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Improving Automated Email Tagging with Implicit Feedback

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OUTLINE

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- **Algorithms**
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  - Implicit Feedback Algorithms
- **The Lab-controlled User Study**
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MOTIVATION

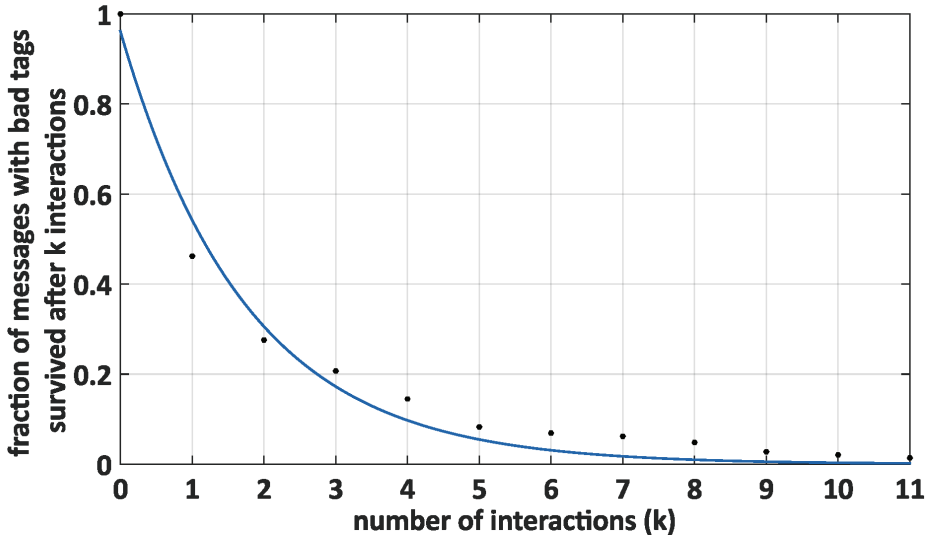
- **Online Email Tagging:**
  - user receives an email message
  - system predicts tags for the message
  - the email user interface shows the predicted tags
  - if a predicted tag is wrong:
    user **may** correct the tag
    (if so, the system receives training)
  - if a predicted tag is right:
    user **does not** have to do anything
    (the system *never* receives training)

MOTIVATION

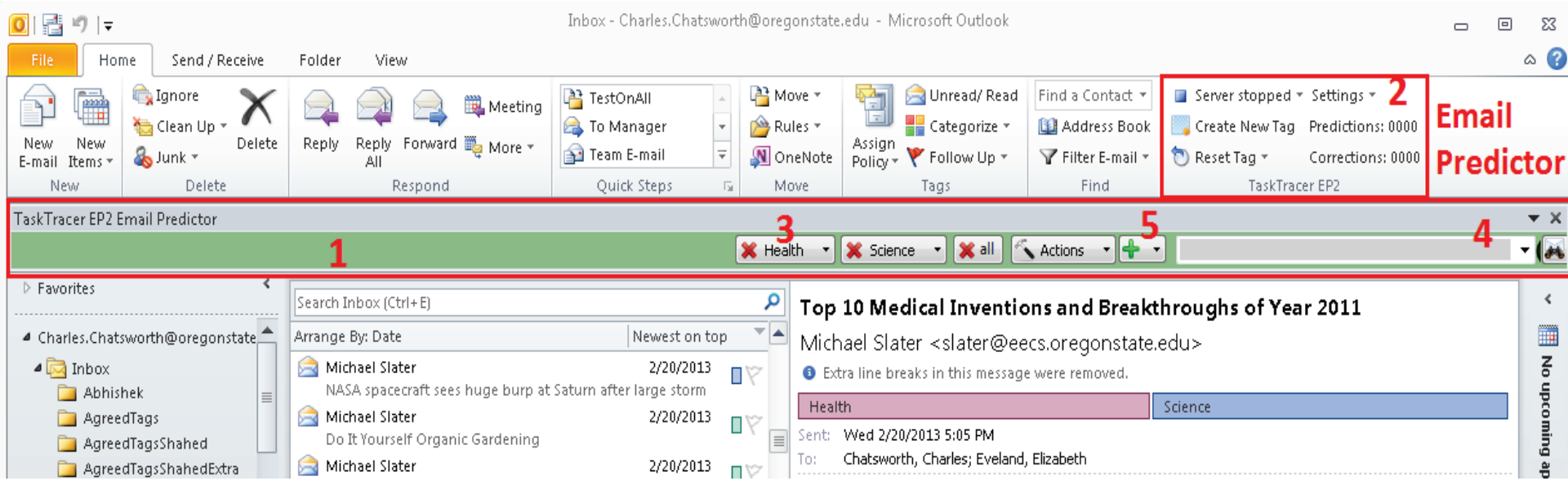
- **Challenges:**
  - learning algorithm never receives confirmation that its predictions are correct
  - the learning algorithm would benefit from positive feedback.

- **Survival Curve:**
  - the more time a user spends on a message, the more likely that the user will notice tag errors and correct them.

- **Implicit Feedback!**



THE EMAIL PREDICTOR (UI)



EP2 INSTRUMENTATION

- **Implicit Feedback Features:**
  - message was opened and read in either the Outlook Explorer or the Outlook Inspector
  - user added or removed a tag on the message
  - user added or removed a flag from the message
  - user moved the message to a folder
  - user copied, replied, forwarded, or printed a message
  - user saved an attachment from the message

ALGORITHMS

Baseline Algorithms:

- **No Implicit Feedback (NoIF)**
  - never creates implicit feedback training examples
  - only trains on user corrections
  - standard behavior of EP (**Lower-bound on performance**)
- **Online**
  - ignores all implicit feedback events
  - after making a prediction, creates training examples with the ground truth tags
  - provides perfect feedback to EP (**Upper-bound on performance**)

Implicit Feedback Algorithms

- **Simple Implicit Feedback (SIF)**
  - when the user changes any tag immediately treats all remaining tags as correct
- **Implicit Feedback without SIF (IFwoSIF)**
  - maintains a count of the total number of implicit feedback events
  - treats tag changes just like all other implicit feedback events
  - when this count exceeds a specified threshold, then it creates the implicit feedback training examples
- **Implicit Feedback with SIF (IFwSIF)**
  - combines IFwoSIF and SIF

THE USER STUDY

- **Participants**
  - 15 participants (1 dropped out)
  - only adult email users who receive 20 or more emails per day, regularly use tags, categories, labels, or folders
- **The Study Data**
  - an email data set containing a total of 330 messages created from a variety of web sources
  - Train60, Test270
- **The Study Sessions**
  - three two-hour sessions on three separate days
  - 1 hour practice, 5 hours performing study tasks (reading emails, correct tags if necessary, follow instructions in the message)
  - user ground truth collected at the end

THE EMAIL DATA SET

- Email life of a knowledge worker—a student in this case
  - a total of 330 messages
  - average number of tags per email message = 1.24
  - messages with information, requests to send file, search online, save attachment, forward message etc.

Tags	%messages
Economics	15
Entertainment	18
Gardening	19
Health	23
Math	17
Meeting/Event	31

POST-STUDY SIMULATION

- The participants did not provide very much explicit feedback
  - mean percentage of messages for which they corrected tags was 16.3%

- **Solution:** combine the observed implicit feedback events with simulated explicit feedback

POST-STUDY SIMULATION

- **Algorithm *SampleEF (`user, TargetEF`)*:**

  Estimate the (fitted) probability, *`P(EF | totalIF)`*

  FOR every message, compute p_i = `P(EF(i) | totalIF(i))`

  Compute the observed level of EF (*`obs_EF`*) in '*`user`*' data

  IF *`obs_EF > TargetEF`* :

  DO:delete EF from the message (that has EF) with the smallest p_i

  UNTIL *`obs_EF =TargetEF`*

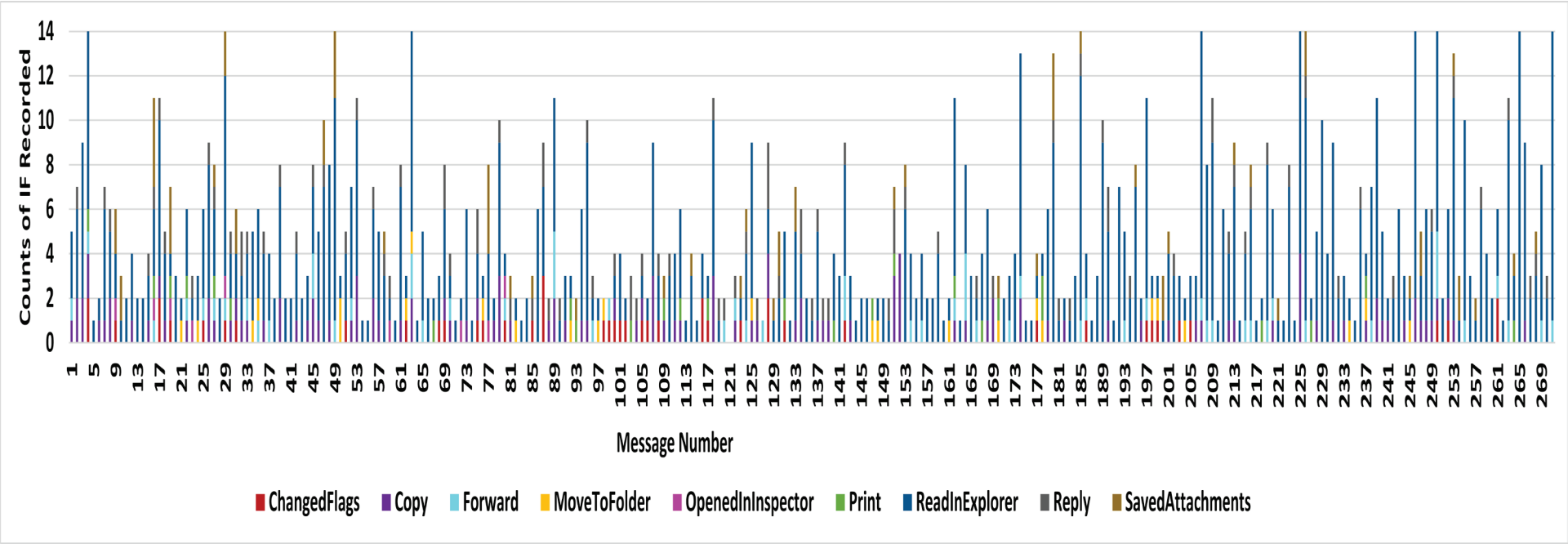
  ELSE :

  DO:add EF to the message (that has no EF) with the largest p_i

  UNTIL *`obs_EF =TargetEF`*

RESULTS

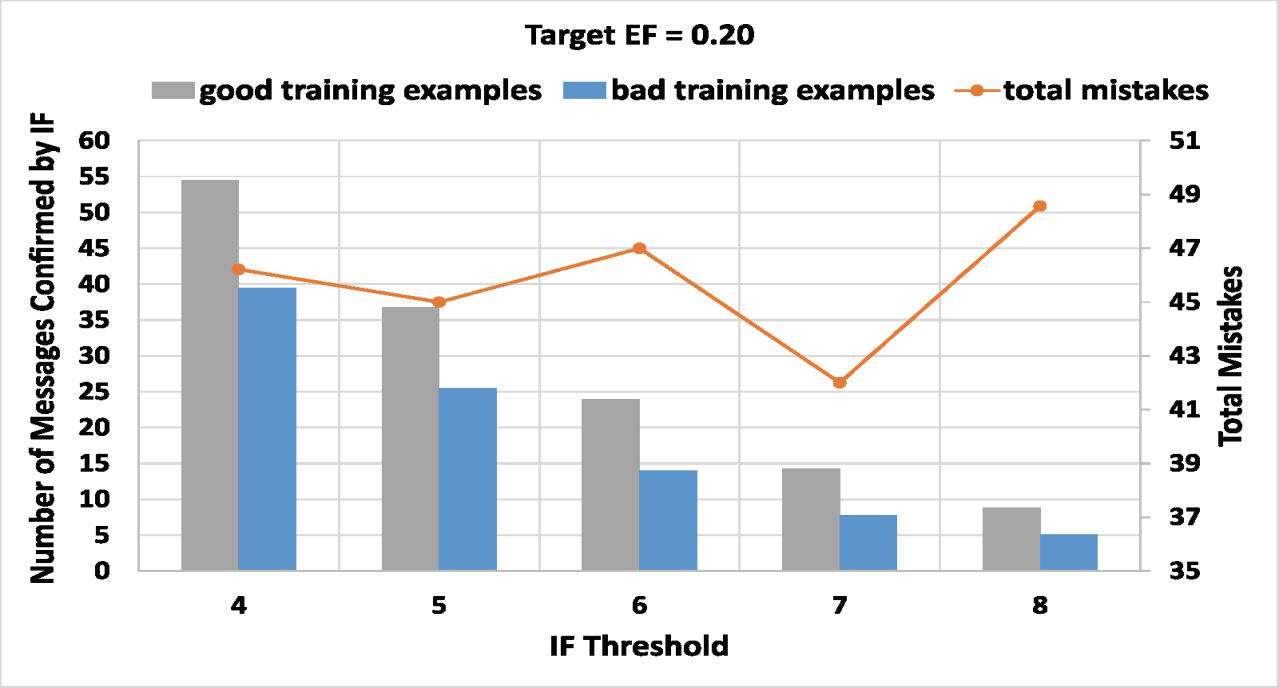
- Implicit feedback captured during the study sessions of one participant.
- The first session ends after message 66, and the second session ends after message 168.



RESULTS

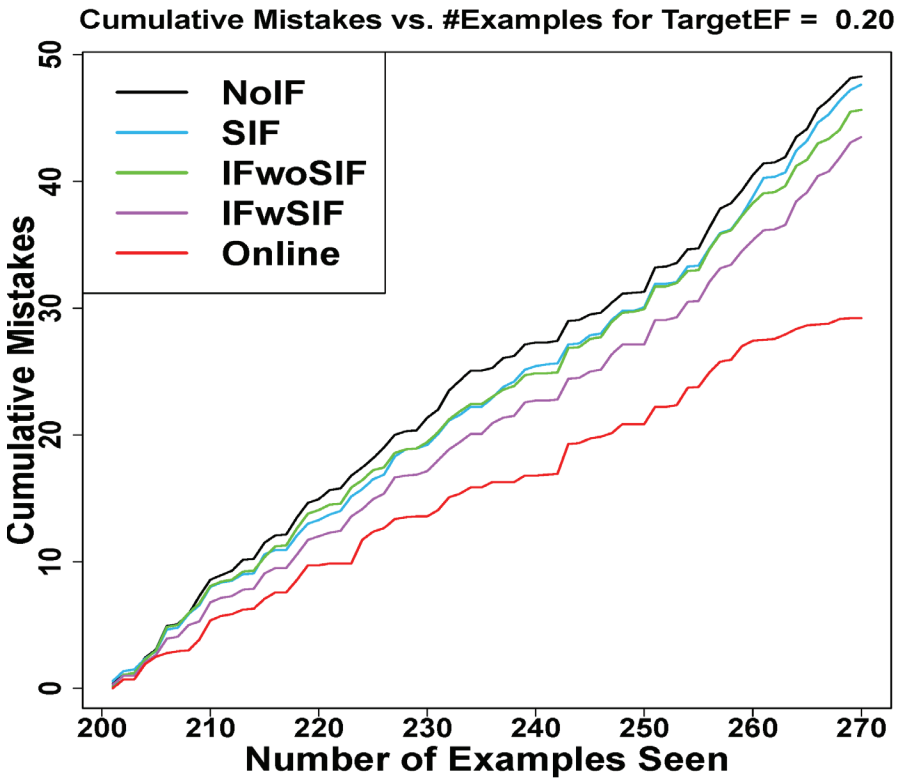
- **Implicit Feedback Threshold Selection**

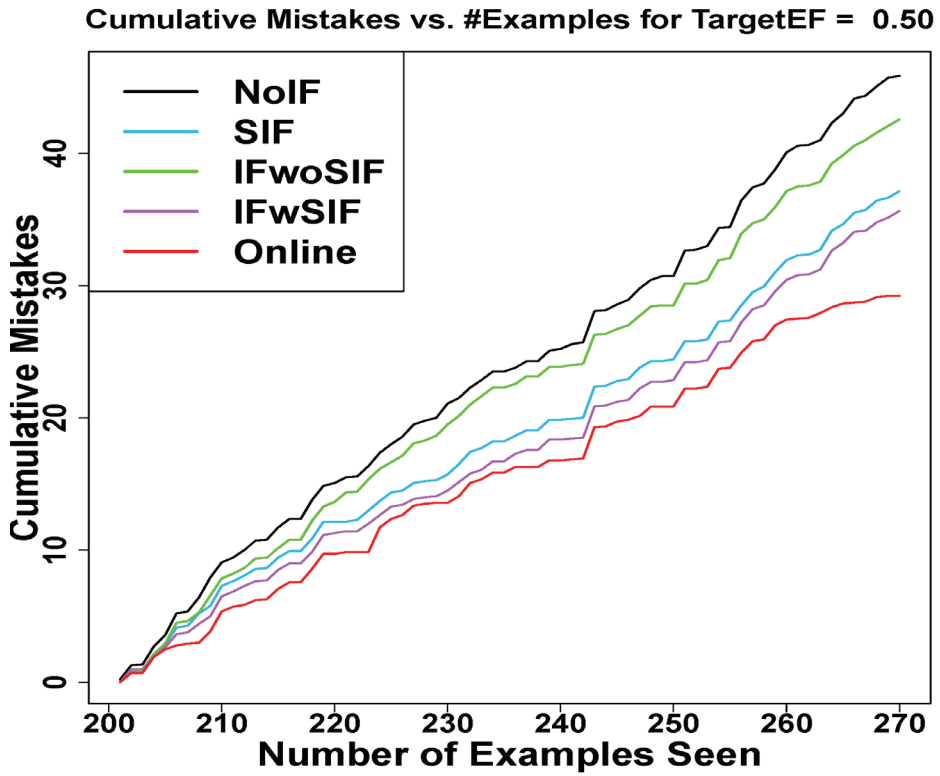
  - a threshold exists such that the loss in accuracy of the resulting incorrect training is out-weighed by the gain of the resulting correct training examples



RESULTS

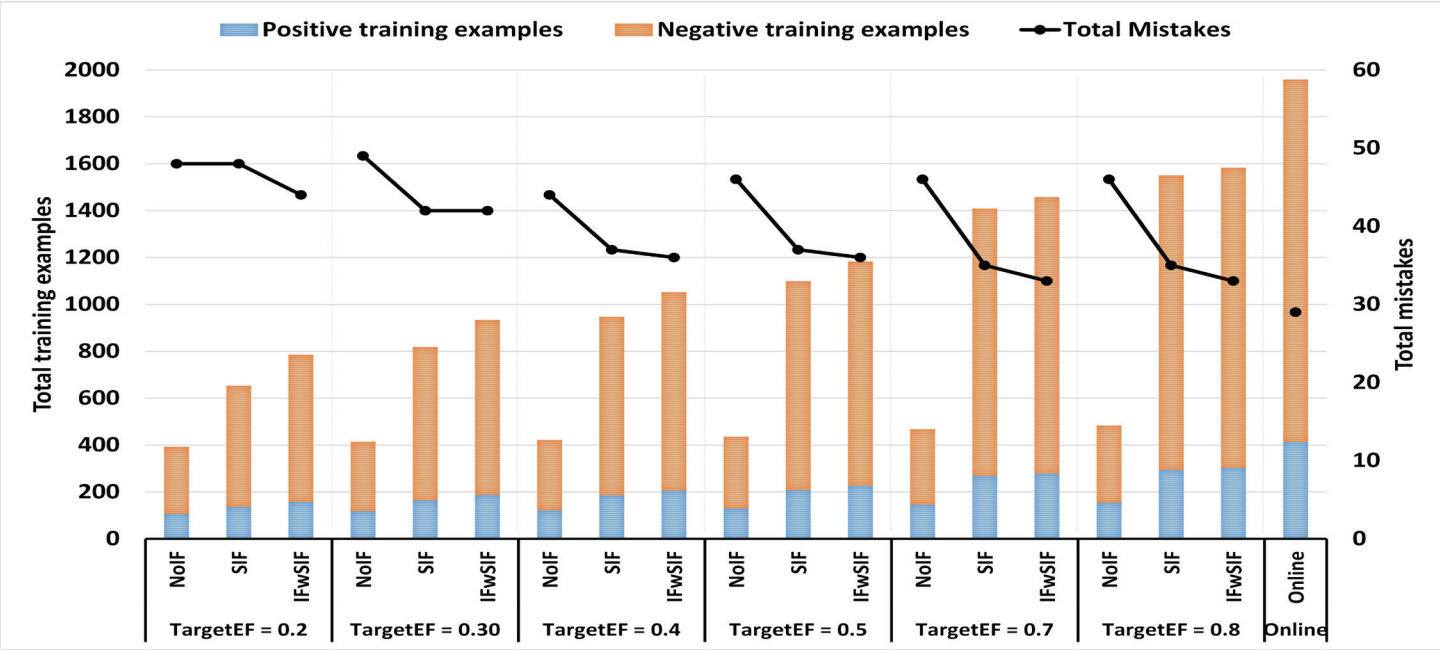
- **Cumulative Mistakes**
  - plotted as a function of number of examples seen from the test data
  - SIF and IFwSIF algorithms have largely eliminated the gap between NoIF and Online





RESULTS

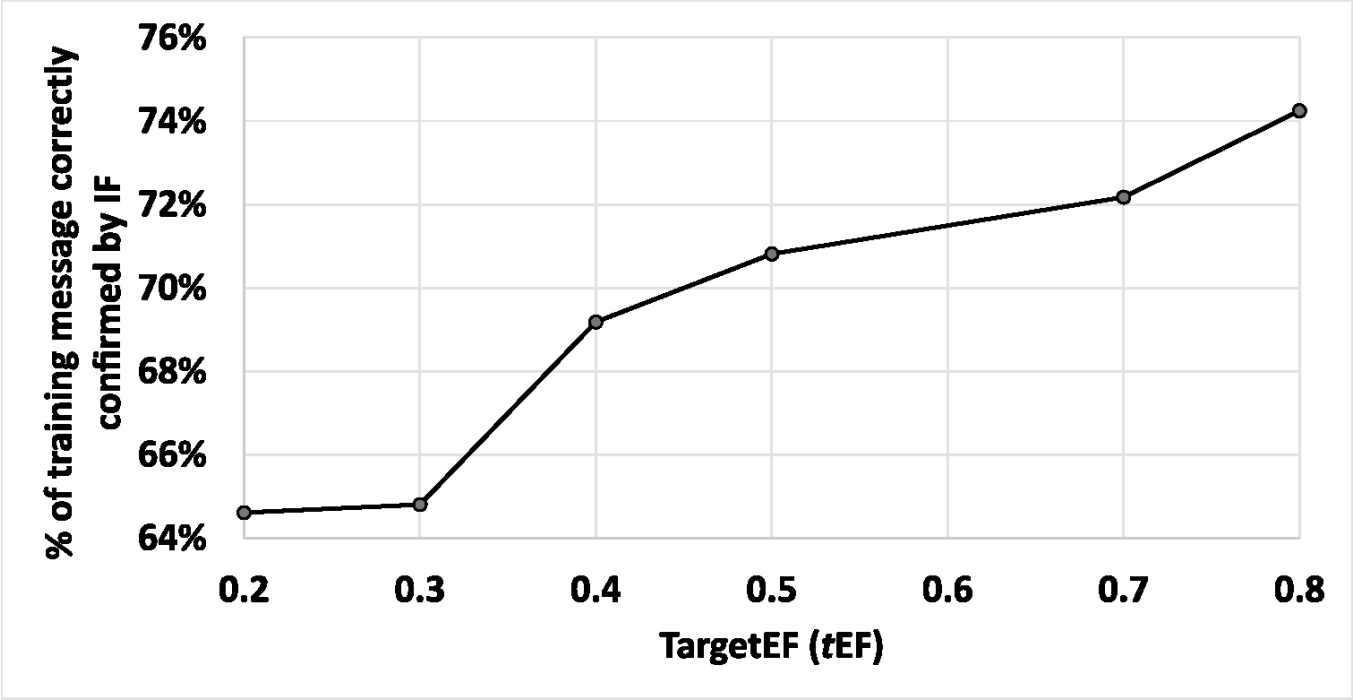
- SIF produces the predominant share of the training examples
- Additional examples added by implicit feedback have a substantial effect on further reducing prediction errors
- IFwSIF receives 64% more training than NoIF, and
  14% more training than SIF



RESULTS

- Quality of the implicitly-confirmed training examples
  - at TargetEF 0.20, only 64% of the confirmed messages have correct tags
  - at TargetEF 0.80, only 74% of the confirmed messages have correct tags

- Although implicit feedback is noisy, on balance the classifiers still benefited!



SUMMARY

- Automated tagging of email with user-defined tags is possible
- By instrumenting the UI, we can detect “implicit positive feedback” with reasonable accuracy
- Incorporating implicit feedback into the classifier(s) improves the performance of the email predictor

QUESTIONS?

Thank you

SUMMARY

- Highly-accurate tagging of email with user-defined tags is possible
- By instrumenting the UI, we can detect “implicit positive feedback” with reasonable accuracy
- Incorporating implicit feedback into the classifier(s) improves the performance of the email predictor