Humble Active Learning from Peers

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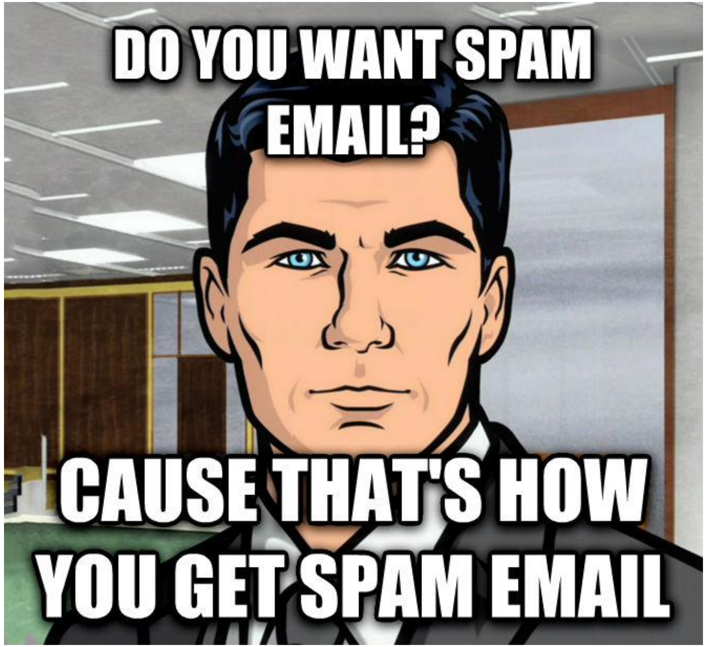
A Real World Problem

Personalized spam filters for everyone



A Real World Problem

Suppose we want to train personalized spam filters for 15 users.

- Each user has his own personalized spam filter
- Needs 1000 labelled emails for each user to train a good model.
- Total 15000 labels needed.
- Total 15 models/learners needed.

Question

What if we have 15 MILLION users in the system? Do we really need that much labels for each user?

Possible Solutions

- ***Multi-task learning*** leverages the relationship between tasks to transfer relevant knowledge from information-rich tasks to information-poor ones.
  - Batch learning - an entire training set is available
  - Online learning - the learner sees the data sequentially
- ***Active learning*** allows the learner to make a decision on whether to ask the oracle to provide the true label for the current example and incur a cost or to skip this example.

Possible Solutions

Maybe we can take advantage of the knowledge about the relationship among users?

- Some spams are universal to all users
    - E.g., financial spams
- Some messages might be useful to certain affinity groups
    - Kobe and Lebron are interested in invitations to play NBA All Star but Obama and Trump might not

We can keep track of these similarity/relationship information and also improve our knowledge through learning (asking feedback from oracles).

Active learning from peers

Here we go,

Online Multitask learning with selective sampling

Active learning from peers

1. Receive an example $x^{(t)}$ for the task k
2. If the task k is not confident in the prediction for this example, ask the *peers* or *related tasks* whether they can give a confident label to this example.
3. If the *peers* are not confident enough, ask the oracle for the true label $y^{(t)}$.

Algorithm 1: Active Learning from Peers

Input : $b_1 > 0, b_2 > 0$ s.t., $b_2 \geq b_1$, $\lambda > 0$, Number of rounds T

Initialize $w_m^{(0)} = \mathbf{0}\ \forall m \in [K], \boldsymbol{\tau}^{(0)}$.

for $t = 1 \dots T$ **do**

  Receive $(x^{(t)}, k)$

  Compute $\hat{p}_{kk}^{(t)} = \langle x^{(t)}, w_k^{(t-1)} \rangle$

  Predict $\hat{y}^{(t)} = sign(\hat{p}_{kk}^{(t)})$

  Draw a Bernoulli random variable $P^{(t)}$ with probability $\frac{b_1}{b_1 + |\hat{p}_{kk}^{(t)}|}$

  if $P^{(t)} = 1$ **then**

    Compute $\hat{p}_{km}^{(t)} = \langle x^{(t)}, w_m^{(t-1)} \rangle\ \forall m \neq k, m \in [K]$

    Compute $\tilde{p}^{(t)} = \sum_{m \neq k, m \in [K]} \tau_{km}^{(t-1)} \hat{p}_{km}^{(t)}$ and $\tilde{y}^{(t)} = sign(\tilde{p}^{(t)})$

    Draw a Bernoulli random variable $Q^{(t)}$ with probability $\frac{b_2}{b_2 + |\tilde{p}^{(t)}|}$

  end

  Set $Z^{(t)} = P^{(t)} Q^{(t)}$ & $\tilde{Z}^{(t)} = P^{(t)}(1 - Q^{(t)})$

  Query true label $y^{(t)}$ if $Z^{(t)} = 1$ and set $M^{(t)} = 1$ if $\hat{y}^{(t)} \neq y^{(t)}$

  Update $w_k^{(t)} = w_k^{(t-1)} + (M^{(t)} Z^{(t)} y^{(t)} + \tilde{Z}^{(t)} \tilde{y}^{(t)}) x^{(t)}$

  Update τ:

$$\tau_{km}^{(t)} = \frac{\tau_{km}^{(t-1)} e^{-\frac{Z^{(t)}}{\lambda} \ell_{km}^{(t)}}}{\sum_{\substack{m' \in [K] \\ m' \neq k}} \tau_{km'}^{(t-1)} e^{-\frac{Z^{(t)}}{\lambda} \ell_{km'}^{(t)}}} \quad m \in [K], m \neq k \tag{1}$$

end

Active Learning from Peers -- a Humble Approach

The above algorithm suffers from the problem that in making predictions, it cannot make good use of peer tasks' advices.

- During the training period, the algorithm decides whether to ask peer tasks by sampling from a Bernoulli random variable.
- In the test period, when making predictions, it does not make sense to make decisions based on a random variable. So it cannot use the same strategy as it uses in the training period.
- We proposed a new algorithm, called "humble active learning from peers". It is called humble because in the training period it will always ask peer tasks.

Algorithm 2 Humble Active Learning from Peers

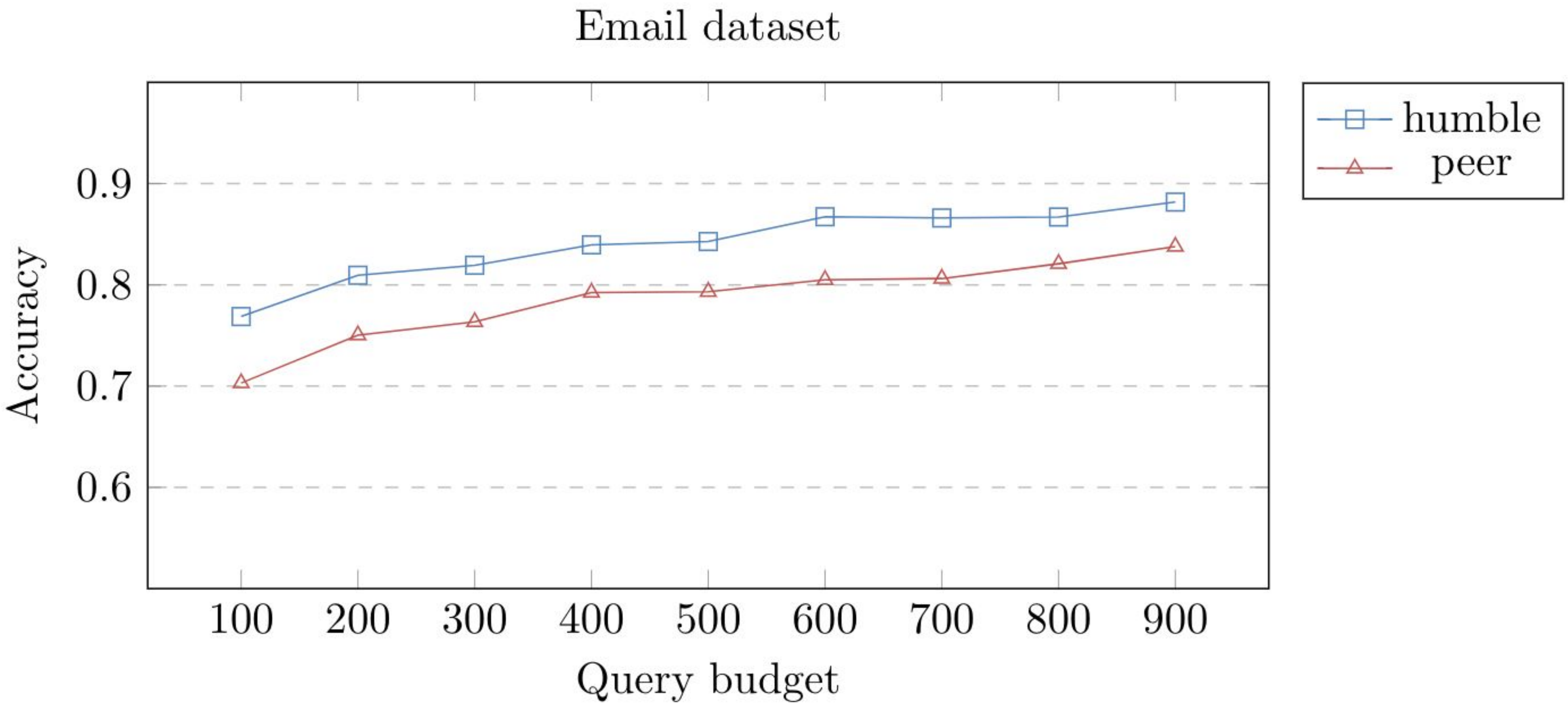
Input $b > 0, C > 0$, number of rounds T

initialize $w_m^{(0)} = 0, \forall m \in [K], \boldsymbol{\tau}^{(0)}$
for $t = 1, 2, .., T$ **do**
  Receive $(x^{(t)}, k)$
  Compute $p_{km}^{(t)} = \langle x^{(t)}, w_m^{(t-1)} \rangle$ for $m \in [K]$
  $p = \sum_{m \in [K]} p_{km}^{(t)} \tau_{km}^{(t-1)}$
  Predict $\hat{y}(t) = sign(p)$
  Draw a Bernoulli random variable $P^{(t)}$ with probability $\frac{b}{b+|p|}$
  if $P^{(t)} = 1$ **then**
    Query true label $y^{(t)}$
    if $y^{(t)} \neq \hat{y}^{(t)}$ **then**
      Update $w_k^{(t)} = w_k^{(t-1)} + y^{(t)} x^{(t)}$
    end if
    Update τ:
$$\tau_{km}^{(t)} = \frac{\tau_{km}^{(t-1)} e^{-C \cdot l_{km}^{(t)}}}{\sum_{m' \in [K]} \tau_{km'}^{(t-1)} e^{-C \cdot l_{km'}^{(t)}}}$$
  end if
end for
Output $\boldsymbol{\tau}^{(t)} \cdot w^{(t)}$ as the final weight

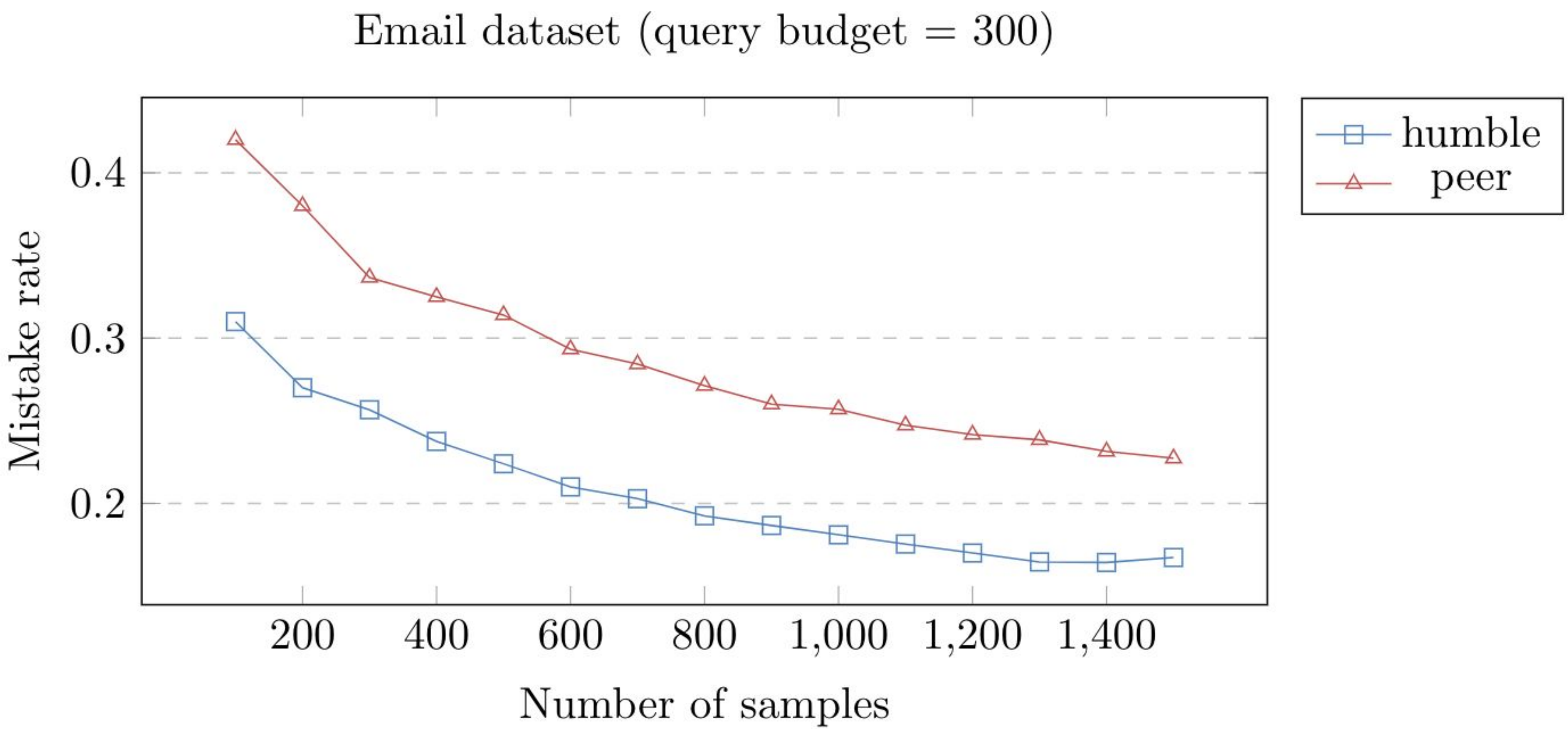
Experiment Results

Spam Email Detection			
Model	Accuracy	#Queries	Mistake rate
PEER	0.8497 (0.007)	1108.8 (32.1)	0.2255 (0.005)
HUMBLE	0.8867 (0.031)	1046.6 (14.74)	0.1735 (0.006)

Experiment Results



Experiment Results



Contribution and Future Work

- Contribution
  - Re-implement active learning from peers algorithm as proposed in [1], and achieve similar results on all datasets in that paper
  - Propose a new algorithm - ***humble*** active learning from peers, and achieve ***better*** result on spam email data set and similar results on other datasets.
- Future work
  - Test both algorithms on a new dataset from *KKBox's Music Recommendation Challenge*, where we will predict whether a user will listen to a song again based on song information.
  - Learn more than ***10000*** personalized recommenders from ***230 Million*** Songs

Main References

- [1] Murugesan, Keerthiram, and Jaime Carbonell. "Active learning from peers." Advances in Neural Information Processing Systems. 2017.
- [2] Murugesan, Keerthiram, et al. "Adaptive smoothed online multi-task learning." Advances in Neural Information Processing Systems. 2016.

Questions?

Thank You!