Vowpal Wabbit

Scalable machine learning library

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Vowpal Wabbit [1]

VOWPAL WABBIT

- Fast, online , scalable learning system
- Supports out of core execution with in memory model
- Scalable (Terascale)
  - 1000 nodes [13, 1]
  - Billions of examples
  - Trillions of unique features.
- Actively developed

[1] https://github.com/JohnLangford/vowpal_wabbit

Features

- Command line support
- Multi-langauge support: Python, C#, Java bindings
- Flexible input format: Allows free form text, identifying tags, multiple labels
- Speed: Supports online learning
- Scalable
  - Streaming removes row limit.
  - Hashing removes dimension limit
- Distributed training: models merged using *AllReduce* operation.
- Cross product features: Allows multi-task learning

Vowpal wabbit tricks

- Feature hashing
    - Makes the model fit on one machine.
    - Provides some degree of regularization
- Caching
    - Converts sparse input data to compact dense binary format. Makes multiple passes faster
- MPI style *AllReduce*
    - Provides scaling over large amounts of data
- Namespaces and interactions
    - Makes specifying cross product features easy
    - Allows multi-task learning using a single model (e.g. personalized spam filter)

Detour: Feature hashing

- Feature hashing can be used to reduce dimensions of sparse features.
  - Unlike random projections [9] , retains sparsity
  - Preserves dot products (random projection preserves distances).
  - Model can fit in memory.
- **Unsigned** [19]

  Consider a hash function $h(x) : [0 \dots N] \to [0 \dots m], m << N$.

  $$\phi_i(x) = \sum_{j:h(j)=i} x_j$$

- **Signed** [21]

  Consider additionaly a hash function $\xi(x) : [0 \dots N] \to \{1, -1\}$.

  $$\phi_i(x) = \sum_{j:h(j)=i} \xi(j) x_j$$

Optimization

VW solves optimization of the form

$$\sum_i l(w^T x_i; y_i) + \lambda R(w)$$

Here, $l()$ is convex, $R(w) = \lambda_1 |w| + \lambda_2 ||w||^2$.

VW support a variety of loss function

Linear regression	$(y - w^T x)^2$
Logistic regression	$\log(1 + exp(-yw^T x))$
SVM regression	$\max(0, 1 - yw^T x)$
Quantile regression	$\tau(w^T x - y)I(y < w^T x) + (1 - \tau)(y - w^T x)I(y > w^T x)$
Poisson regression	$y \log y - yw^T x - y + \exp(w^T x)$

Generalized linear models

A generalized linear predictor specifies

- A linear predictor of the form $\eta(x) = w^T x$
- A mean estimate μ
- A link function $g(\mu)$ such that $g(\mu) = \eta(x)$ that relates the mean estimate to the linear predictor.

This framework supports a variety of regression problems

Linear regression	$\mu = w^T x$
SVM regression	$\mu = w^T x$
Quantile regression	$\mu = w^T x$
Logistic regression	$\log(\frac{\mu}{1-\mu}) = w^T x$
Poisson regression	$\log(\mu) = w^T x$

Swiss army knife of online algorithms

- **Binary classification**
- **Multiclass classification**
- **Linear regression**
- **Quantile regression**
- **Topic modeling (online LDA)**
- Structured prediction
- Active learning
- **Recommendation (Matrix factorization)**
- Contextual bandit learning (explore/exploit algorithms)
- Reductions

Vowpal Wabbit: One stop shop

Challenge	Variant	VW option
Filtering	Quantile regression	`--loss_function quantile`
Item recommendation	Content based filtering	`--lrq`
	Collaborative filtering	`--rank`
Value estimation	Linear regression	`--loss_function square`
	Logistic regression	`--loss_function logistic`
	Poisson regression	`--loss_function poisson`
Budget allocation	Bandit optimization	`--cb`
Creative testing	Bandit optimization	`--cb`
User segmentation	Multiclass classification	`--ooa | --csooa`
	Topic modeling	`--lda`

Practical matters

Input format

Label Importance [Tag]—namespace Feature . . . — namespace Feature . . .

namespace = String[:Float]

feature = String[:Float]

Examples:

- 1 — 1:0.01 32:-0.1
- example—namespace normal text features
- 1 3 tag—ad-features ad description —user-features name address age

Input options

- data file -d datafile
- network --daemon --port <port=26542>
- compressed data --compressed
- stdin cat <data> — vw

Manipulation options

- ngrams `--ngram`
- skips `--skips`
- quadratic interaction `-q args`. e.g `-q ab`
- cubic interaction `--cubic args`. e.g. `--cubic ccc`

Output options

- Examining feature construction `--audit`
- Generating prediction `--predictions` or `-p`
- Unnormalized predictions `--raw_predictions`
- Testing only `--testonly` or `-t`

Model options

- Model size `--bit_precision` or `-b` . Number of coefficients limited to 2^b
- Update existing model `--initial_regressor` or `-i`.
- Final model destination `--final_regressor` or `-f`
- Readable model definition `--readable_model`
- Readable feature values `--invert_hash`
- Snapshot model every pass `--save_per_pass`
- Weight initialization `--initial_weight` or `--random_weights`

Scaling

Stochastic gradient descent with adaptive updates

Data: λ, T
Initialization w=0, G=0 (diagonal matrix) ;
for *i = 1,2,... m* **do**
  Set $g = \nabla_w l(w^T x_i; y_i)$;
  Set $w = w - G^{-\frac{1}{2}} s(w, x, y)$;
  Set $G_{jj} = G_{jj} + g^2, \forall j \in 1 \dots d$;
end

Algorithm 1: Single node algorithm

Multi node algorithm using gradient descent

Data: Data split across nodes $1 \dots m$

for *iteration* $t \in 1, 2 \dots T$ **do**

  for *node* $k \in 1, 2, \dots m$ **do**

    Compute w^k and G^k ;

  end

  Compute a weighted average $\bar{w}$ using *AllReduce* ;

  $\bar{w} = \left(\sum_k G^k\right)^{-1} \left(\sum_k w^k G^k\right)$;

  Compute a weighted average $\bar{G}$ using *AllReduce* ;

  $\bar{G} = \left(\sum_k G^k\right)^{-1} \left(\sum_k (G^k)^2\right)$;

  for *node* $k \in 1, 2, \dots m$ **do**

    Set $w^k = \bar{w}$ and $G^k = \bar{G}$;

  end

end

All reduce

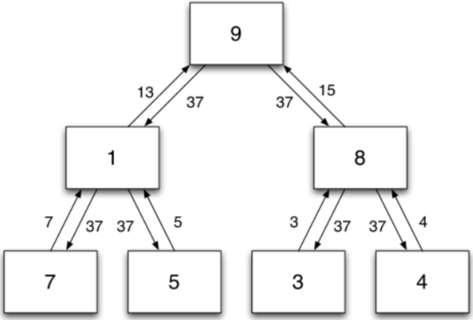


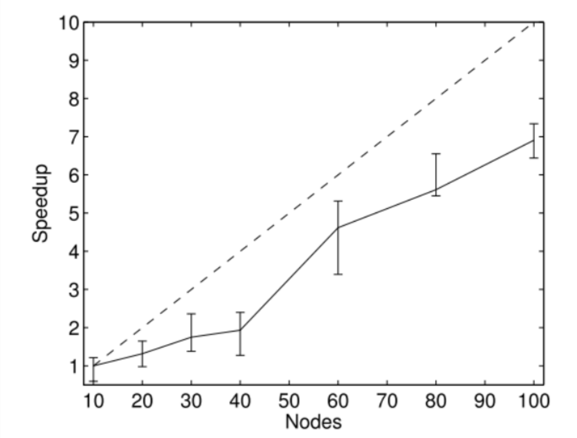
Figure 1: AllReduce operation. Initially, each node holds its own value. Values are passed up the tree and summed, until the global sum is obtained in the root node (reduce phase). The global sum is then passed back down to all other nodes (broadcast phase). At the end, each node contains the global sum.

Empirical results

Datasets

- Display ad CTR
    - 2.3B examples
    - 125 non zero features per instance.
    - hashed to 24 bits
- Splice site recognition
    - 50M examples
    - 3300 non zero features per instance

Speedup



- Results for display advertising dataset
- Relative to time required for a 10 node run
- All data points have the same test error

RTB Optimization using Vowpal Wabbit

Challenge	Variant	VW option
Filtering	Quantile regression	`--loss_function quantile`
Item recommendation	Content based filtering Collaborative filtering	`--lrq` `--rank`

Value estimation	Linear regression
	Logistic regression
	Poisson regression
		`--loss_function square`
		`--loss_function logistic`
		`--loss_function poisson`

Budget allocation	Bandit optimization	`--cb`
Creative testing	Bandit optimization	`--cb`
User segmentation	Multiclass classification Topic modeling	`--ooa | --csooa` `--lda`

Demos

Installing

Mac

```
git clone https://github.com/JohnLangford/vowpal_wabbit
make
```

Linux

```
apt-get install libboost-program-options-dev zlib1g-dev
apt-get install libboost-python-dev
git clone git://github.com/JohnLangford/vowpal_wabbit.git
make
```

Regression (Demo)

- Linear regression `--loss_function square`
- Quantile regression
  `--loss_function quantile --quantile_tau <=0.5>`

Binary classification (Demo)

- Note: a linear regressor can be used as a classifier as well
- Logistic loss
  `--loss_function logistic, --link logistic`
- Hinge loss (SVM loss function) `--loss_function hinge`
- Report binary loss instead of logistic loss `binary`

Multiclass classification (Demo)

- One against all `--oaa <k>`
- Error correcting tournament `--ect <k>`
- Online decision trees `---log_multi <k>`
- Cost sensitive one-against-all `--csoaa <k>`

LDA options (Demo)

- Number of topics `--lda`
- Prior on per-document topic weights `--lda_alpha`
- Prior on topic distributions `--lda_rho`
- Estimated number of documents `--lda_D`
- Convergence parameter for topic estimation `--lda_epsilon`
- Mini batch size `--minibatch`

Daemon mode (Demo)

- Loads model and answers any prediction request coming over the network
- Preferred way to deploy a VW model
- Options
  - `--daemon`. Enables demon mode
  - `--testonly` or `-t`. Does not update the model in response to requests
  - `--initial_model` or `-i`. Model to load
  - `--port <arg>`. Port to listen to the request
  - `--num_children <arg>`. Number of threads listening to request

Python (Demo)

- VW supports two python interfaces
    - pyvw provides low level wrapper
    - sklearn_vw provides sklearn compatible interface

References

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