Vowpal Wabbit

http://hunch.net/~vw/

git clone
git://github.com/JohnLangford/vowpal_wabbit.git

Vowpal Wabbit: Research Delivery Vehicle

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6. Learn2Search. See Hal/Kai-Wei later
7. others....

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An example

`vw -c rcv1.train.raw.txt -b 22 --ngram 2 --skips 4 -l 0.25 --binary` provides stellar performance in 12 seconds.

Improved: Learning Reductions

The core idea: reduce complex problem A to simpler problem B then use solution on B to get solution on A.

Problems:

1. How do you make it efficient enough?
2. How do you make it natural to program?

The Reductions Interface

```
void learn(learner& base, example& ec)
{
   base.learn(ec); // The recursive call
   if ( ec.pred.scalar > 0) //Thresholding
      ec.pred.scalar = 1;
   else
      ec.pred.scalar = -1;
   if (ec.l.simple.label == ec.pred.scalar)
      ec.loss = 0.; // Loss Definition
   else
      ec.loss = ec.l.simple.weight;
}
```

New: Logarithmic Online Multiclass Tree

See: http://arxiv.org/abs/1406.1822

Repeatedly:

1. See x
2. Predict $\hat{y} \in \{1, ..., K\}$
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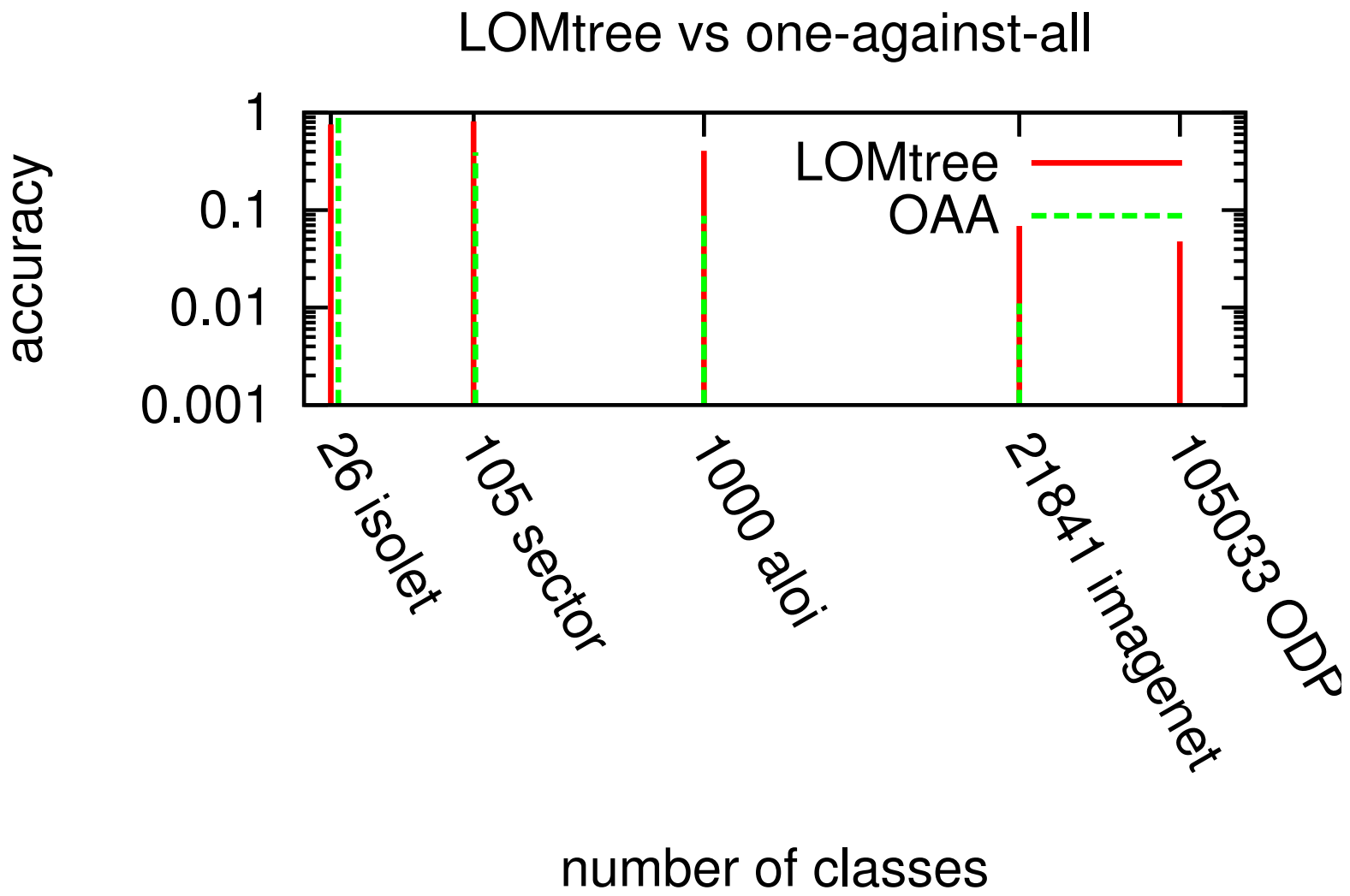
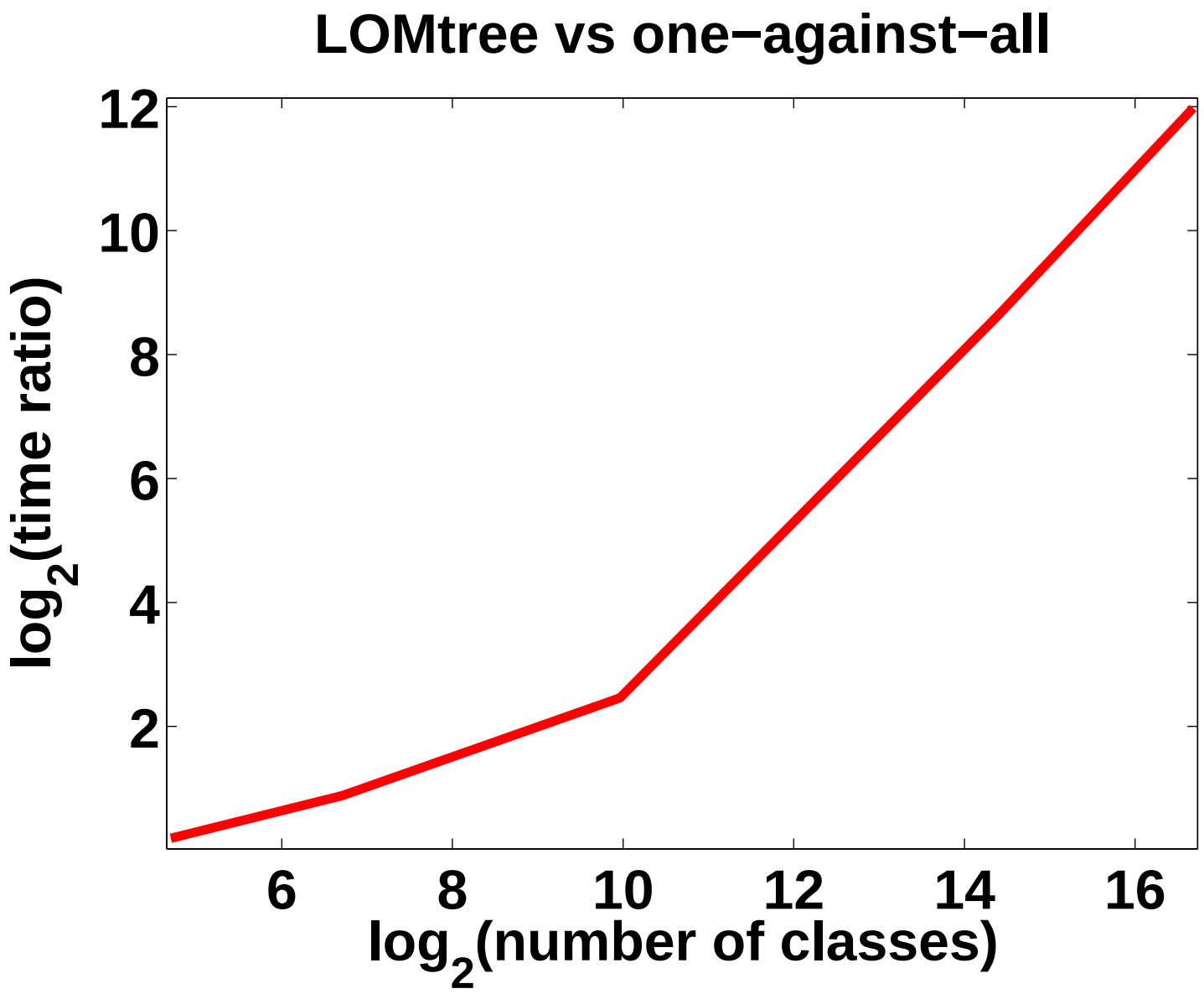
Goal: Goal in $O(\log K)$ time minimize loss.

Accuracy for a fixed training time



Classes vs Test time ratio



The Method

A dynamically created tree with classifiers in the nodes and multiple leaves per label operating by reduction. ~550 LOC.

Usage:

```
vw --log_multi <nodes> <dataset>
```

New: The Exploration Library

(With: Luong Hoang, Sid Sen, Sarah Bird)

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Problem: Exploration must happen deep inside existing systems.
Solution: An exploration library which randomizes correctly & helps log the right things.

New: VW in AzureML

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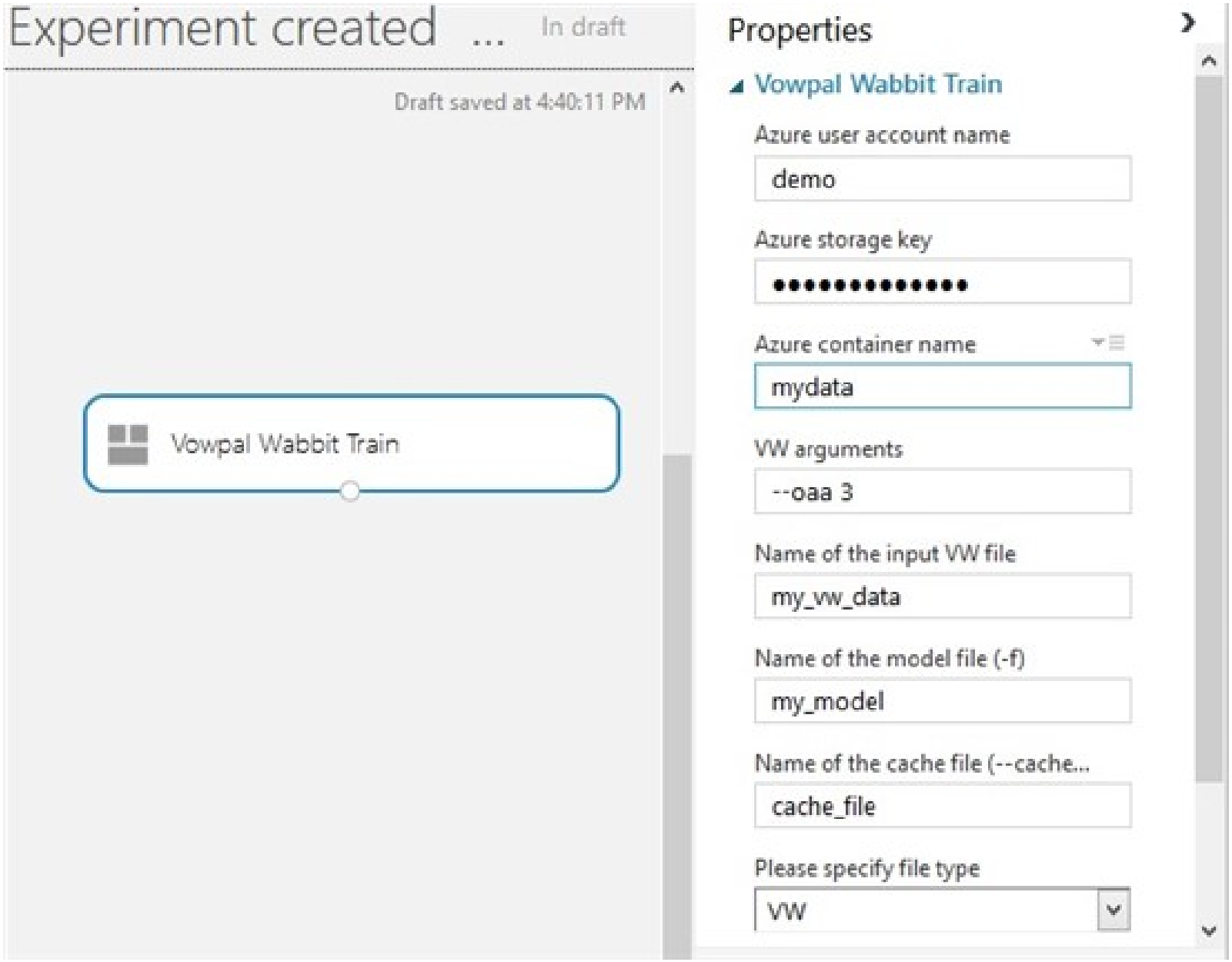
Problem: You want to deploy a model for large scale use.
Solution: Azure ML cloud service.

It even has browser GUI



The plan

1. John: Intro++
2. Matus: Polynomial learning
3. Paul: LRQ + Hogwild mode
4. Hal: Learning 2 search + Python
5. Kai-Wei: Entity Relation + Dependency Parsing
6. Alekh: Online SVM