Big Data Infrastructure

CS 489/698 Big Data Infrastructure (Winter 2016)

Week 8: Data Mining (2/4)

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These slides are available at http://lintool.github.io/bigdata-2016w/

The Task

label

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

(sparse) feature vector

$$\mathrm{x}_i = [x_1, x_2, x_3, \ldots, x_d]$$
$$y \in \{0, 1\}$$

- Induce $f : X \to Y$
  - Such that loss is minimized

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

loss function

- Typically, consider functions of a parametric form:

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

model parameters

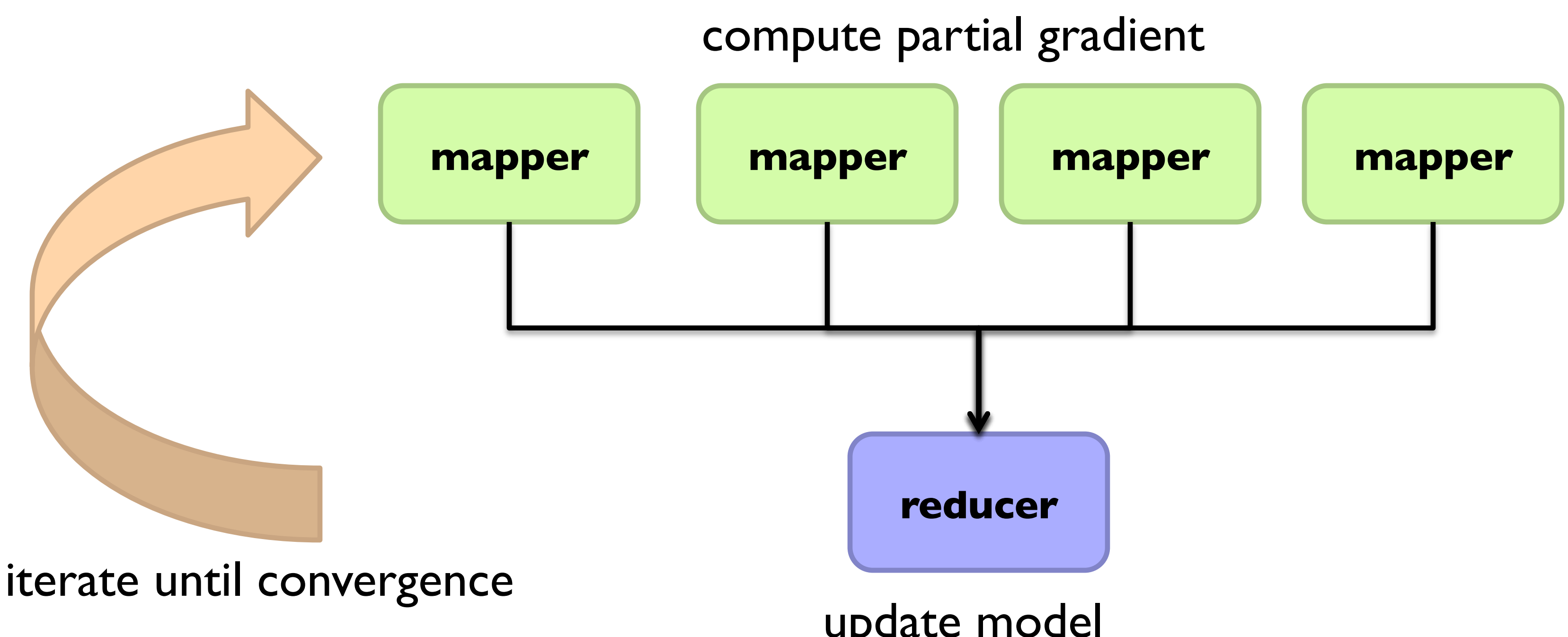
Gradient Descent

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \gamma^{(t)} \frac{1}{n} \sum_{i=0}^{n} \nabla \ell(f(\mathrm{x}_i; \theta^{(t)}), y_i)$$

Source: Wikipedia (Hills)

MapReduce Implementation

$$\theta^{(t+1)} \leftarrow \underbrace{\theta^{(t)} - \gamma^{(t)} \frac{1}{n} \underbrace{\sum_{i=0}^{n} \nabla \ell(f(\mathrm{x}_i;\theta^{(t)}), y_i)}_{\text{mappers}}}_{\text{single reducer}}$$

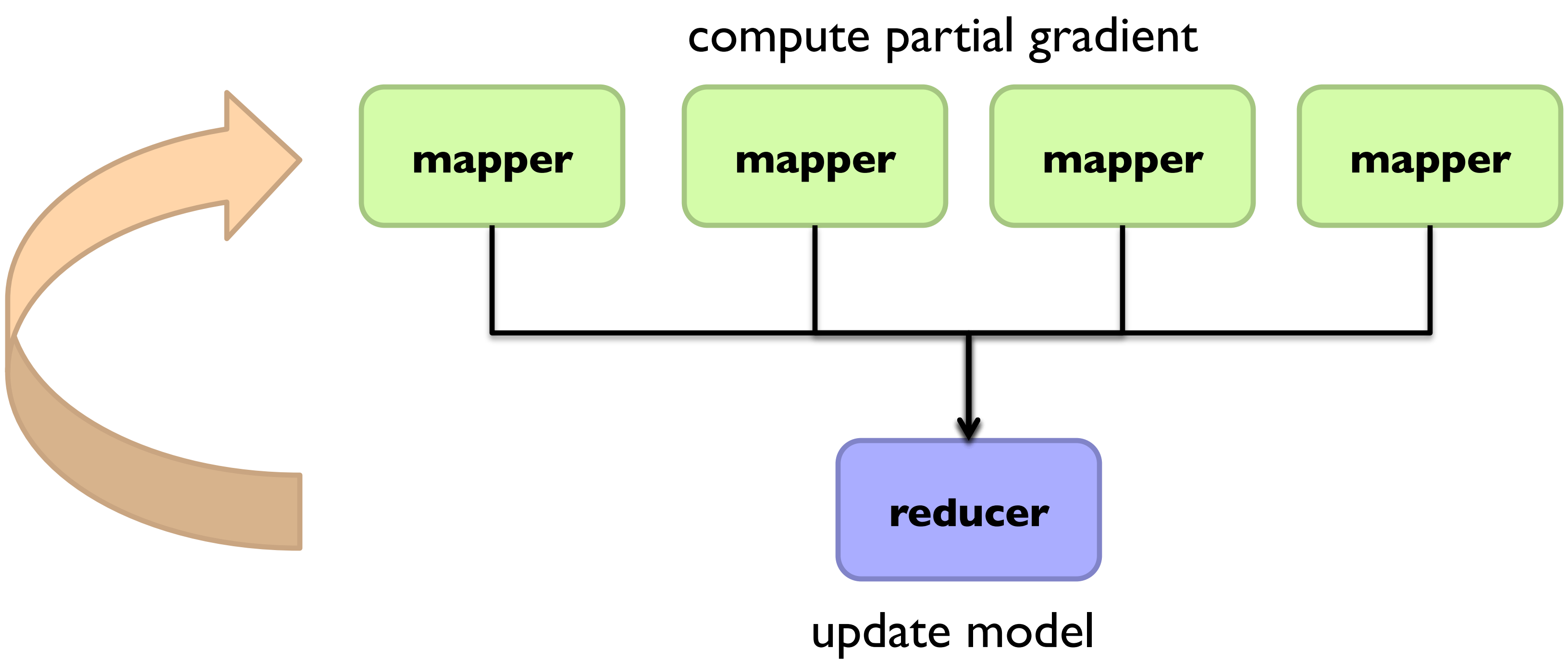


Spark Implementation

```
val points = spark.textFile(...).map(parsePoint).persist()

var w = // random initial vector
for (i <- 1 to ITERATIONS) {
  val gradient = points.map{ p =>
    p.x * (1/(1+exp(-p.y*(w dot p.x)))-1)*p.y
  }.reduce((a,b) => a+b)
  w -= gradient
}
```

What's the difference?



Gradient Descent

Source: Wikipedia (Hills)

Stochastic Gradient Descent

Source: Wikipedia (Water Slide)

Batch vs. Online

Gradient Descent

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \gamma^{(t)} \frac{1}{n} \sum_{i=0}^{n} \nabla \ell(f(\mathrm{x}_i; \theta^{(t)}), y_i)$$

“batch” learning: update model after considering all training instances

Stochastic Gradient Descent (SGD)

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \gamma^{(t)} \nabla \ell(f(\mathrm{x}; \theta^{(t)}), y)$$

“online” learning: update model after considering *each* (randomly-selected) training instance

In practice… just as good!

Opportunity to interleaving prediction and learning!

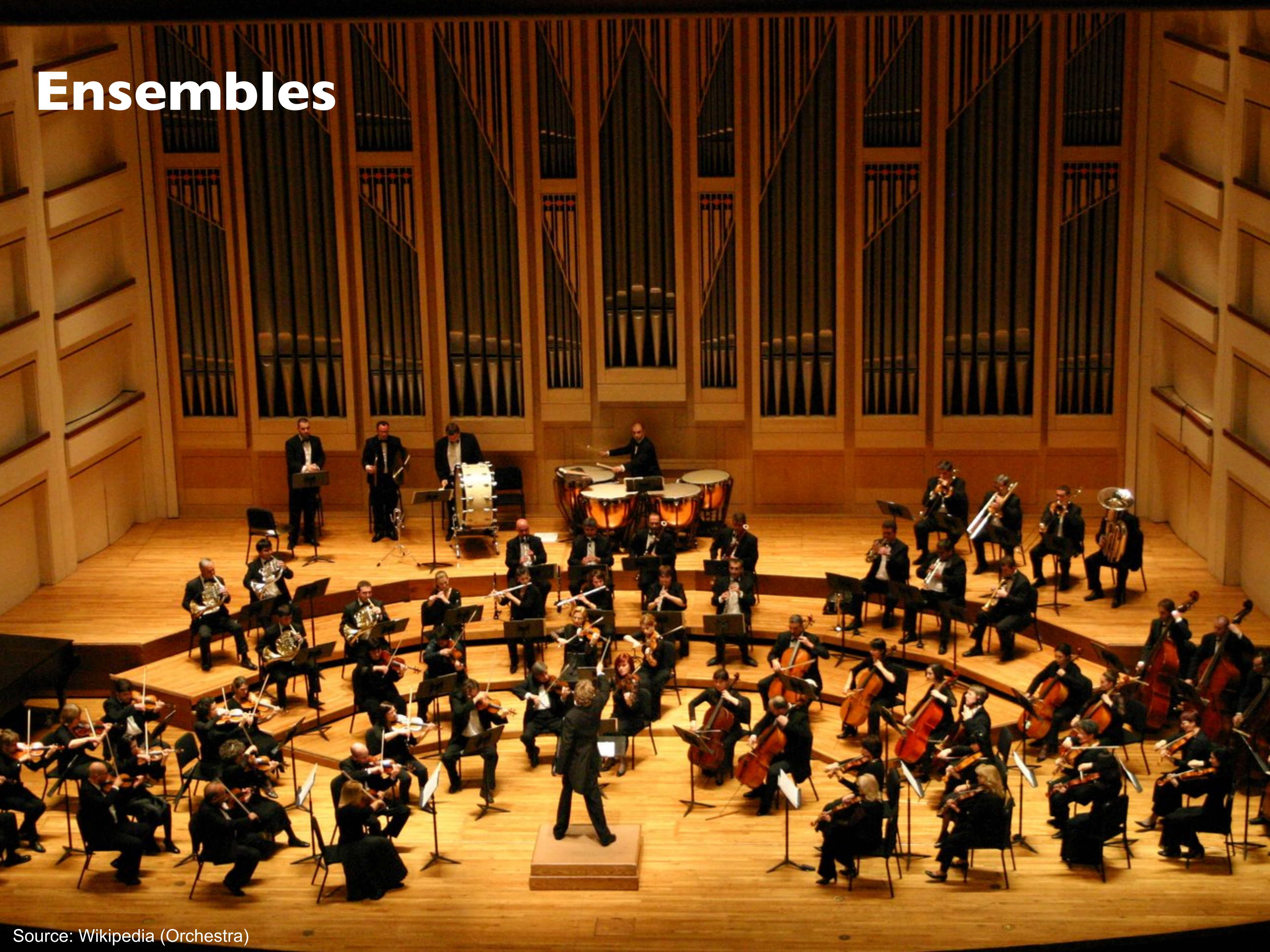
Practical Notes

- Order of the instances important!
- Most common implementation:
  - Randomly shuffle training instances
  - Stream instances through learner
- Single vs. multi-pass approaches
- “Mini-batching” as a middle ground between batch and stochastic gradient descent

We’ve solved the iteration problem!

What about the single reducer problem?

Ensembles



Source: Wikipedia (Orchestra)

Ensemble Learning

- Learn multiple models, combine results from different models to make prediction
- Why does it work?
  - If errors uncorrelated, multiple classifiers being wrong is less likely
  - Reduces the variance component of error
- A variety of different techniques:
  - Majority voting
  - Simple weighted voting:

$$y = \arg\max_{y \in Y} \sum_{k=1}^{n} \alpha_k p_k(y|\mathrm{x})$$

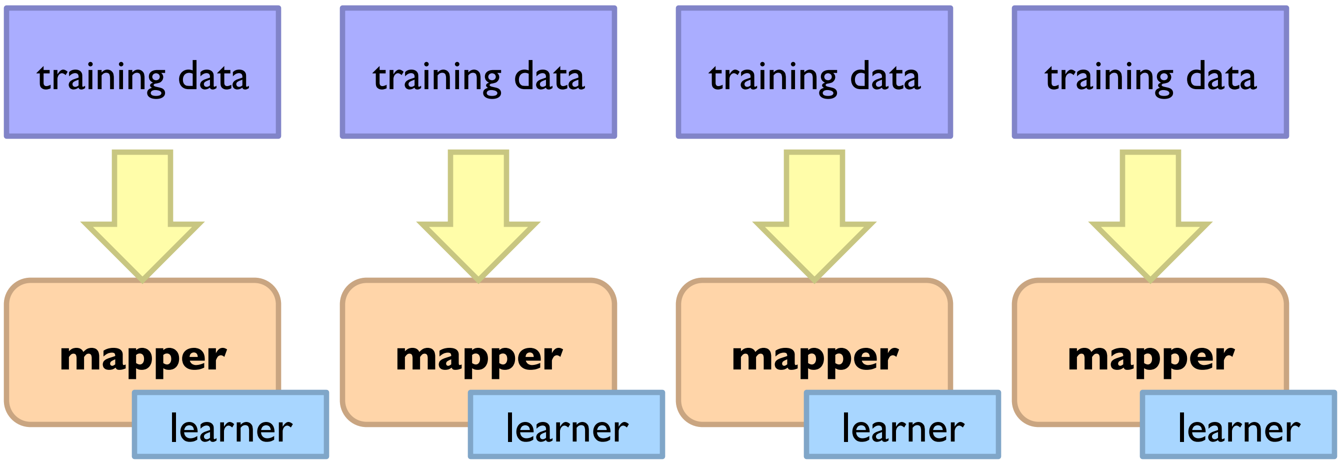
  - Model averaging
  - …

Practical Notes

- Common implementation:
  - Train classifiers on different input partitions of the data
  - Embarrassingly parallel!
- Contrast with other ensemble techniques, e.g., boosting

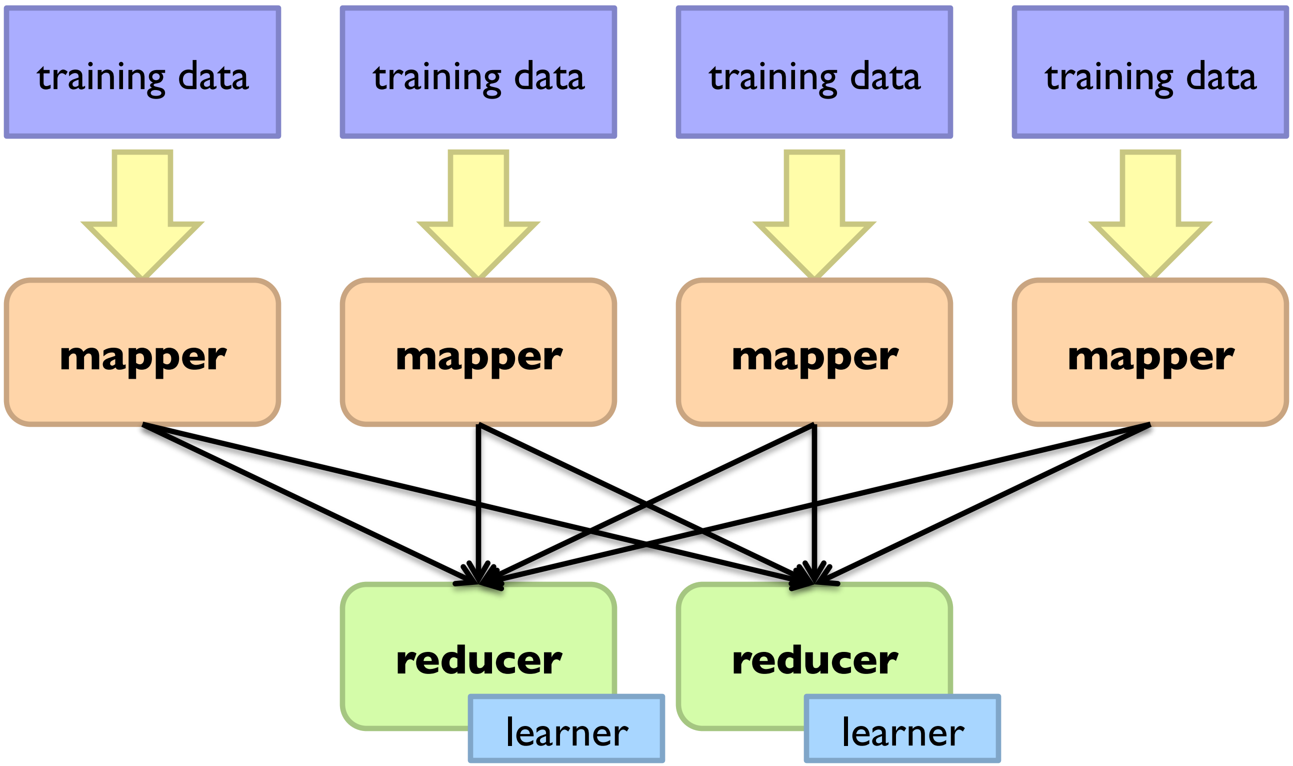
MapReduce Implementation

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \gamma^{(t)} \nabla \ell(f(\mathrm{x}; \theta^{(t)}), y)$$



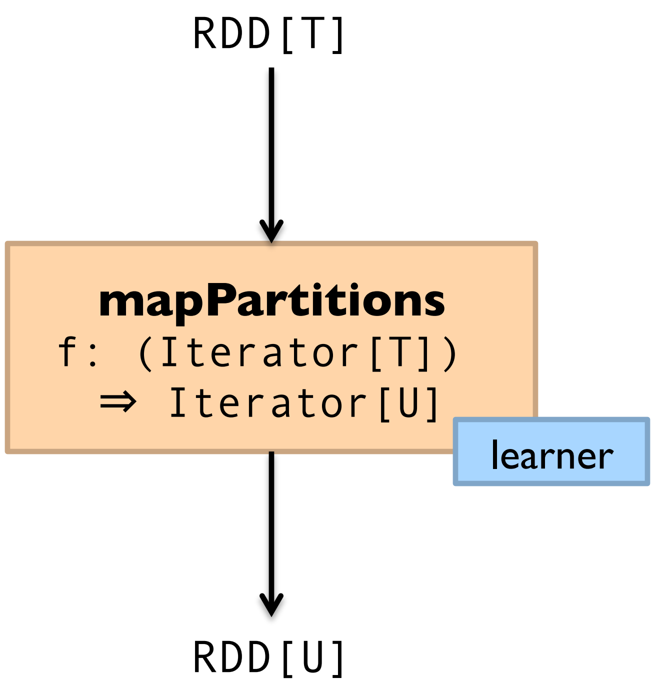
MapReduce Implementation

$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \gamma^{(t)} \nabla \ell(f(\mathrm{x}; \theta^{(t)}), y)$$



What about Spark?

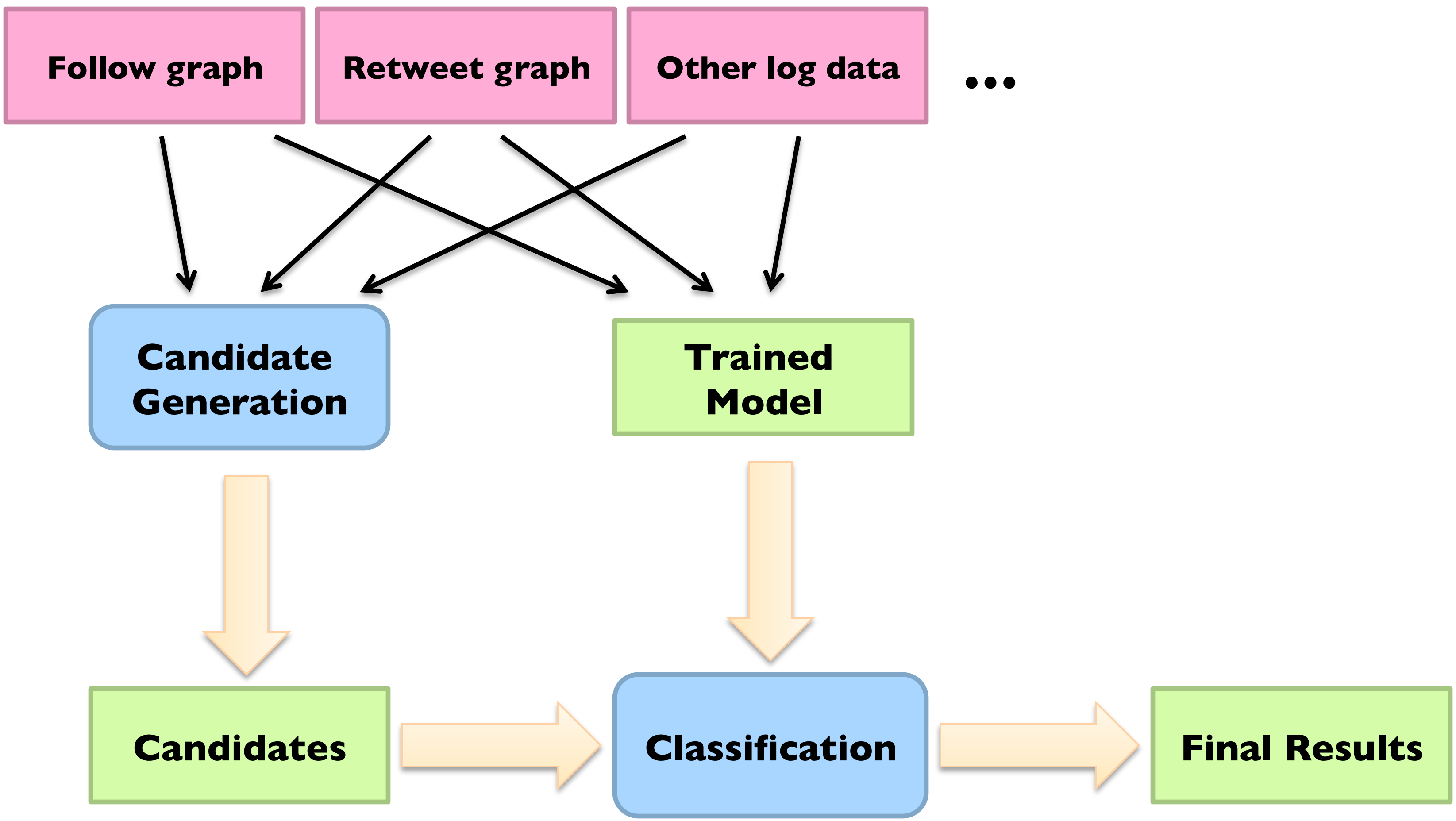
$$\theta^{(t+1)} \leftarrow \theta^{(t)} - \gamma^{(t)} \nabla \ell(f(\mathrm{x}; \theta^{(t)}), y)$$



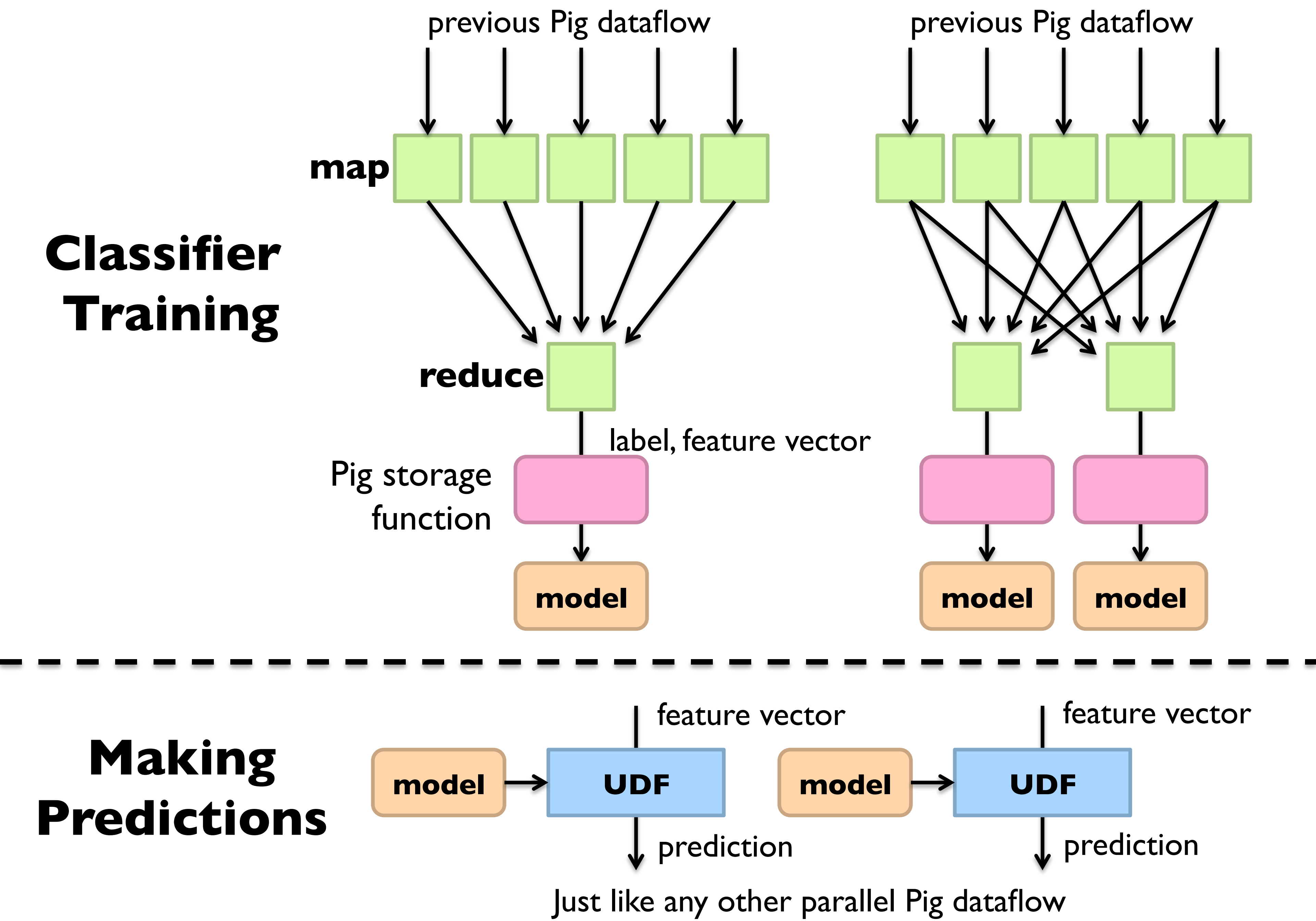
MapReduce Implementation: Details

- Two possible implementations:
  - Write model out as "side data"
  - Emit model as intermediate output

Case Study: Link Recommendation



Lin and Kolcz. Large-Scale Machine Learning at Twitter. SIGMOD 2012.


Classifier Training
previous Pig dataflow
previous Pig dataflow
map
reduce
label, feature vector
Pig storage function
model
model
model
Making Predictions
model
UDF
feature vector
prediction
model
UDF
feature vector
prediction
Just like any other parallel Pig dataflow

Classifier Training

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

store training into 'model/'
        using FeaturesLRClassifierBuilder();
```

Logistic regression + SGD (L2 regularization)
Pegasos variant (fully SGD or sub-gradient)

Want an ensemble?

```
training = foreach training generate
        label, features, RANDOM() as random;
training = order training by random parallel 5;
```

Making Predictions

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

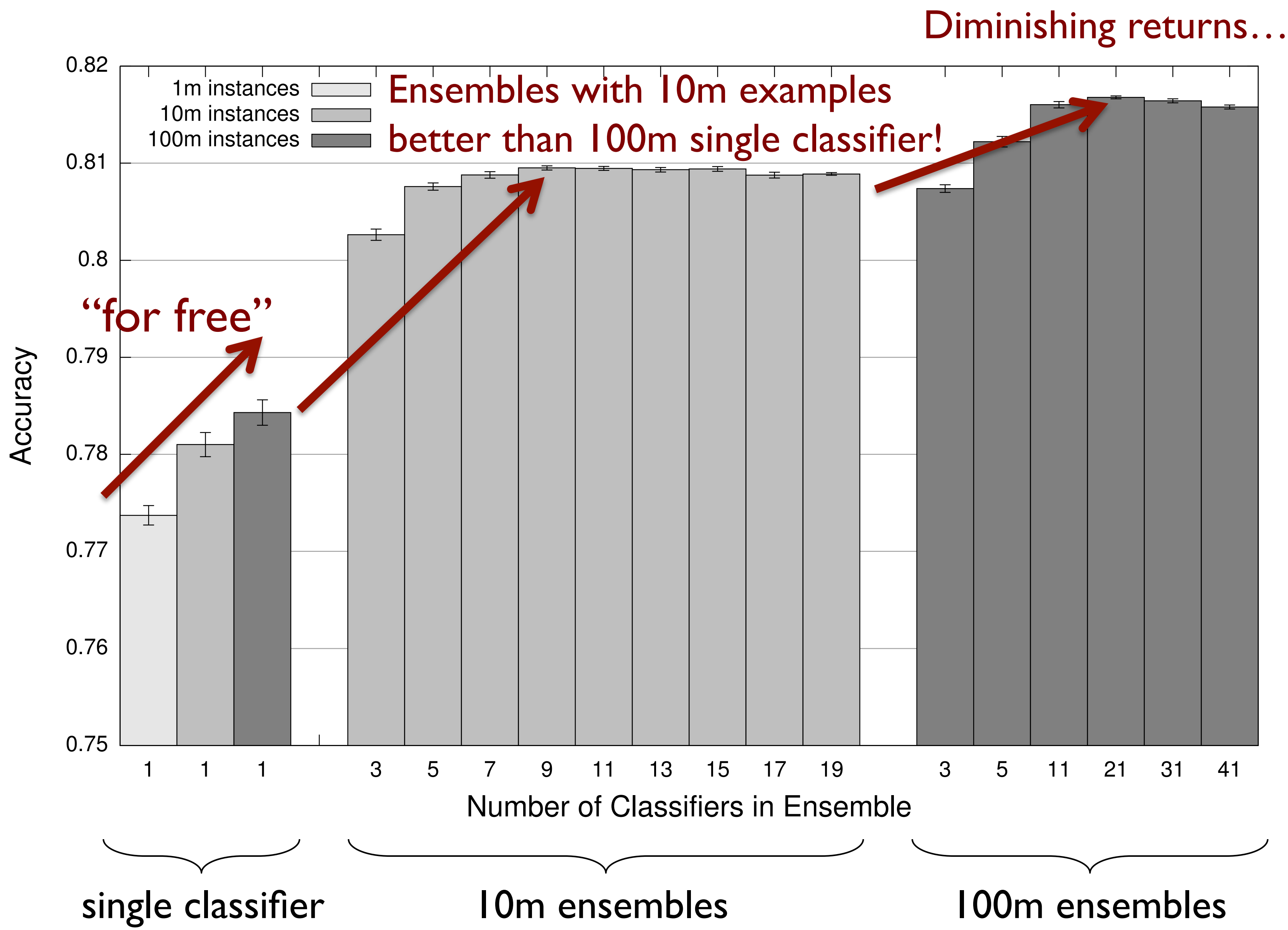
Want an ensemble?

```
define Classify ClassifyWithEnsemble('model/',
'classifier.LR', 'vote');
```

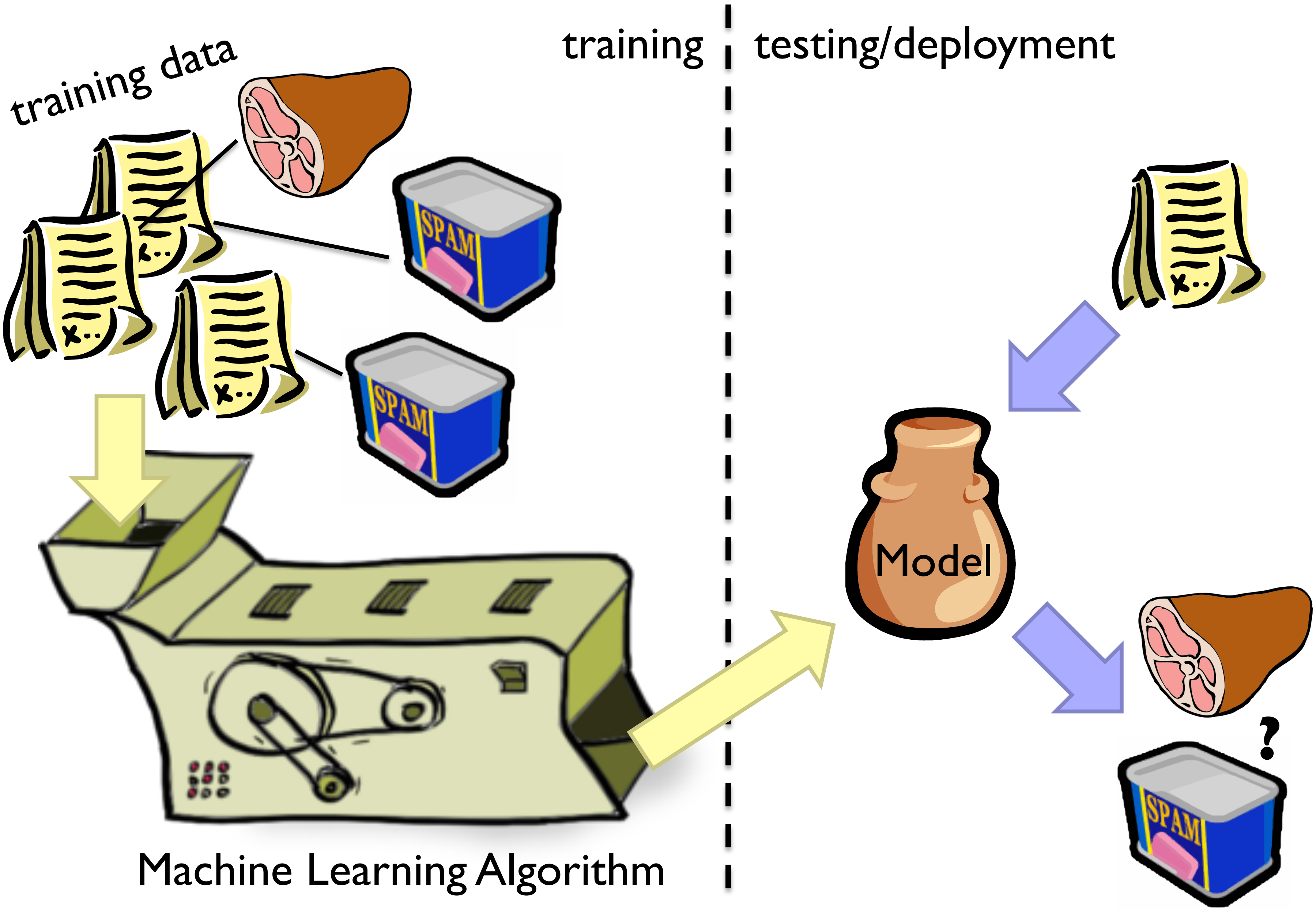
Sentiment Analysis Case Study

Lin and Kolcz, SIGMOD 2012

- Binary polarity classification: {positive, negative} sentiment
  - Independently interesting task
  - Illustrates end-to-end flow
  - Use the "emoticon trick" to gather data
- Data
  - Test: 500k positive/500k negative tweets from 9/1/2011
  - Training: {1m, 10m, 100m} instances from before (50/50 split)
- Features: Sliding window byte-4grams
- Models:
  - Logistic regression with SGD (L2 regularization)
  - Ensembles of various sizes (simple weighted voting)


Diminishing returns…
Ensembles with 10m examples
better than 100m single classifier!
"for free"
1m instances
10m instances
100m instances
Accuracy
0.82
0.81
0.8
0.79
0.78
0.77
0.76
0.75
1
1
1
3
5
7
9
11
13
15
17
19
3
5
11
21
31
41
Number of Classifiers in Ensemble
single classifier
10m ensembles
100m ensembles

Supervised Machine Learning



Applied ML in Academia

- Download interesting dataset (comes with the problem)
- Run baseline model
  - Train/test
- Build better model
  - Train/test
- Does new model beat baseline?
  - Yes: publish a paper!
  - No: try again!

Three Commandants of Machine Learning

Thou shalt not mix training and testing data
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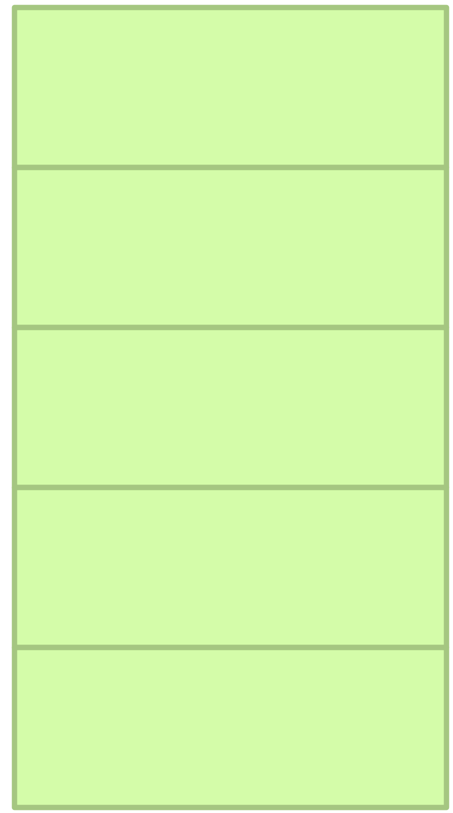
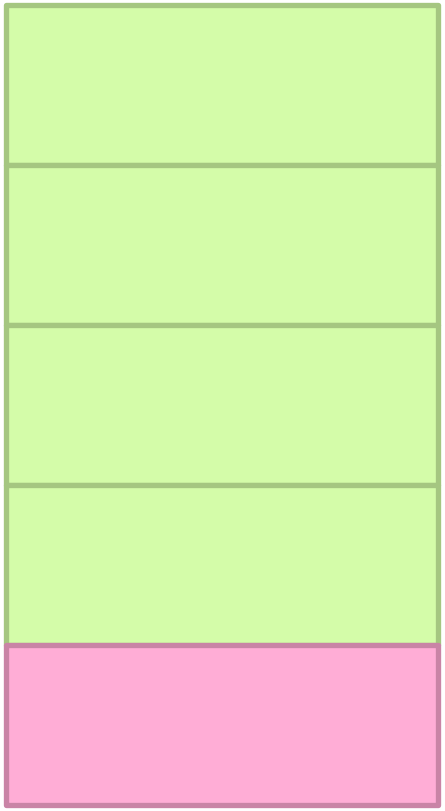
Training/Testing Splits



What happens if you need more?

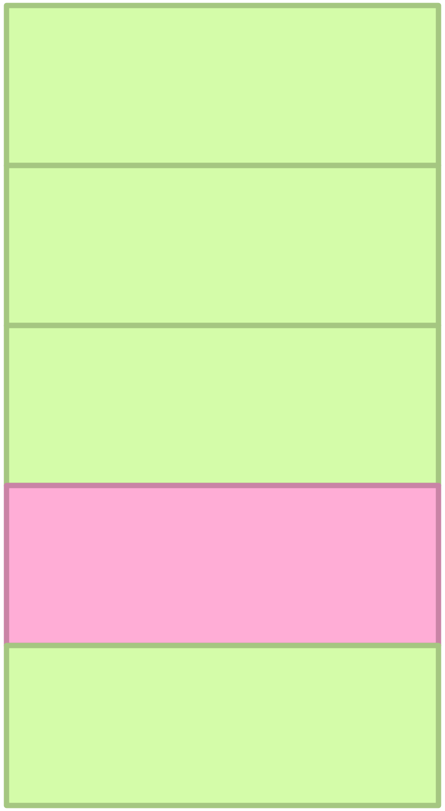
Cross-Validation

Training/Testing Splits



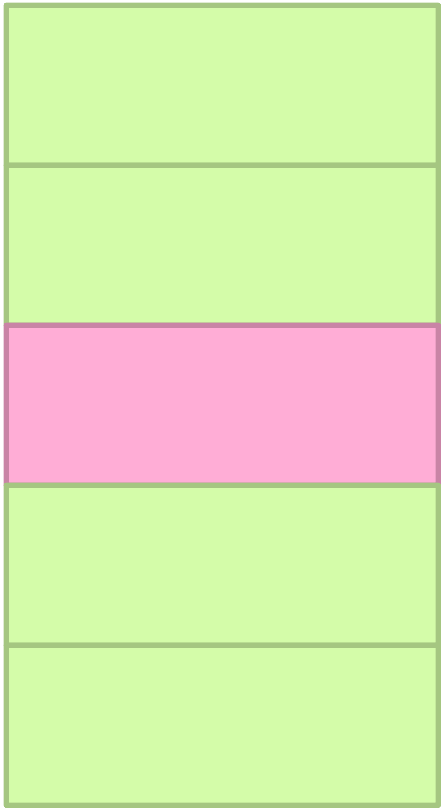
Cross-Validation

Training/Testing Splits



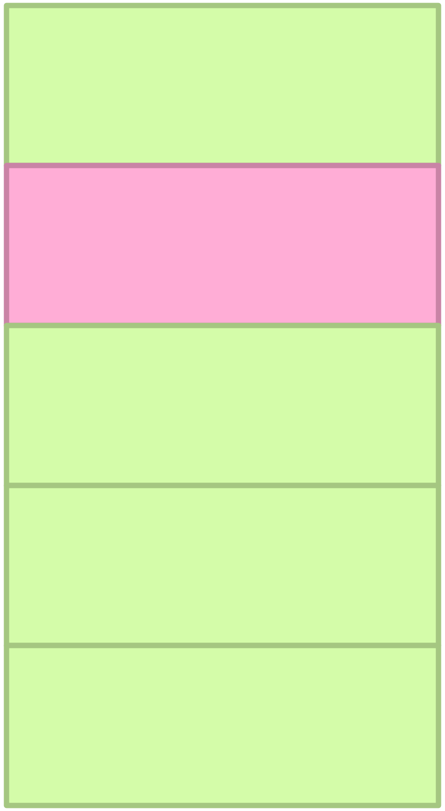
Cross-Validation

Training/Testing Splits



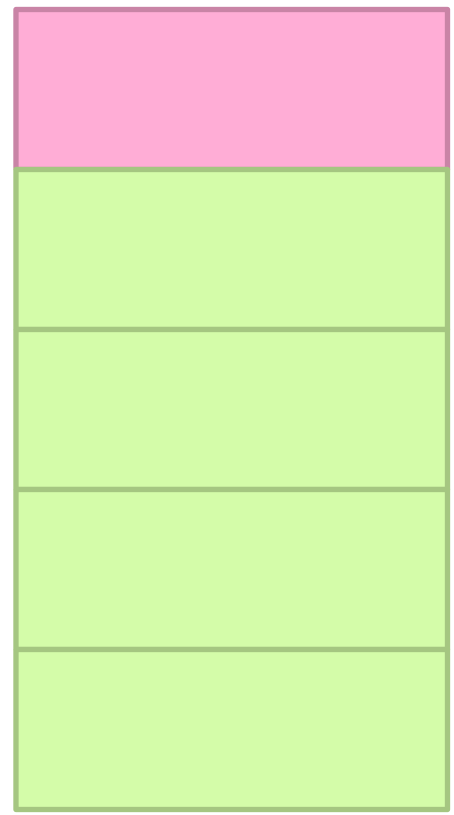
Cross-Validation

Training/Testing Splits



Cross-Validation

Training/Testing Splits



Cross-Validation

Applied ML in Academia

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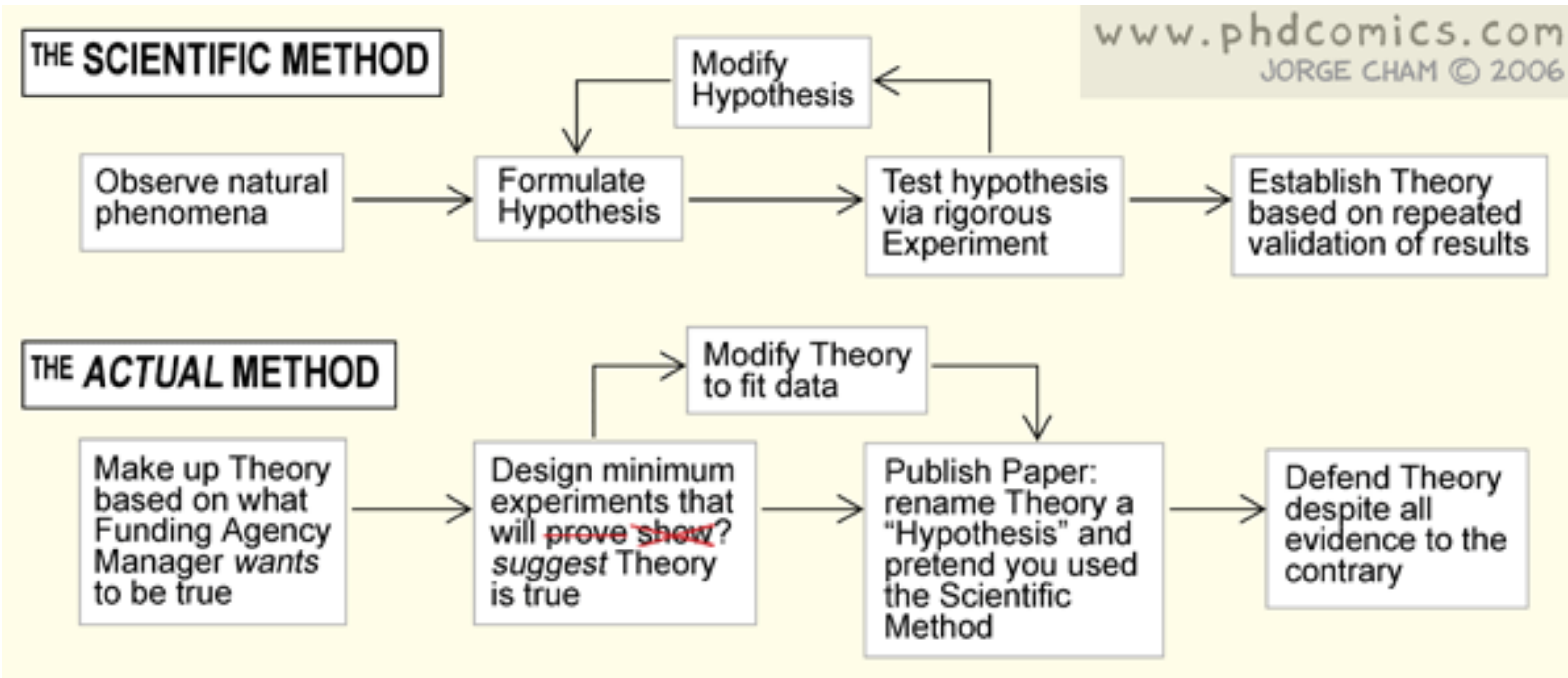

www.phdcomics.com
JORGE CHAM © 2006
THE SCIENTIFIC METHOD
Observe natural phenomena
Formulate Hypothesis
Modify Hypothesis
Test hypothesis via rigorous Experiment
Establish Theory based on repeated validation of results
THE ACTUAL METHOD
Make up Theory based on what Funding Agency Manager *wants* to be true
Design minimum experiments that will ~~prove~~ ~~show~~? *suggest* Theory is true
Modify Theory to fit data
Publish Paper: rename Theory a "Hypothesis" and pretend you used the Scientific Method
Defend Theory despite all evidence to the contrary

Harvard Business Review

DATA

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

FROM THE OCTOBER 2012 ISSUE

Fantasy

Extract features

Develop cool ML technique

#Profit

Reality

What's the task?

Where's the data?

What's in this dataset?

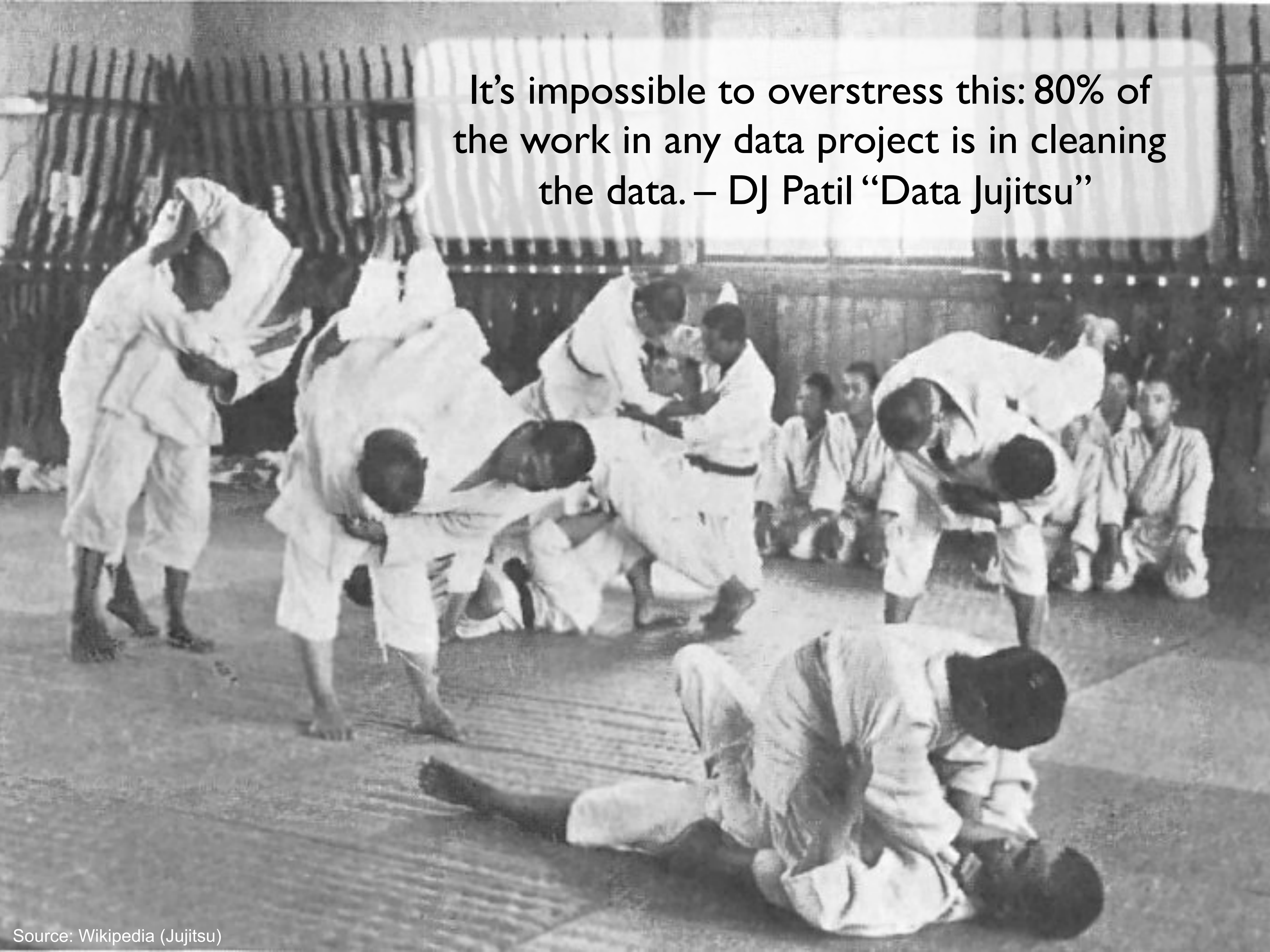
What's all the f#$!* crap?

Clean the data

Extract features

"Do" machine learning

Fail, iterate…



It’s impossible to overstress this: 80% of the work in any data project is in cleaning the data. – DJ Patil “Data Jujitsu”

Source: Wikipedia (Jujitsu)

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The New York Times

TECHNOLOGY

For ‘Big Data’ Scientists, Hurdle to Insights Is ‘Janitor Work’

By STEVE LOHR AUG. 17, 2014

Monica Rogati, Jawbone’s vice president for data science, with Brian Wilt, a senior data scientist.

Peter DaSilva for The New York Times

On finding things…

On finding things...

uid
UserId
userId
userid
user_id
user_Id

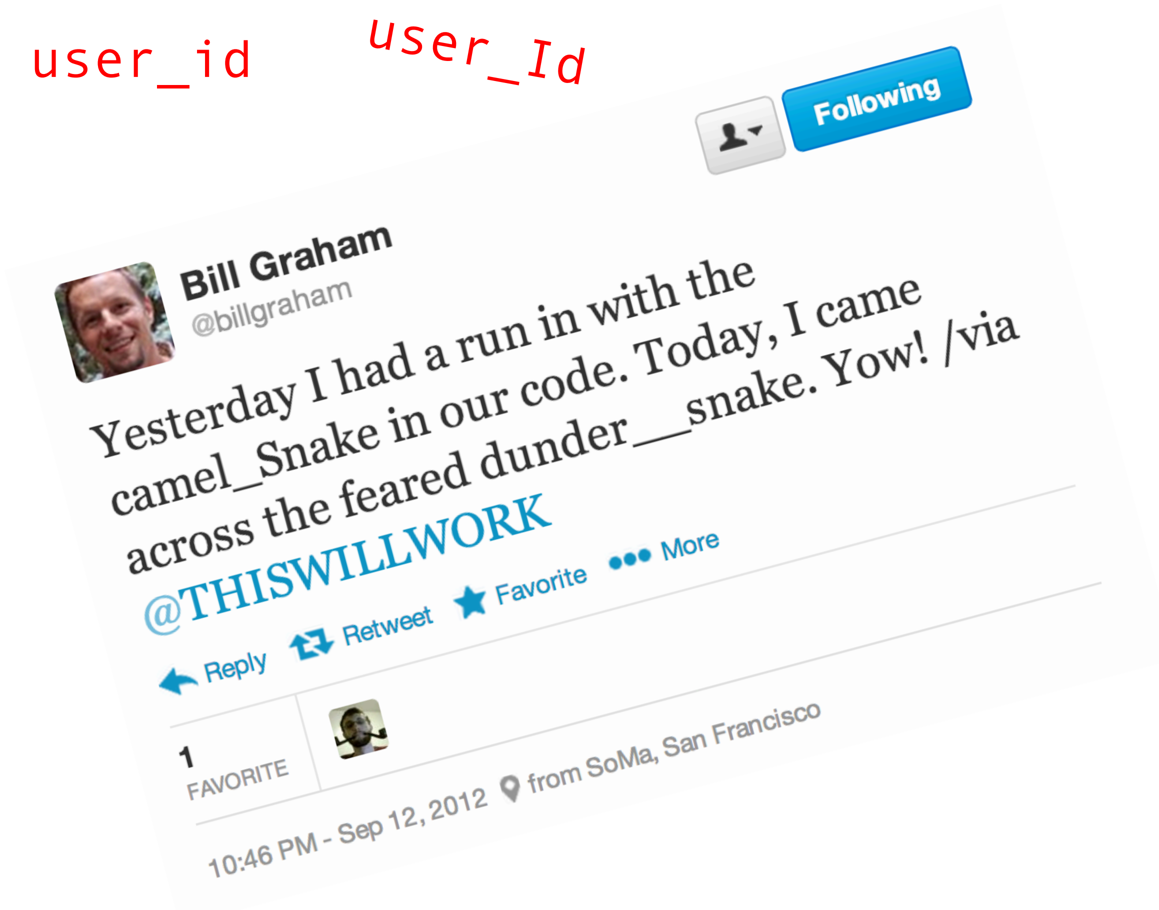
CamelCase

smallCamelCase

snake_case

camel_Snake

dunder__snake



On feature extraction...

```
^(\\w+\\s+\\d+\\s+\\d+:\\d+:\\d+)\\s+
([^@]+?)@(\\S+)\\s+(\\S+):\\s+(\\S+)\\s+(\\S+)
\\s+((?:\\S+?,\\s+)*(?:\\S+?))\\s+(\\S+)\\s+(\\S+)
\\s+\\[([^\\]]+)\\]\\s+\"(\\w+)\\s+([^\"\\\\]*
(?:\\\\.[^\"\\\\]*)*)\\s+(\\S+)\"\\s+(\\S+)\\s+
(\\S+)\\s+\"([^\"\\\\]*(?:\\\\.[^\"\\\\]*)*)
\"\\s+\"([^\"\\\\]*(?:\\\\.[^\"\\\\]*)*)\"\\s*
(\\d*-[\\d-]*)?\\s*(\\d+)?\\s*(\\d*\\.[\\d\\.]*)?
(\\s+[-\\w]+)?.*$
```

An actual Java regular expression used to parse log message at Twitter circa 2010

Friction is cumulative!

Data Plumbing... Gone Wrong!

[scene: consumer internet company in the Bay Area…]

Okay, let's get going… where's the click data?

It's over here…

Well, that's kinda non-intuitive, but okay…

Well, it wouldn't fit, so we had to shoehorn…

Oh, BTW, where's the timestamp of the click?

Hang on, I don't remember…

Uh, bad news. Looks like we forgot to log it…

[grumble, grumble, grumble]

Frontend Engineer

Develops new feature, adds logging code to capture clicks

Data Scientist

Analyze user behavior, extract insights to improve feature

Fantasy

Extract features

Develop cool ML technique

#Profit

Reality

What's the task?

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Clean the data

Extract features

"Do" machine learning

Fail, iterate…

Finally works!

Congratulations, you’re halfway there…

Source: Wikipedia (Hills)

Congratulations, you're halfway there…

Does it actually work?
A/B testing

Is it fast enough?

Good, you're two thirds there…

Productionize

Source: Wikipedia (Oil refinery)

Productionize

What are your jobs' dependencies?
How/when are your jobs scheduled?
Are there enough resources?
How do you know if it's working?
Who do you call if it stops working?

Infrastructure is critical here!
(plumbing)

Takeaway lesson:
Plumbing matters!

Source: Wikipedia (Plumbing)

Questions?

Source: Wikipedia (Japanese rock garden)