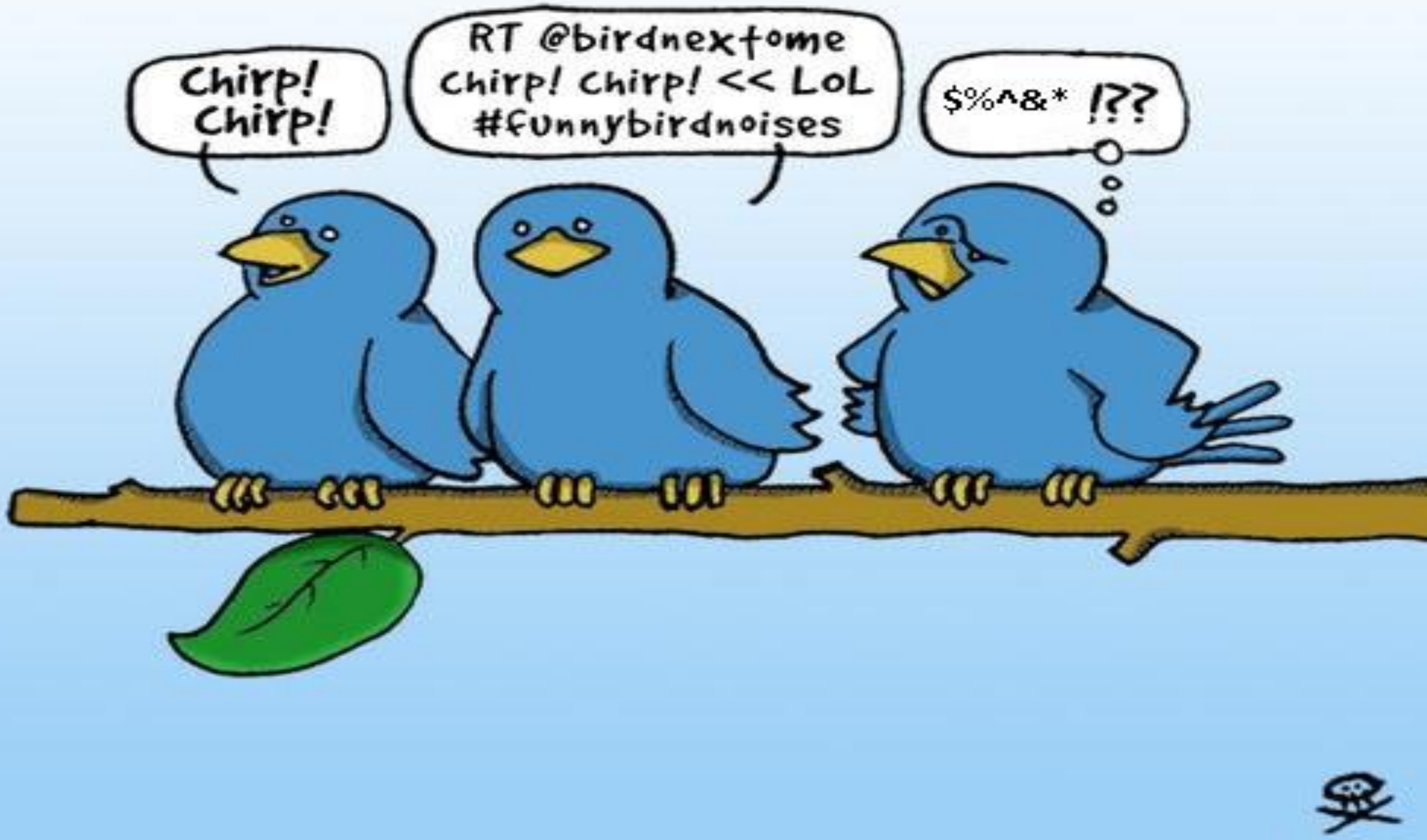
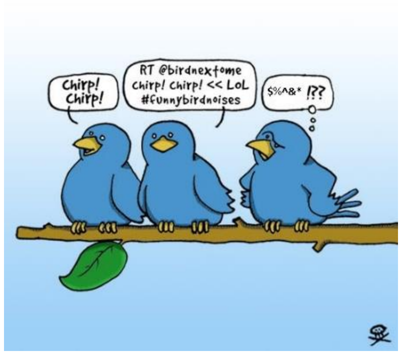
Large-Scale Machine Learning at Twitter

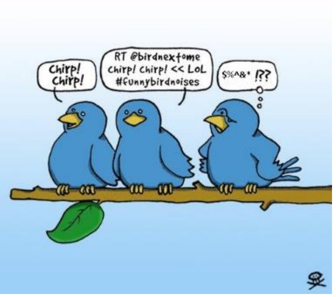




Large-Scale Machine Learning at Twitter

Jimmy Lin and Alek Kolcz
Twitter, Inc.

Image source:google.com/images

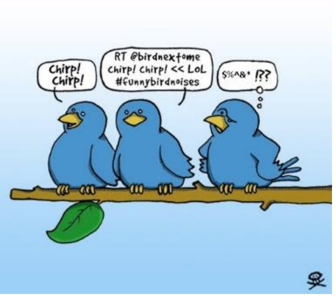


Outline

- Is twitter big data?
- How can machine learning help twitter?
- Existing challenges?

- Existing literature of large-scale learning
- Overview of machine learning
- Twitter analytic stack
- Extending pig

- Scalable machine learning
- Sentiment analysis application



Large-Scale Machine Learning at Twitter

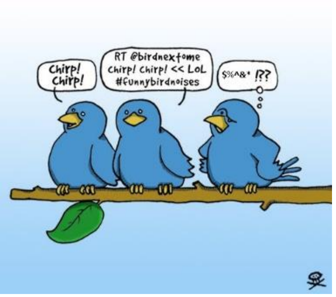
Focus of talk..

What we will not talk about :

- Different “useful” application of twitter
- Why Twitter is a great product and one of its kind

What we will talk about :

- Challenges faced while making it a good product
- Solution approach by “Insiders”



Large-Scale Machine Learning at Twitter

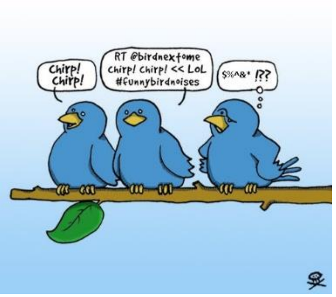
Some twitter bragging ..

The Scale of Twitter

- Twitter has more than 280 million active users
- 500 million Tweets are sent per day
- 50 million people log into Twitter every day
- Over 600 million monthly unique visitors to twitter.com

Large scale infrastructure of information delivery

- Users interact via web-ui, sms, and various apps
- Over 70% of our active users are mobile users
- Real-time redistribution of content
- At Twitter HQ we consume 1,440 hard boiled eggs weekly
- We also drink 585 gallons of coffee per week



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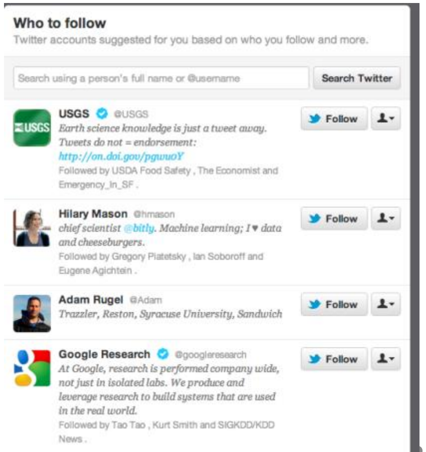
Problems in hand ..

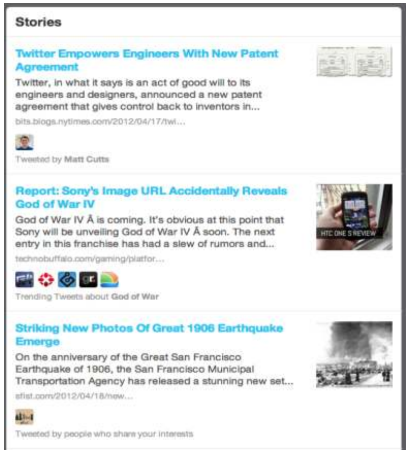
Support for user interaction

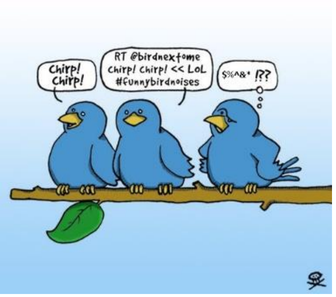
- Search
  - Relevance ranking
- User recommendation
  - WTF or Who To Follow
- Content recommendation
  - Relevant news, media, trends

(other) problems we are trying to solve

- Trending topics
- Language detection
- Anti-spam
- Revenue optimization
- User interest modeling
- Growth optimization







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To put learning formally ..

Supervised classification in a nutshell

Given $D = \{(\mathrm{x}_i, y_i)\}_i^n$

label

(sparse) feature vector

Induce $f : X \rightarrow Y$ s.t. loss is minimized

empirical loss = $\frac{1}{n}\sum_{i=0}^{n} \ell(f(\mathrm{x}_i), y_i)$

loss function

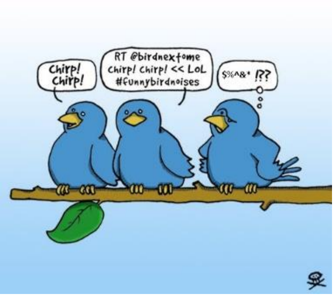
Consider functions of a parametric form:

$$\arg\min_{\theta} \frac{1}{n}\sum_{i=0}^{n} \ell(f(\mathrm{x}_i;\theta), y_i)$$

model parameters

Key insight: machine learning as an optimization problem!

(closed form solutions generally not possible)



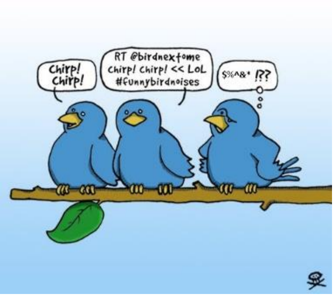
Literature

- Traditionally, the machine learning community has assumed sequential algorithms on data fit in memory (which is no longer realistic)
- Few publication on machine learning work-flow and tool integration with data management platform
  - Google – adversarial advertisement detection
  - Predictive analytic into traditional RDBMSes
  - Facebook – business intelligence tasks
  - LinkedIn – Hadoop based offline data processing

But they are not for machine learning specificly.

- Spark
- ScalOps

But they result in end-to-end pipeline.



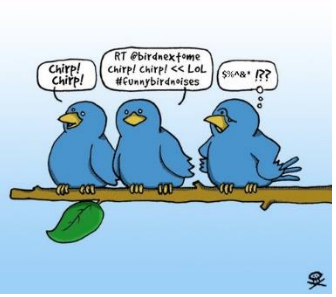
Large-Scale Machine Learning at Twitter

What is author’s contribution ..

Contribution

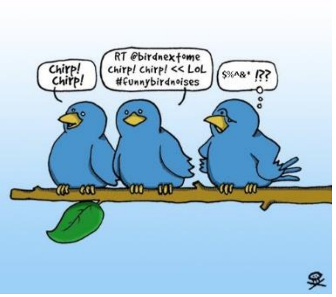
- Provided an overview of Twitter’s analytic stack
- Describe pig extension that allow seamless integration of machine learning capability into production platform
- Identify stochastic gradient descent and ensemble methods as being particularly amenable to large-scale machine learning

Note that,
No fundamental contributions to machine learning



Scalable Machine learning

- Techniques for large-scale machine learning
- Stochastic gradient descent
- Ensemble method



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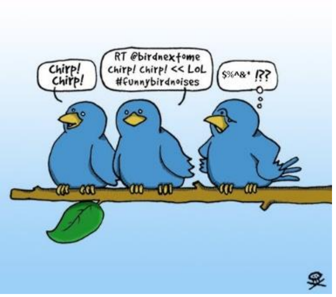
Gradient Descent..



Gradient Descent..

General method for nonlinear optimization

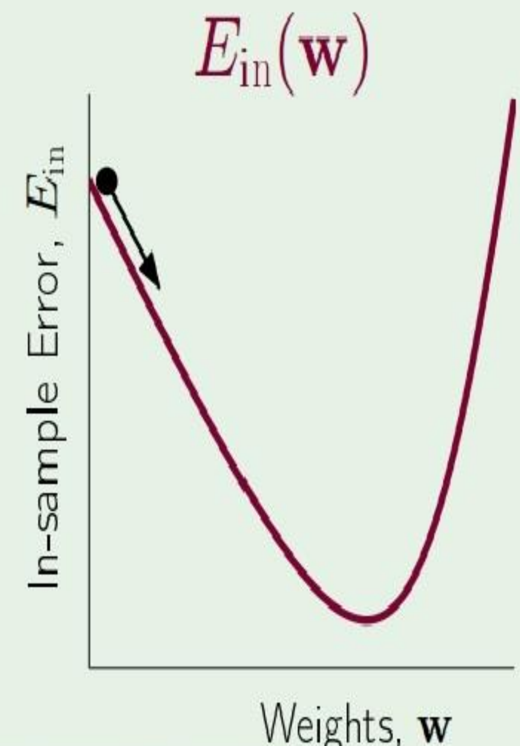
Start at $\mathbf{w}(0)$; take a step along steepest slope

Fixed step size: $\mathbf{w}(1) = \mathbf{w}(0) + \eta\, \hat{\mathbf{v}}$

Next Weight = Current Weight + move

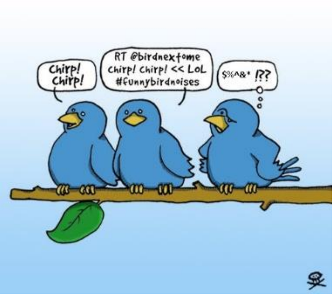
Move = Step Size * Unit Vecor

What is the direction $\hat{\mathbf{v}}$?



Creator : Yaser Abu Mostafa: Cal tech

Slides from Yaser Abu Mostafa-Caltech



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Gradient Descent..

Formula for the direction $\hat{\mathbf{v}}$

$$\Delta E_{\text{in}} = E_{\text{in}}(\mathbf{w}(0) + \eta\hat{\mathbf{v}}) - E_{\text{in}}(\mathbf{w}(0))$$

$$= \eta \nabla E_{\text{in}}(\mathbf{w}(0))^{\mathrm{T}} \hat{\mathbf{v}} + O(\eta^2)$$

Using Taylor's series expansion

Because the surface non linear

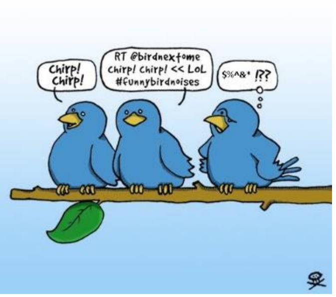
$$\geq -\eta \| \nabla E_{\text{in}}(\mathbf{w}(0)) \|$$

Since $\hat{\mathbf{v}}$ is a unit vector,

$$\hat{\mathbf{v}} = -\frac{\nabla E_{\text{in}}(\mathbf{w}(0))}{\| \nabla E_{\text{in}}(\mathbf{w}(0)) \|}$$

Descent along gradi of error..

Slides from Yaser Abu Mostafa-Caltech



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Stochastic Gradient Descent (SGD)

sto·chas·tic
stəˈkastik/
adjective
1.randomly determined; having a random probability distribution or pattern that may be analyzed statistically but may not be predicted precisely.

Stochastic gradient descent

GD minimizes:

$$E_{\text{in}}(\mathbf{w}) = \frac{1}{N}\sum_{n=1}^{N} \underbrace{\mathrm{e}\left(h(\mathbf{x}_n), y_n\right)}_{\ln\left(1+e^{-y_n \mathbf{w}^{\mathsf{T}} \mathbf{x}_n}\right)} \quad \longleftarrow \text{ in logistic regression}$$

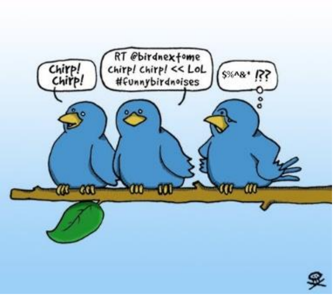
by iterative steps along $-\nabla E_{\text{in}}$:

$$\Delta \mathbf{w} = -\,\eta\, \nabla E_{\text{in}}(\mathbf{w})$$

∇E_{in} is based on all examples $(\mathbf{x}_n, y_n)$

"batch" GD

Slides from Yaser Abu Mostafa-Caltech



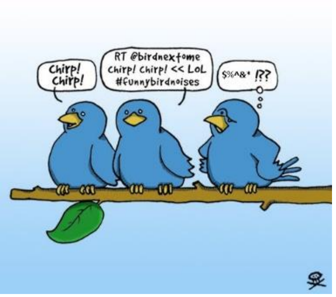
Stochastic gradient descent

Gradient Descent

$$w^{(t+1)} = w^{(t)} + \gamma^{(t)} \frac{1}{n} \sum_{i=0}^{n} \nabla l \left(f(\mathrm{x}_i; \theta^{(t)}), y_i \right)$$

Compute the gradient in the loss function by optimizing value in dataset. This method will do the iteration for all the data in order to one a gradient value.

Inefficient and everything in the dataset must be considered.



Stochastic gradient descent

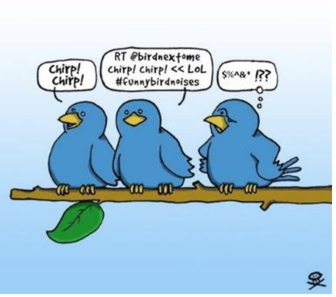
Approximating gradient depends on the value of gradient for one instance.

$$w^{(t+1)} = w^{(t)} + \gamma^{(t)} \nabla l \left(f(x;\theta^{(t)}), y \right)$$

Solve the iteration problem and it does not need to go over the whole dataset again and again.

Stream the dataset through a single reduce even with limited memory resource.

But when a huge dataset stream goes through a single node in cluster, it will cause network congestion problem.



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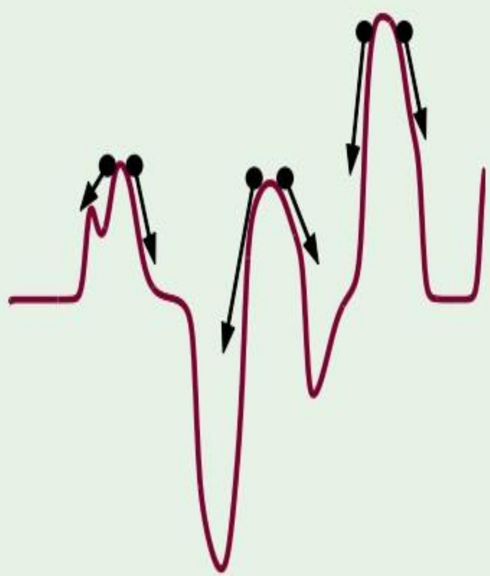
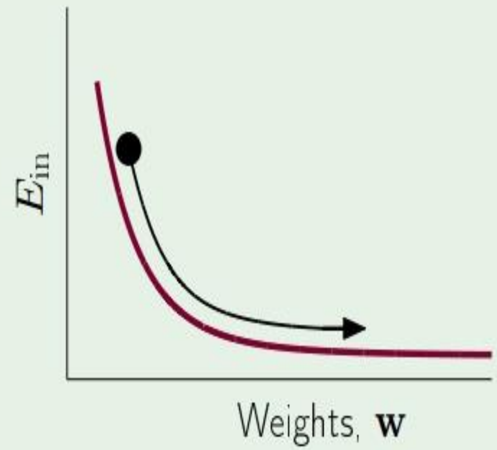
Stochastic Gradient Descent (SGD)

Benefits of SGD

1. cheaper computation
2. randomization
3. simple





randomization helps

Rule of thumb:

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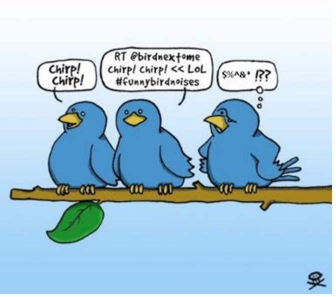
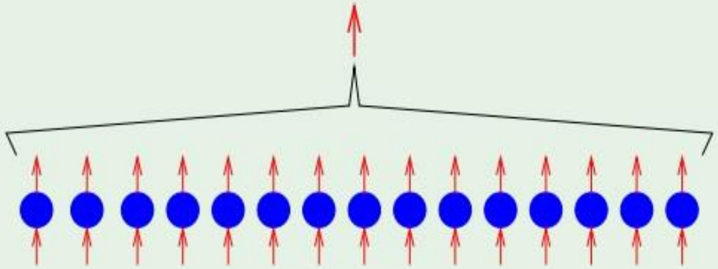


What is aggregation?

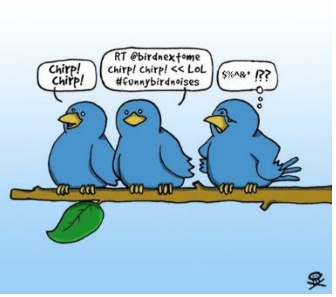
Combining different solutions $h_1, h_2, \cdots, h_T$ that were trained on $\mathcal{D}$:



Regression: take an average

Classification: take a vote

a.k.a. *ensemble learning* and *boosting*



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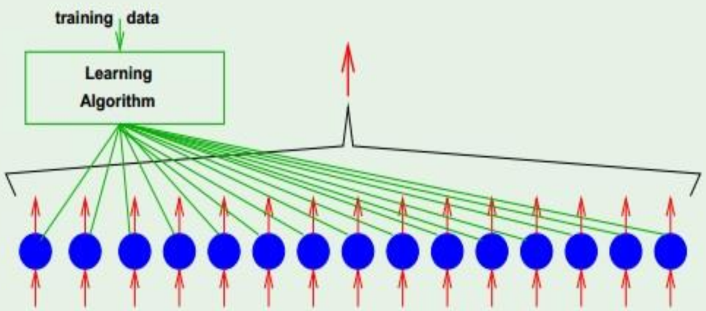
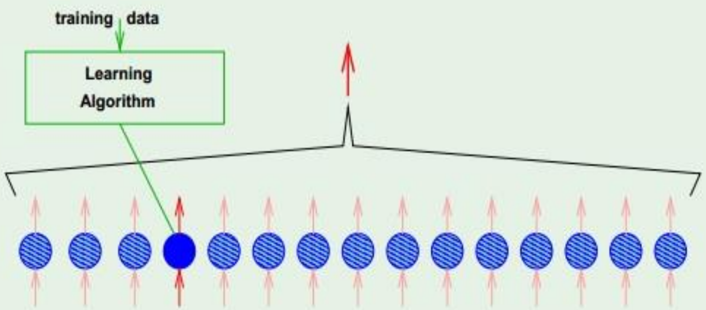
Aggregation a.k.a Ensemble Learning

Different from 2-layer learning

In a 2-layer model, all units learn **jointly**:



In aggregation, they learn **independently** then get combined:



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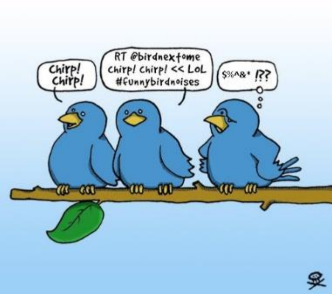


Ensemble Methods

Classifier ensembles: high performance learner

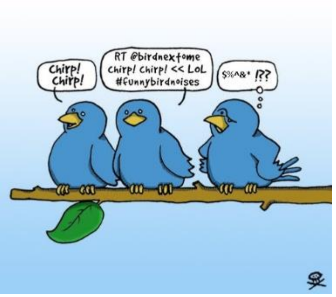
Performance: very well

Some rely mostly on randomization

-Each learner is trained over a subset of features and/or instances of the data

Ensembles of linear classifiers

Ensembles of decision trees (random forest)



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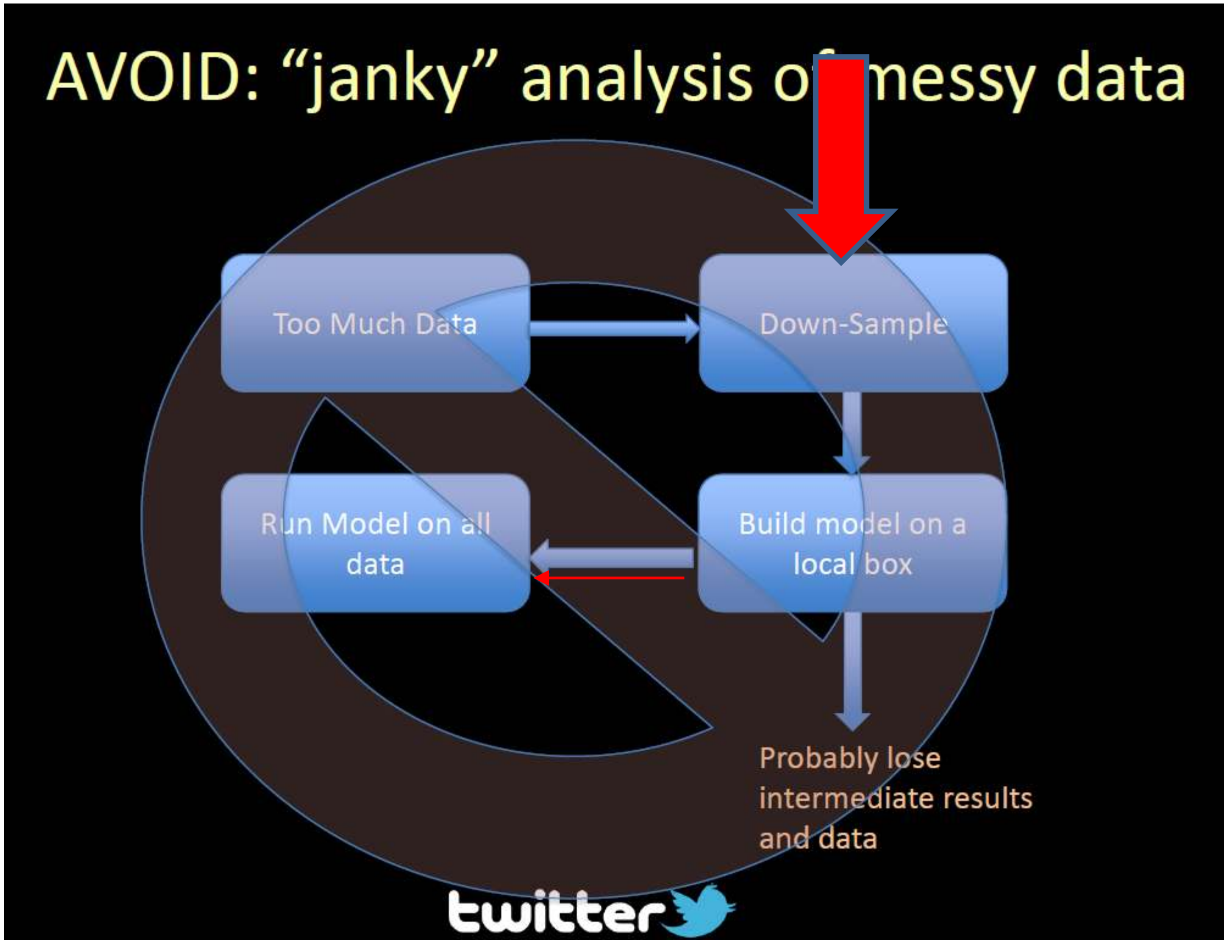
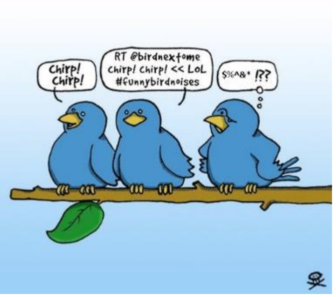
At Twitter …





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Hoeffding's Inequality

In a big sample (large N), ν is probably close to μ (within ϵ).

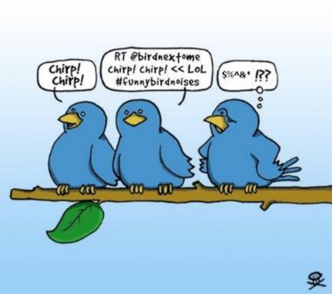
Formally,

$$\mathbb{P}\left[\,|\nu - \mu| > \epsilon\,\right] \leq 2e^{-2\epsilon^2 N}$$

Sample frequency ν is likely lose to bin frequency μ.

This is called **Hoeffding's Inequality**.

Slide taken from Caltech's Learning from Data Course : Dr Yaser Abu Mostafa



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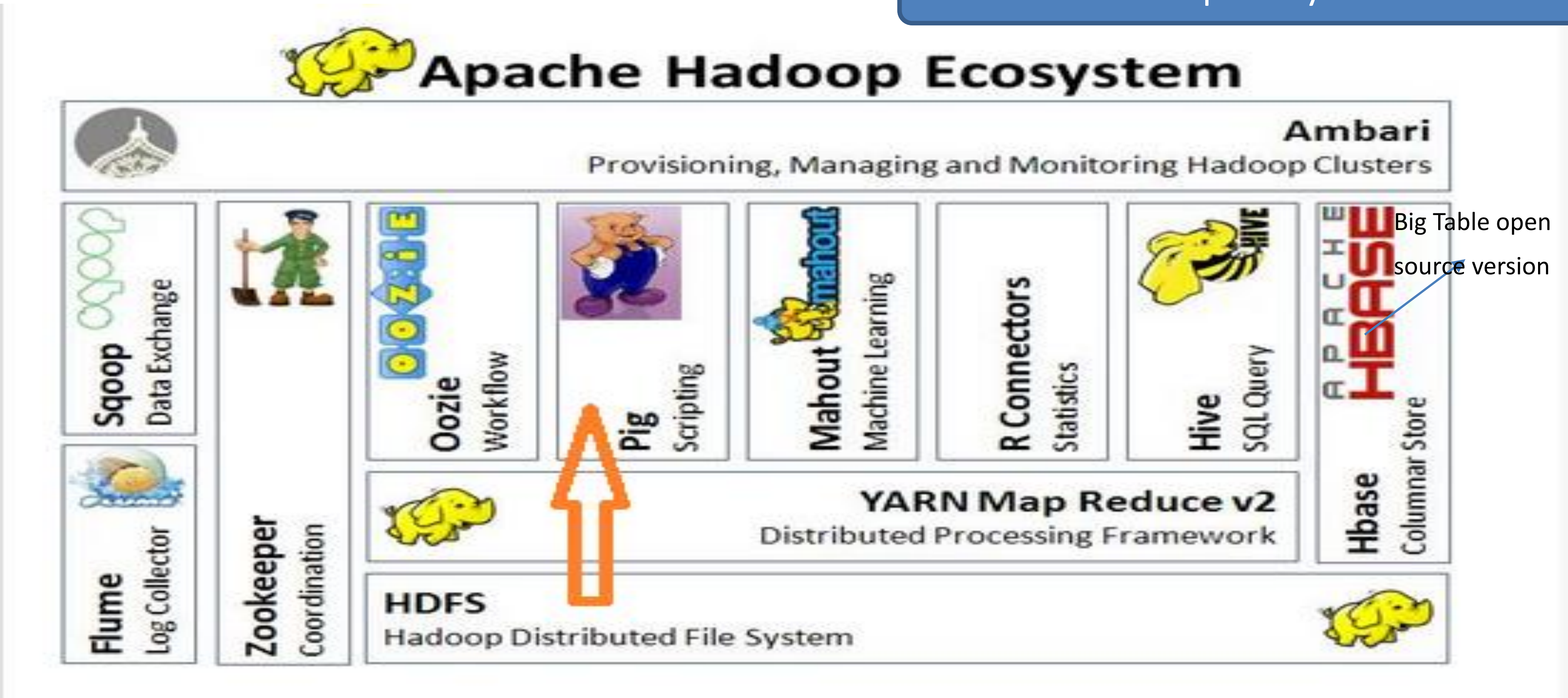
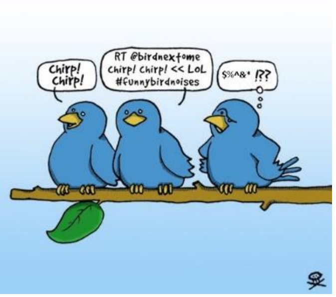
Hadoop Ecosystem



Big Table open source version

Image Source: Apache Yarn Release



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Hadoop Ecosystem at Twitter..

Oink:
- Aggregation query

Standard business intelligence tasks
- Ad hoc query

One-off business request
Prototypes of new function
Experiment by analytic group

Database

Application log

Other sources

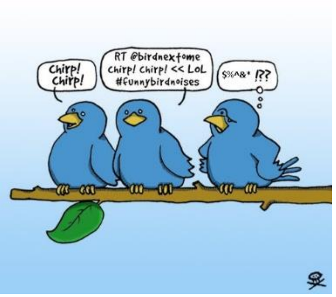
Real-time processes

Batch processes

HDFS

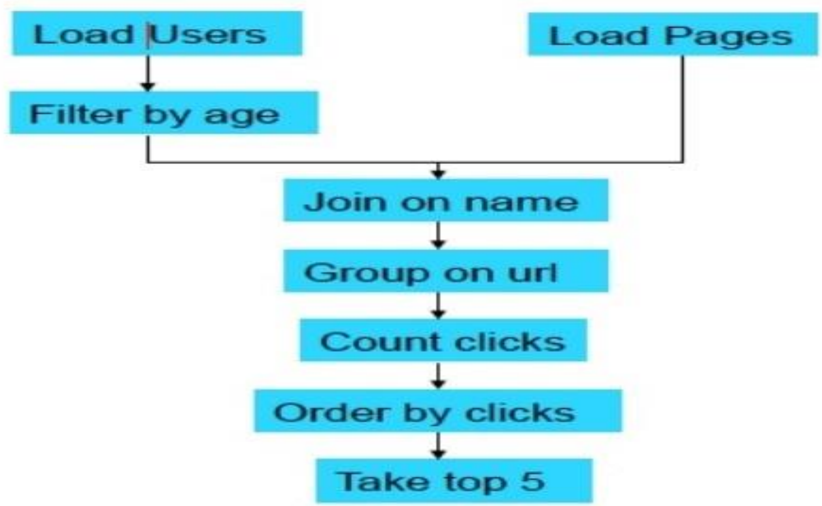
Serialization
Protocol buffer
/Thrift

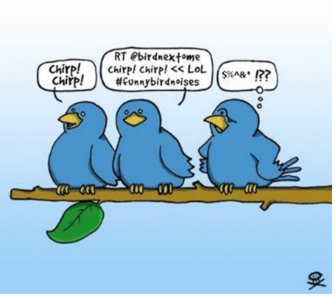
Hadoop cluster



Why use Pig?

- **Suppose you have user data in one file, website data in another, and you need to find the top 5 most visited sites by users aged 18 - 25**





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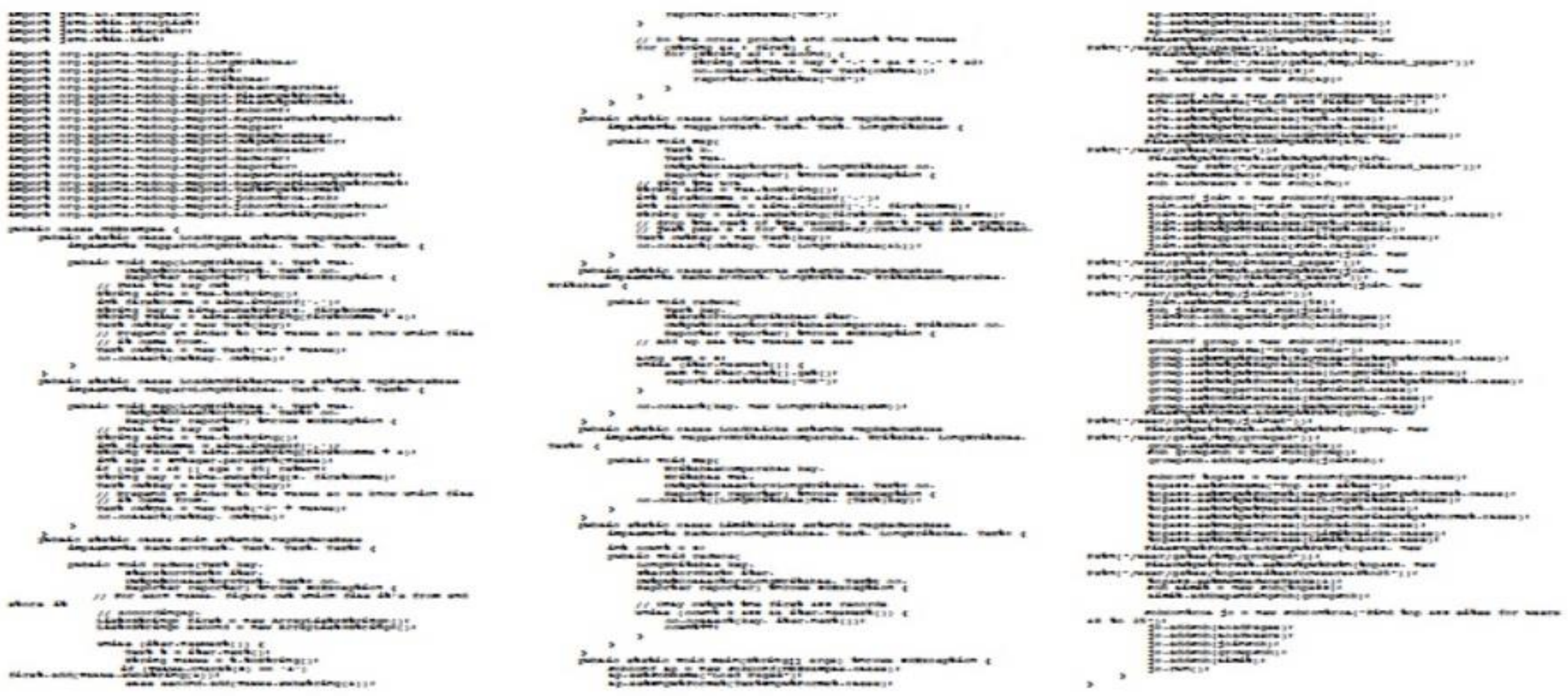
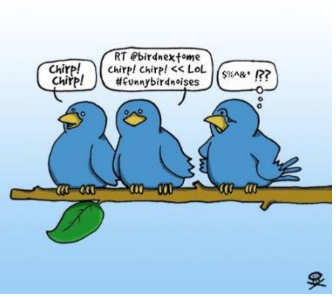
Glorifying PIG

In Map-Reduce



170 lines of code, 4 hours to write Credits : Hortonworks



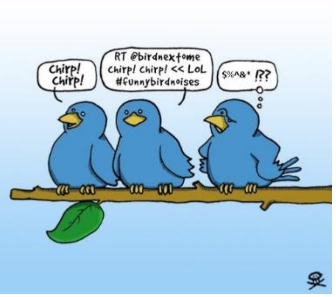
In Pig Latin

```
Users = load 'input/users' using PigStorage(',') as (name:chararray, age:int);
Fltrd = filter Users by age >= 18 and age <= 25;
Pages = load 'input/pages' using PigStorage(',')  as (user:chararray,
url:chararray);
Jnd = join Fltrd by name, Pages by user;
Grpd = group Jnd by url;
Smmd = foreach Grpd generate group,COUNT(Jnd) as clicks;
Srtd = order Smmd by clicks desc;
Top5 = limit Srtd 5;
store Top5 into 'output/top5sites' using PigStorage(',');
```

9 lines of code, 15 minutes to write

170 lines to 9 lines of code

Credits : Hortonworks



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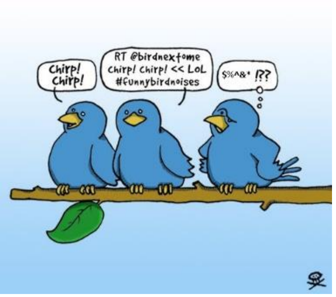
Maximizing the use of Hadoop ..

Maximizing the use of Hadoop

•We cannot afford too many diverse computing environments
•Most of analytics job are run using Hadoop cluster
–Hence, that’s where the data live
–It is natural to structure ML computation so that it takes advantage of the cluster and is performed close to the data

Seamless scaling to large datasets

Integration into production workflows



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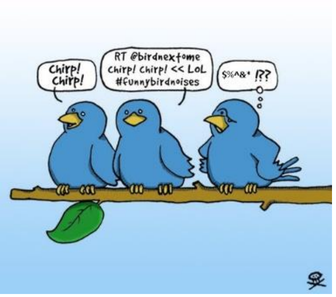
What authors contributed technically ..

Core libraries:

Core Java library
Basic abstractions similar to existing packages (weka, mallet, mahout)
Lightweight wrapper
Expose functionalities in Pig



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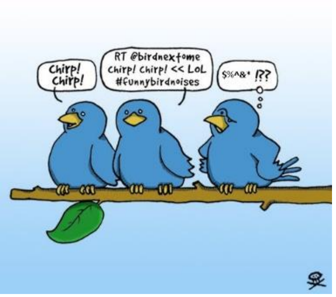
PIG Functions..

Training models:

```
training = load 'training.txt'
               using SVMLightStorage()
               as (target: int, features: map[]);
store training into 'model/'
    using FeaturesLRClassifierBuilder();
```

Storage function

```
-1 1:0.43 3:0.12 9284:0.2 # abcdef
```

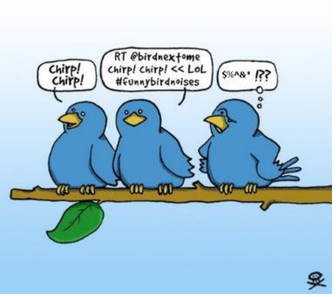


PIG Functions..

Shuffling data:

```
training = foreach training generate
              label, features, RANDOM() as random;
training = order training by random parallel 1;
```

```
data = foreach data generate target, features,
          RANDOM() as random;
split data into training if random <= 0.9,
    test if random > 0.9;
```



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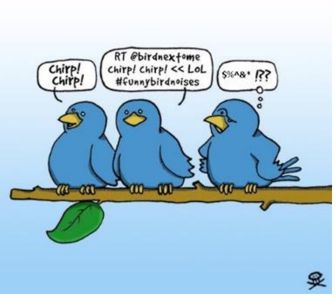
PIG Functions..

Using models:

```
define Classify ClassifyWithLR('model/');
data = load 'test.txt' using SVMLightStorage()
            as (target: double, features: map[]);
data = foreach data generate target,
            Classify(features) as prediction;
```



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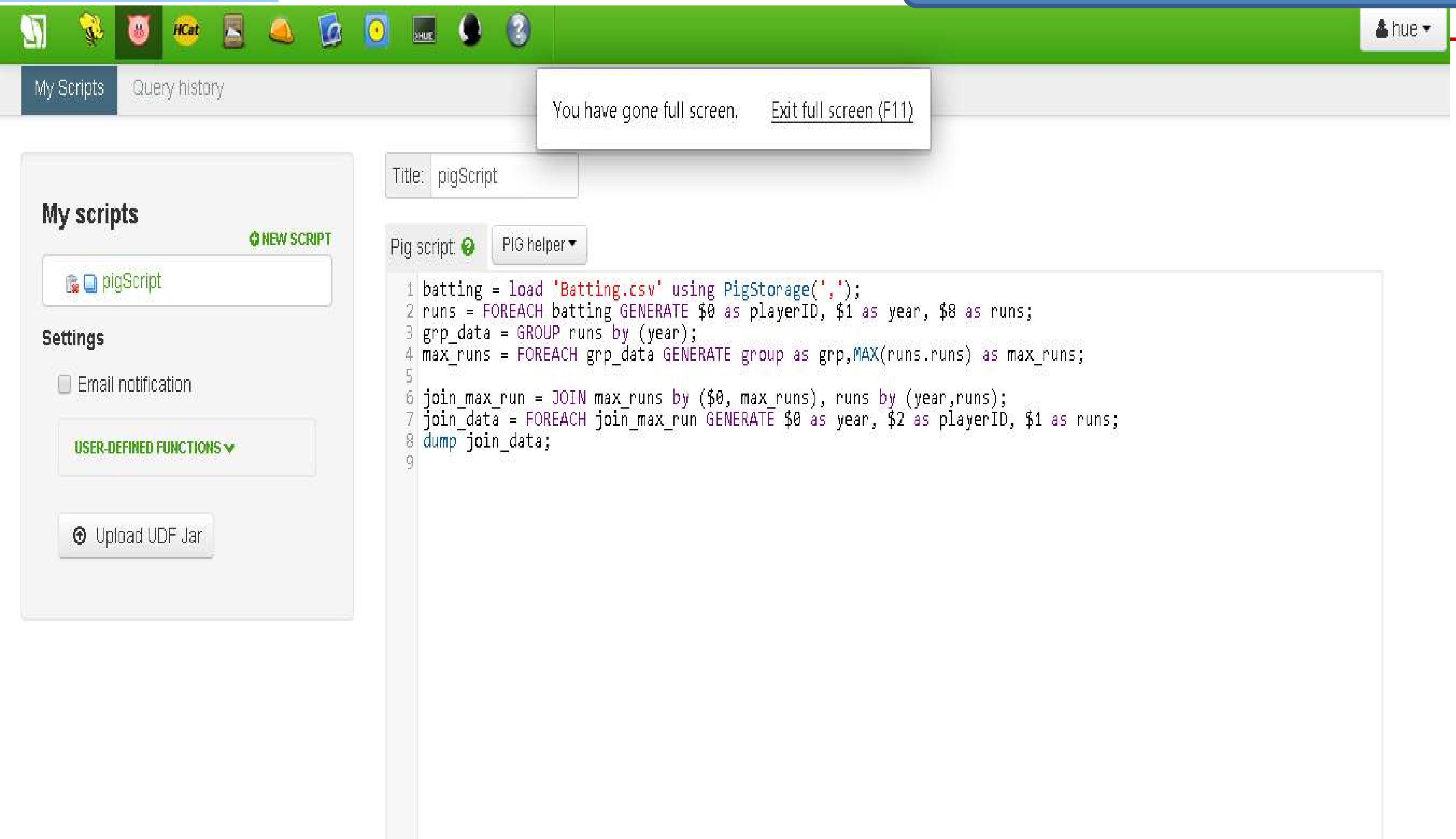
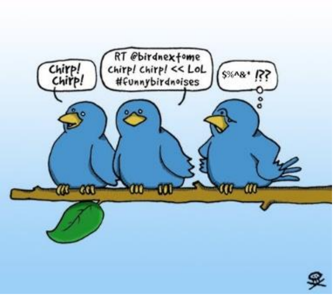
HortonWorks Way..

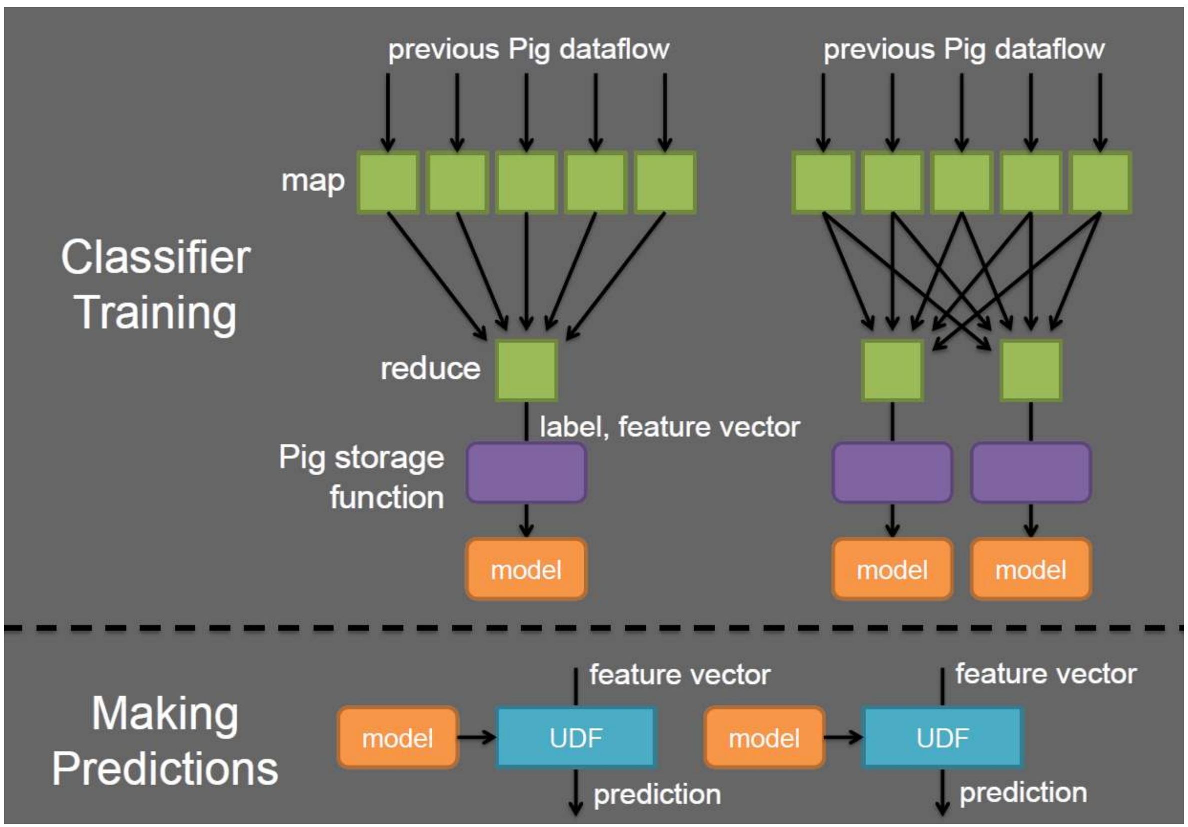


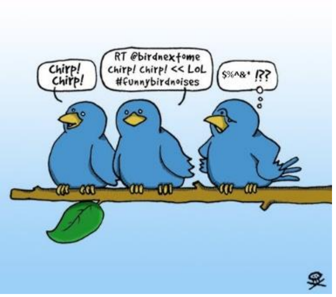
Credits : Hortonworks



Final Model which works!!!

Final Learning - Ensemble Methods





Use case..

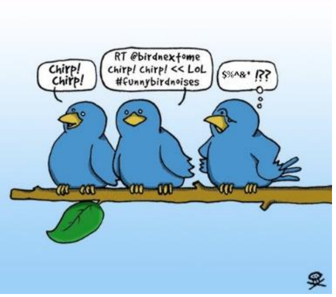
Example: Sentiment Analysis

Emotion Trick ☺ ☹

Test dataset: 1 million English tweets, minimum 20 letters-long

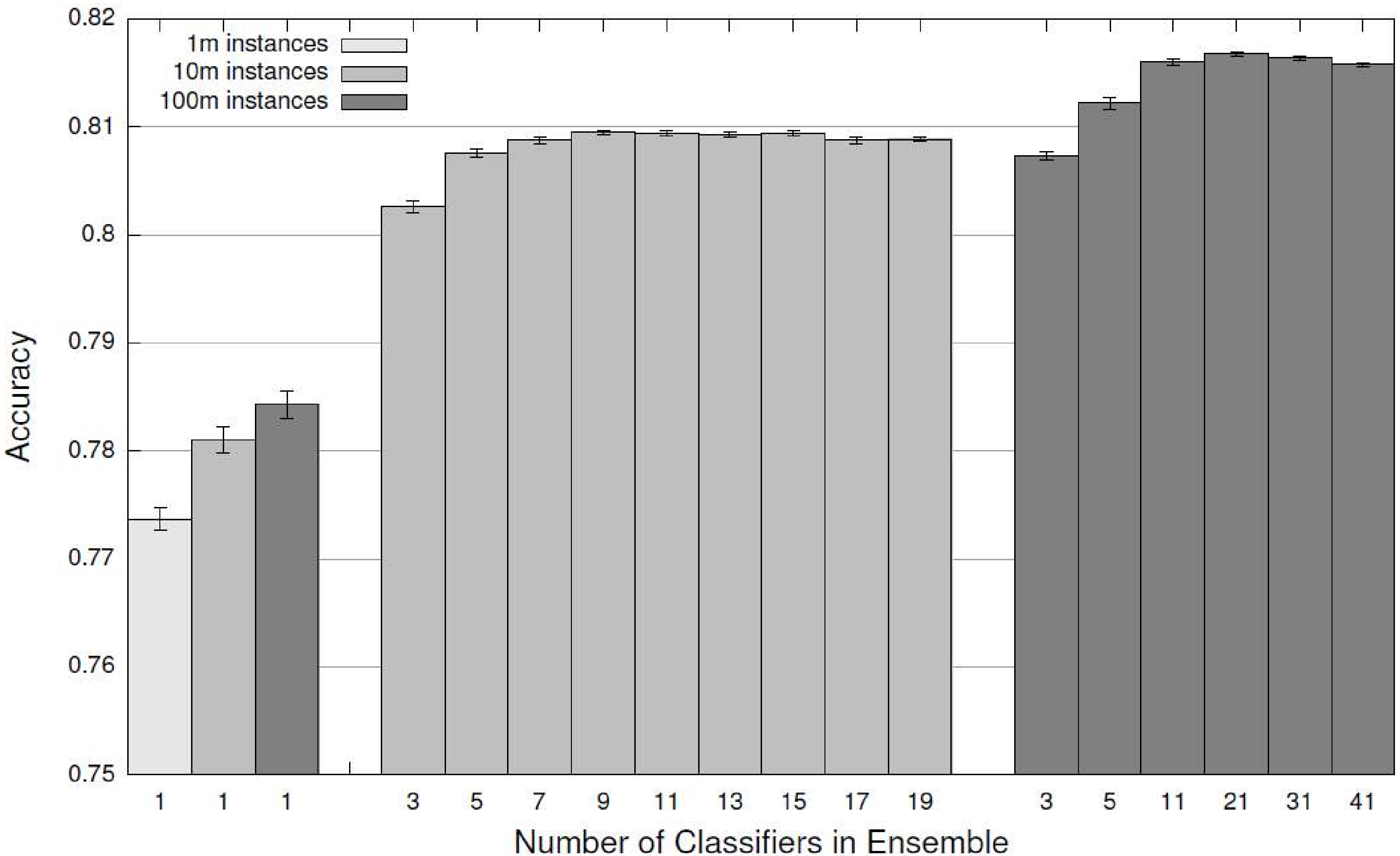
Training data: 1 million, 10 million and 100 million English training examples

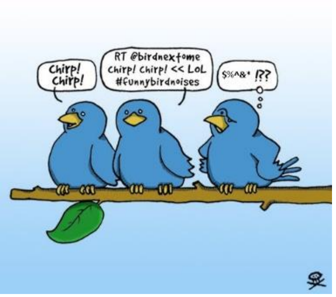
Preparation: training and test sets contains equal number of positive and negative examples, removed all emoticons.



Large-Scale Machine Learning at Twitter

Finally a graph ..





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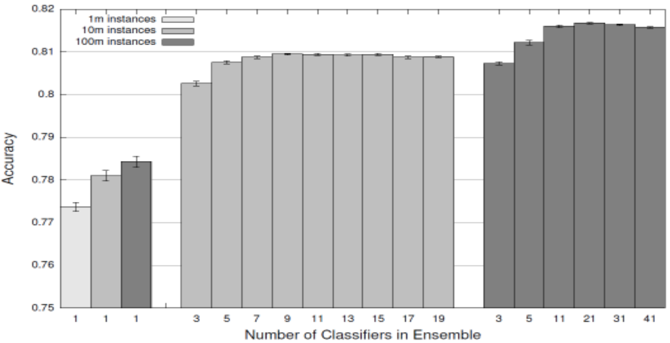
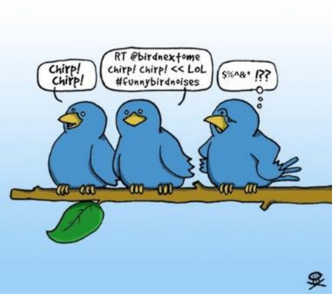
Explaining a bit more of graph ..



1. The error bar denotes 95% confidence interval
2. The leftmost group of bars show accuracy when training a single logistic regression classifier on {1, 10, 100} million training examples.
3. 1-10 Change Sharp , 10 – 100 million : Not that sharp
4. The middle and right group of bars in Figure 2 show the results of learning ensembles
5. Ensembles lead to higher accuracy—and note that an ensemble trained with 10 million examples outperforms a single classifier trained on 100 million examples
6. No accurate running time reported as experiments were run on production clusters – but informal observations are in sync with what the logical mind suggests (ensemble takes shorter to train because models are learned in parallel)
7. In terms of applying the learned models, running time increases with the size of the ensembles—since an ensemble of n classifiers requires making n separate predictions.



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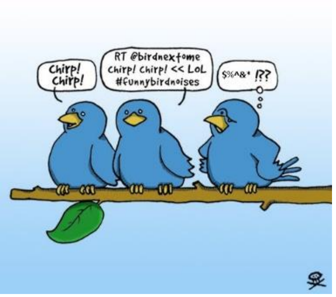
Conclusion

What I loved about paper : I understood it ☺ ?

“our goal has never been to make fundamental contributions to machine learning, we have taken the pragmatic approach of using off-the shelf toolkits where possible. Thus, the challenge becomes how to incorporate third-party software packages along with in-house tools into an existing workflow”..



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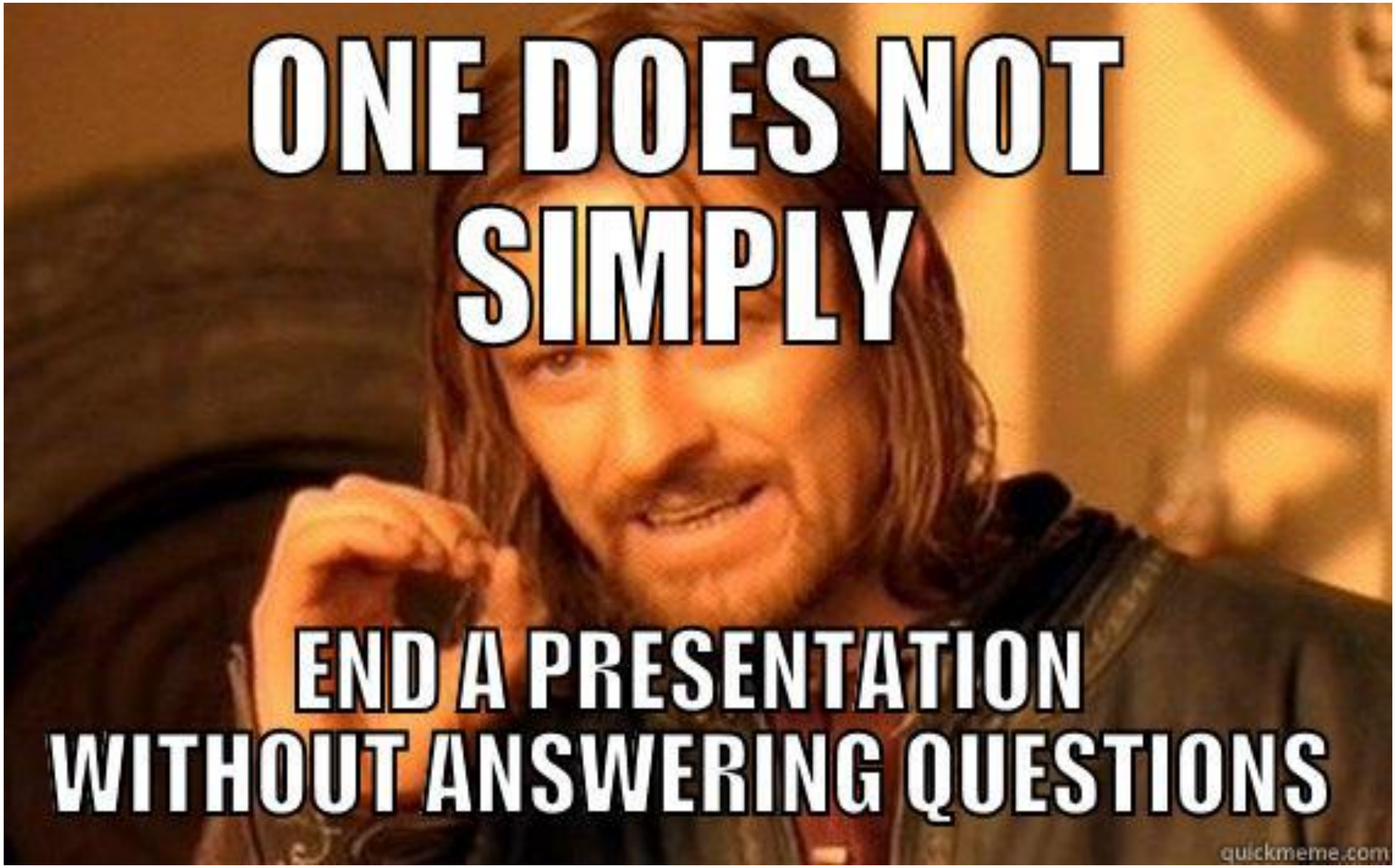

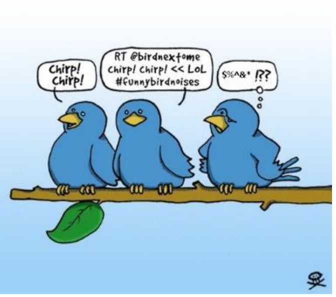

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