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# SafePredict: A Machine Learning Meta-Algorithm That Uses Refusals to Guarantee Correctness

David Ramirez (dard@princeton.edu), Mustafa A. Kocak, Elza Erkip, and Dennis E. Shasha



## Introduction

Machine learning and prediction algorithms are the building blocks of automation and forecasting.

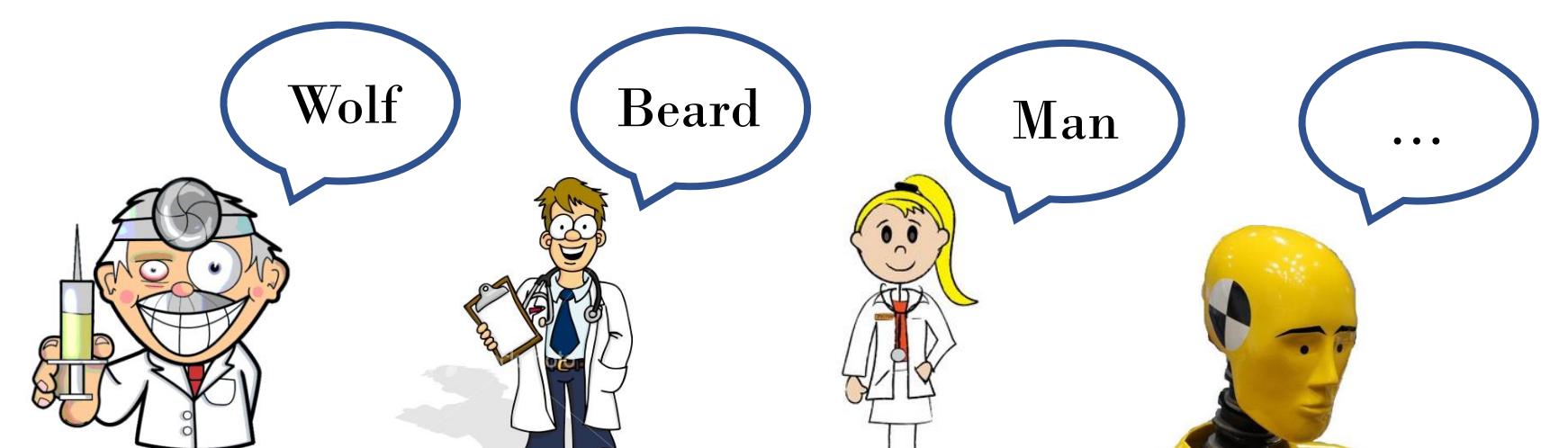


Algorithms benefit from a lower error rate.

*SafePredict*, a meta-algorithm, takes predictions from underlying algorithms and decides whether or not to predict with them.



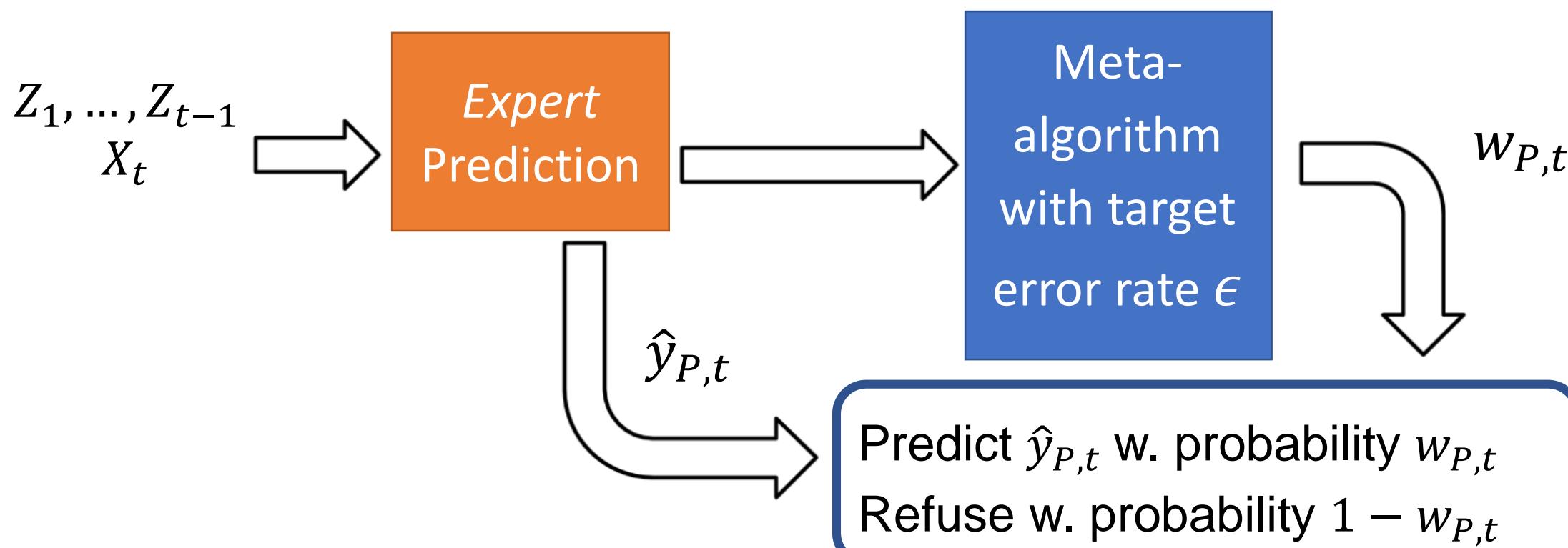
Observation



Crowd of experts (i.e., algorithms) are asked to predict.  
Dummy expert always *refuses* to predict.

## Problem Setup

Online prediction setup with refusal option.



Prediction  $\hat{y}_{P,t}$  or refusal  $\hat{y}_D$  suffer a loss  $l_{P,t}$ ,  $l_D \in [0,1]$ .  
Mistakes are costly, but we learn by observing.

## Definitions

$t$  = time index,  $T$  = total observations,  $\eta$  = learning rate  
 $T^* = \sum_{t=1}^T w_{P,t}$ , expected predictions  
 $L_T^* = \sum_{t=1}^T l_{P,t} w_{P,t}$ , expected cumulative loss  
 $V^* = \sum_{t=1}^T w_{P,t} w_{D,t}$ , variance for number of predictions  
 $w_{P,t+1} = \frac{w_{P,t} e^{-\eta l_{P,t}}}{w_{P,t} e^{-\eta l_{P,t}} + w_D e^{-\eta \epsilon}}$  weight shift rule

## Algorithm Properties

Def. A meta-algorithm is *valid* if, as  $T^* \rightarrow \infty$ , average expected loss  $\leq$  target error rate.

Def. A meta-algorithm is *efficient* if, as  $T^* \rightarrow \infty$ , refusals occur only a finite number of times.

## Main Results

### Safe-Predict is valid and efficient!

Guaranteed with no assumptions on data or underlying experts, but asymptotic in the number of non-refused predictions.

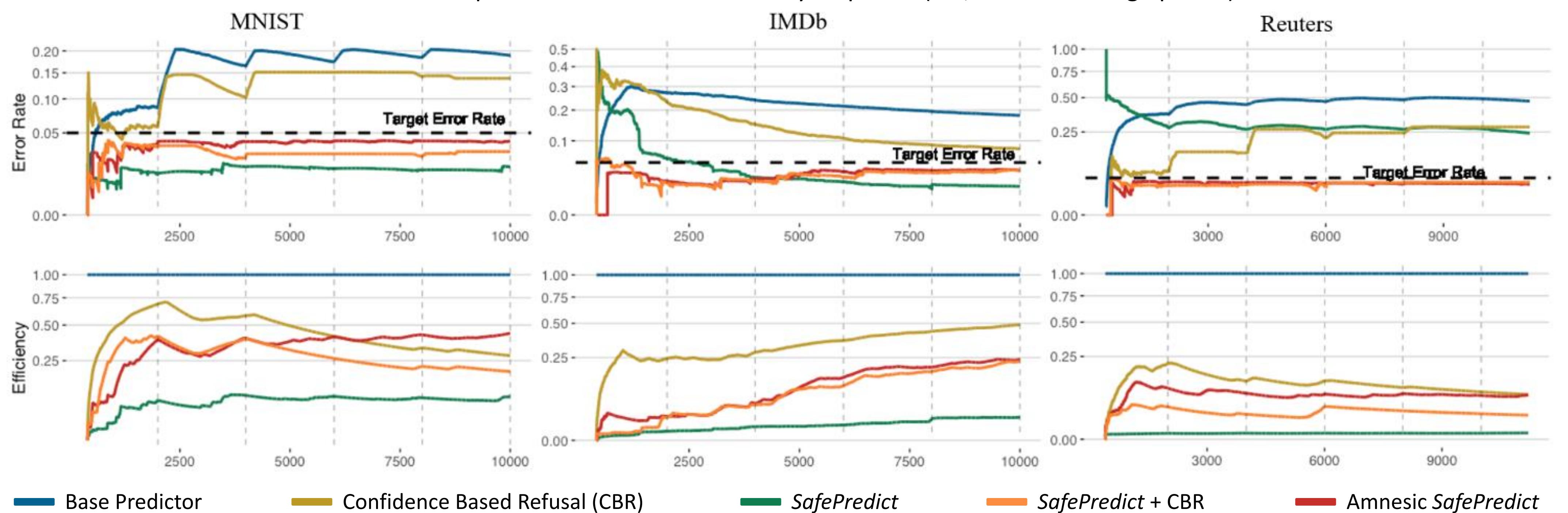
**Theorem 1.**- With learning rate  $\eta = \Theta(\frac{1}{\sqrt{V^*}})$ , *SafePredict* is guaranteed *valid* for any  $P$ . Particularly  $\frac{L_T^*}{T^*} - \epsilon = O\left(\frac{\sqrt{V^*}}{T^*}\right) = \left(\frac{1}{\sqrt{T^*}}\right)$ .

**Theorem 2.**- If  $\limsup_{t \rightarrow \infty} \frac{l_{P,t}}{t} < \epsilon$  and  $\eta T \rightarrow \infty$ , then *SafePredict* is *efficient*.

## Experimental Results

Randomly permute data, choose first 10k points for experiment. Target error rate  $\epsilon = 0.05$ .

Random label permutation introduced every 2k points (i.e., artificial change points).



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