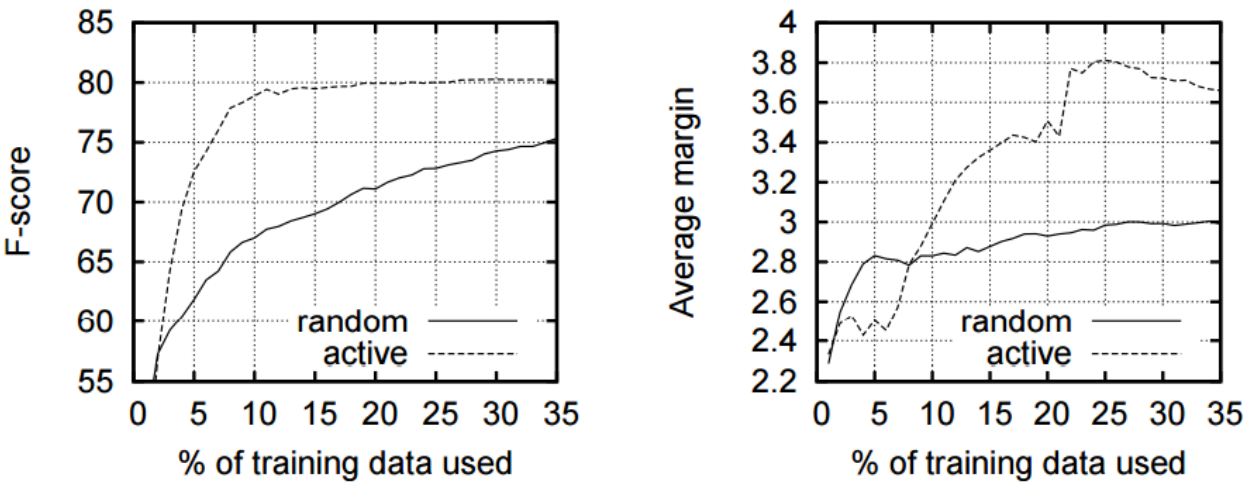
The One-Against-All Scheme

- This is a way to adapt SVMs for multiple classes
- Approach
  - Each classifier classifies true/false for one class
  - Select the class which gives the largest positive margin
- Define Confidence as the difference in the size of
  - The most positive margin
  - The next most positive margin

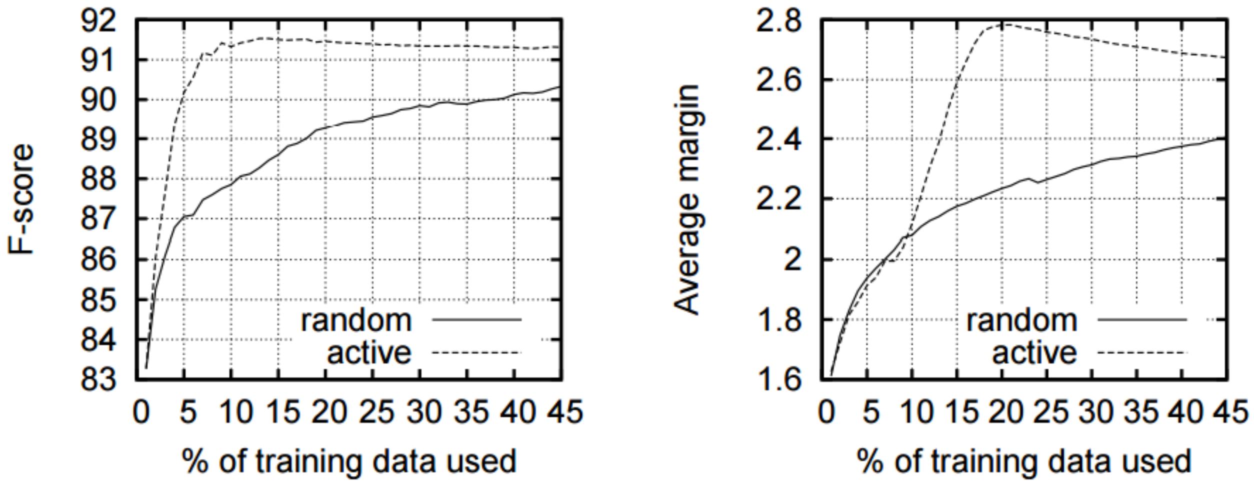
Set-up

- NER experiments
  - As before, but use the four separate classes
- Shallow parsing experiments
  - Goal is to divide text into chunks (“syntactically-related, non-overlapping groups of tokens”)
  - Each token belongs to one syntactic category
  - 23 classes (with widely-varying numbers of instances)
  - Uses a previously-defined feature set

Multiclass SVM Experiments



Multiclass NER Classifier



Shallow Parsing Classifier

Conclusion

Applicability of Stopping Criterion

- These experiments show how a stopping criterion based on the rise-peak-drop pattern could work
- We saw how this pattern appeared consistently with a variety of problems and classifiers

Critique

- Thorough explanation of background and context
- Appears to be a novel, sensible, and effective extension of the then state-of-the-art
- Should be particularly useful for NLP tasks
- Formulation of the criterion wasn’t made very explicit
- Comparisons to alternatives might be interesting