

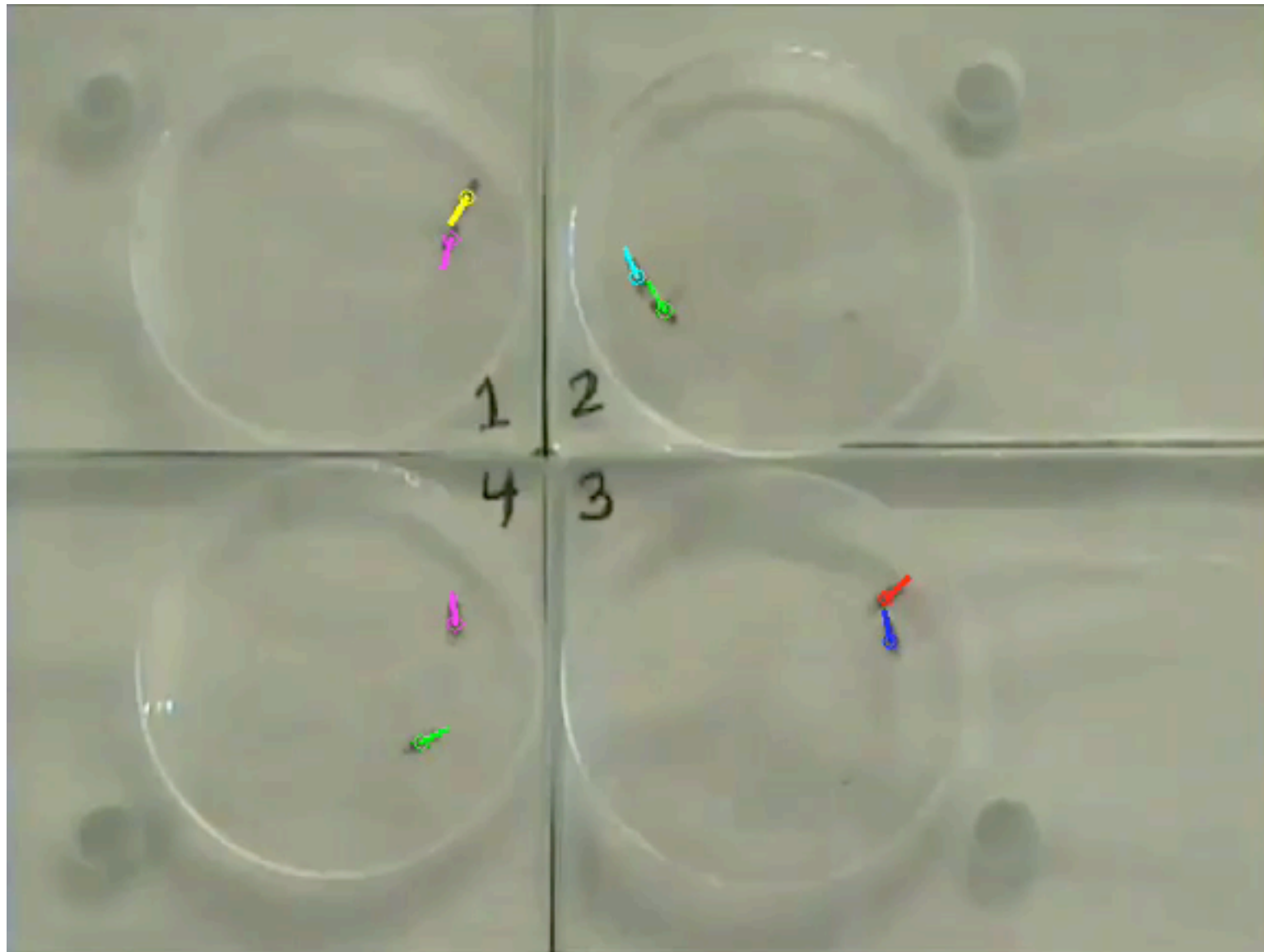
Cloudy Vision

Demystifying On-Demand Scalable Image Processing

Tim Lukins

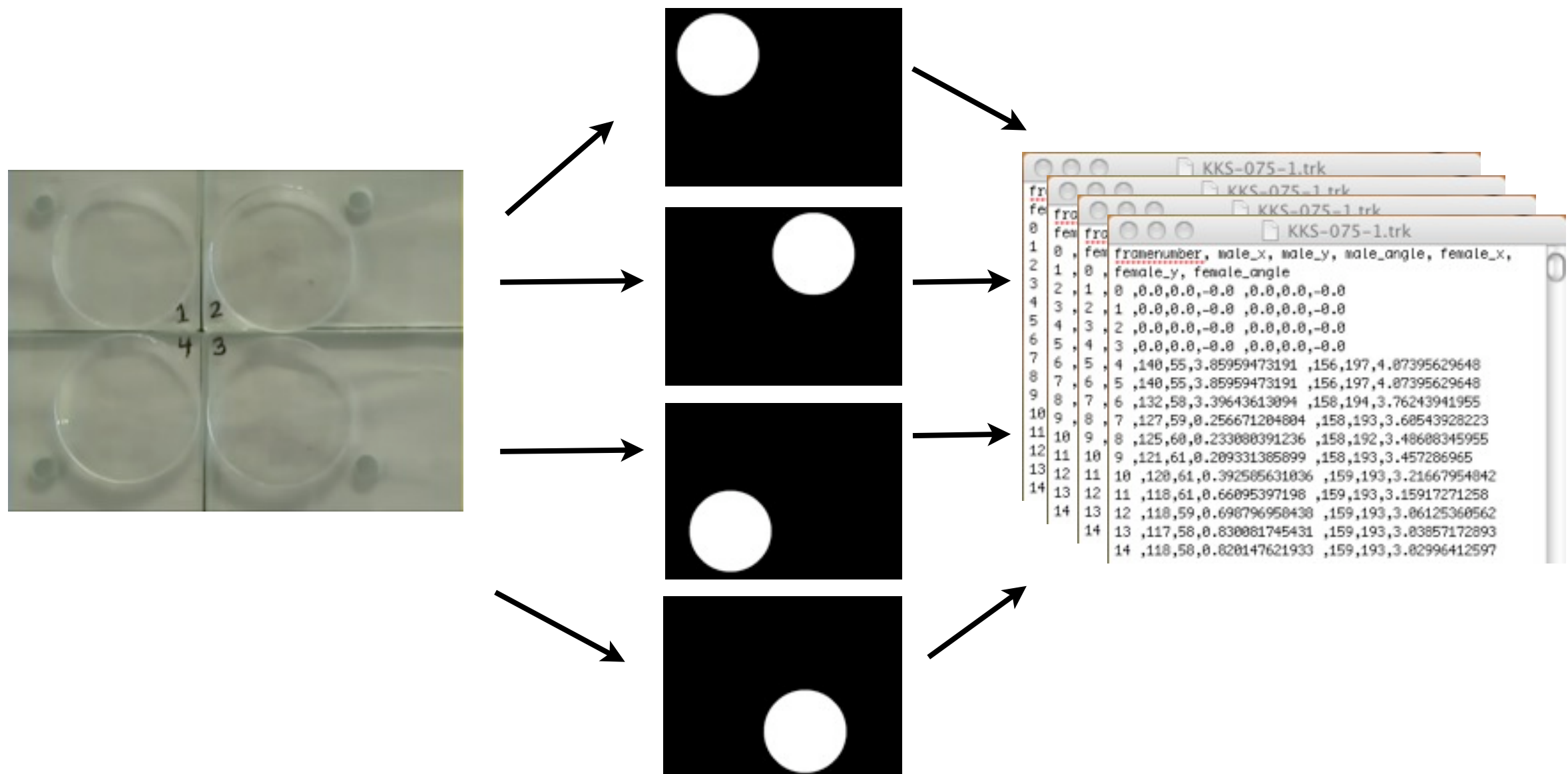
Institute for Adaptive and Neural Computation
School of Informatics, University of Edinburgh

A problem for us...



 **ibehave[®]**

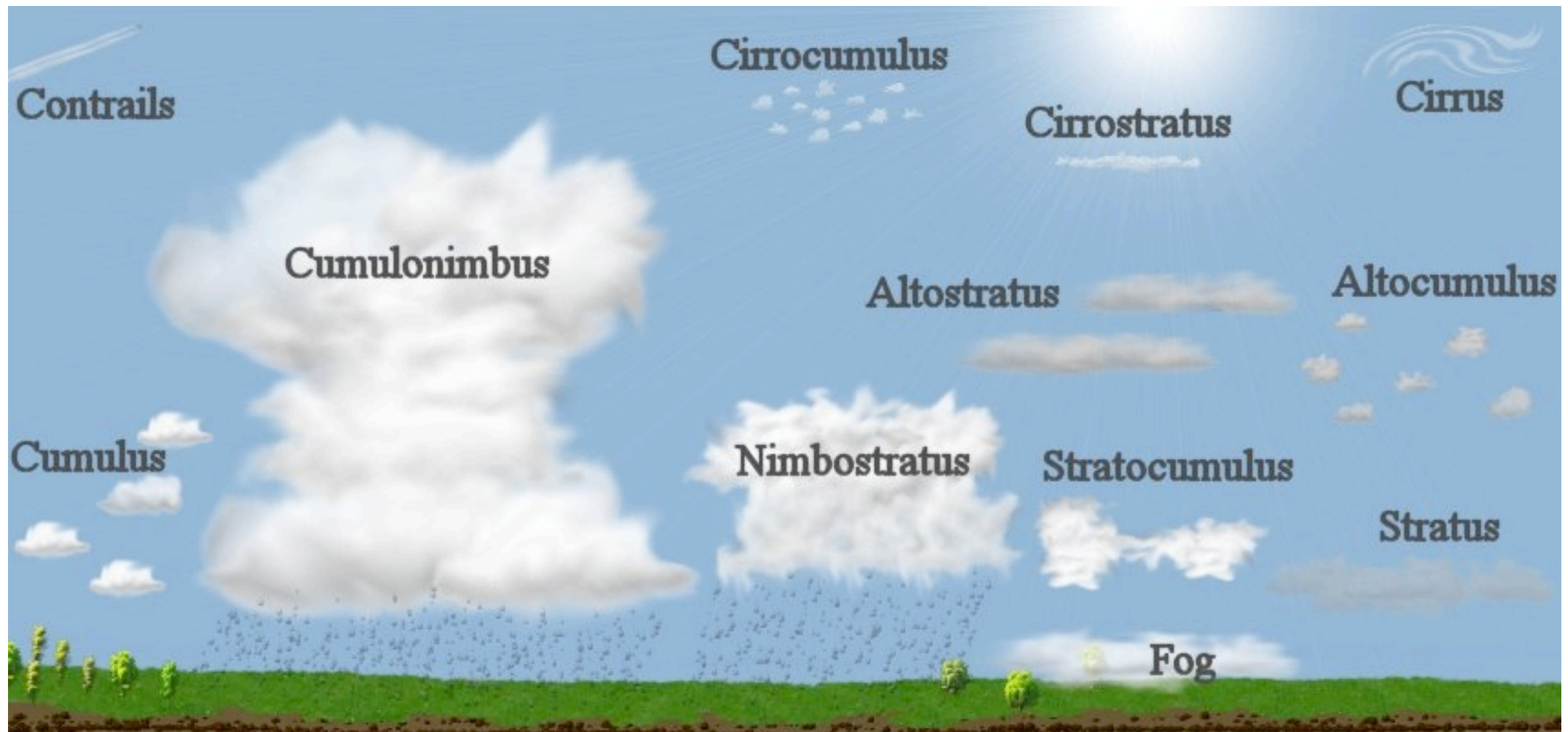
Smarter = Faster



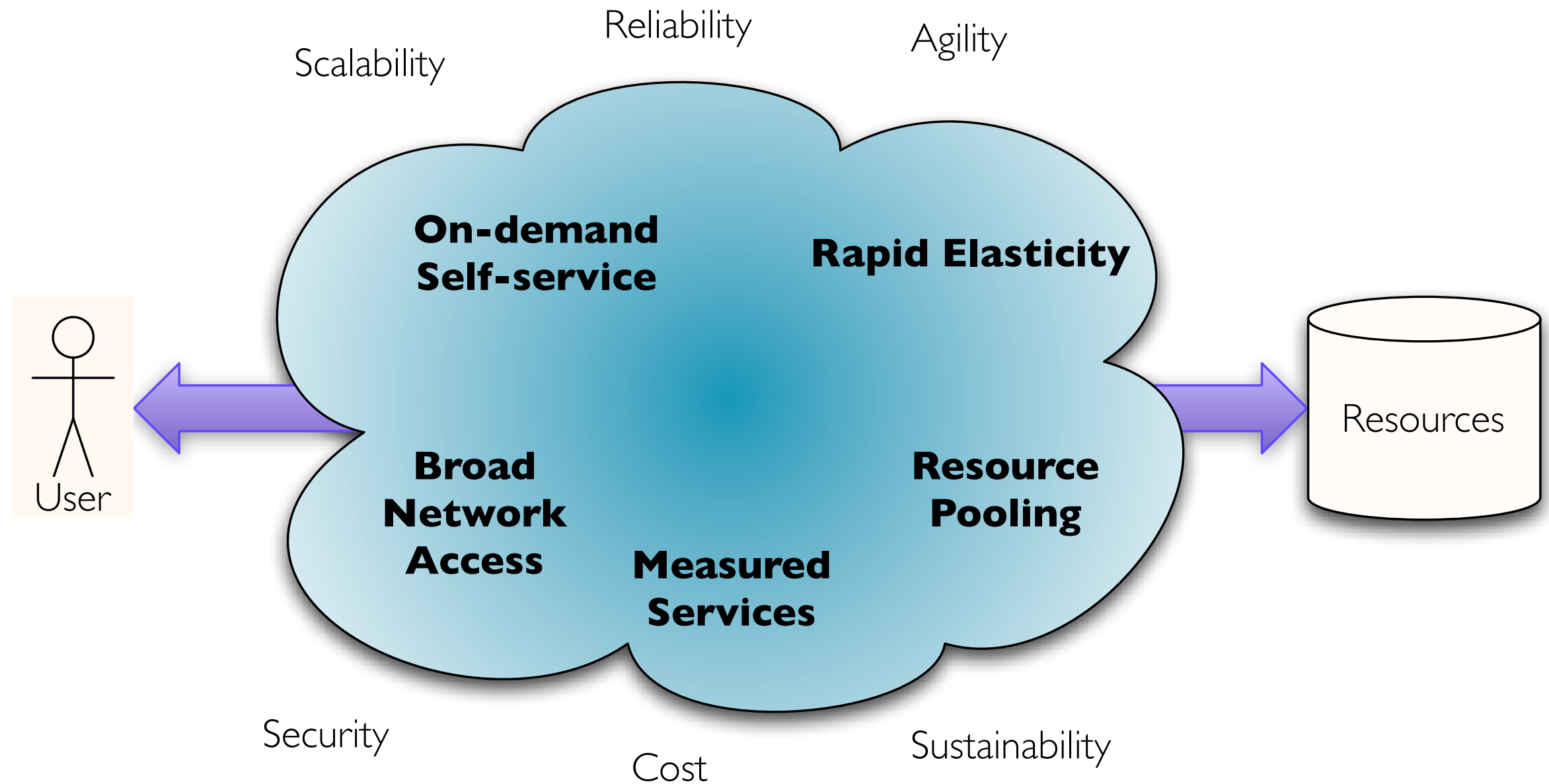
- If 4 trials x 20 videos x 1 hour each at 15fps = 4,320,000 images to process...

Hence this talk...

- The reality of cloud computing for solving complex, scientific, image-based problems.



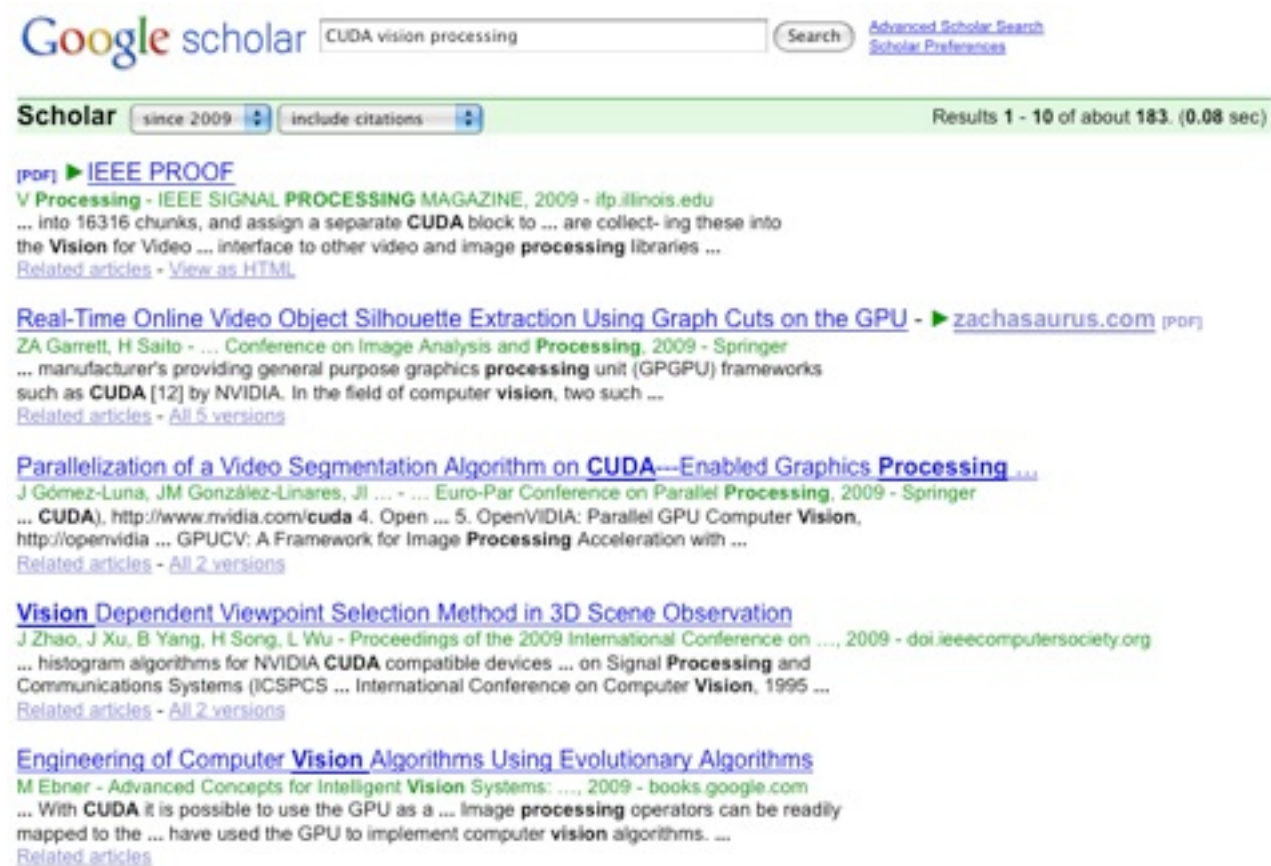
The Cloud



[NIST Working Definition of Cloud Computing (draft)]

Déjà vu?

- Real time parallelism: CUDA, OpenCL, Erlang, Occam, etc.
- Distributed processing: HPC, Beowulf clustering, The Grid...



[Bob Jones, Comparative Study: Grids and Clouds, Evolution or Revolution?, CERN EGEE Technical Report, 2008]

What's so different?

Big Data - Simple Processing

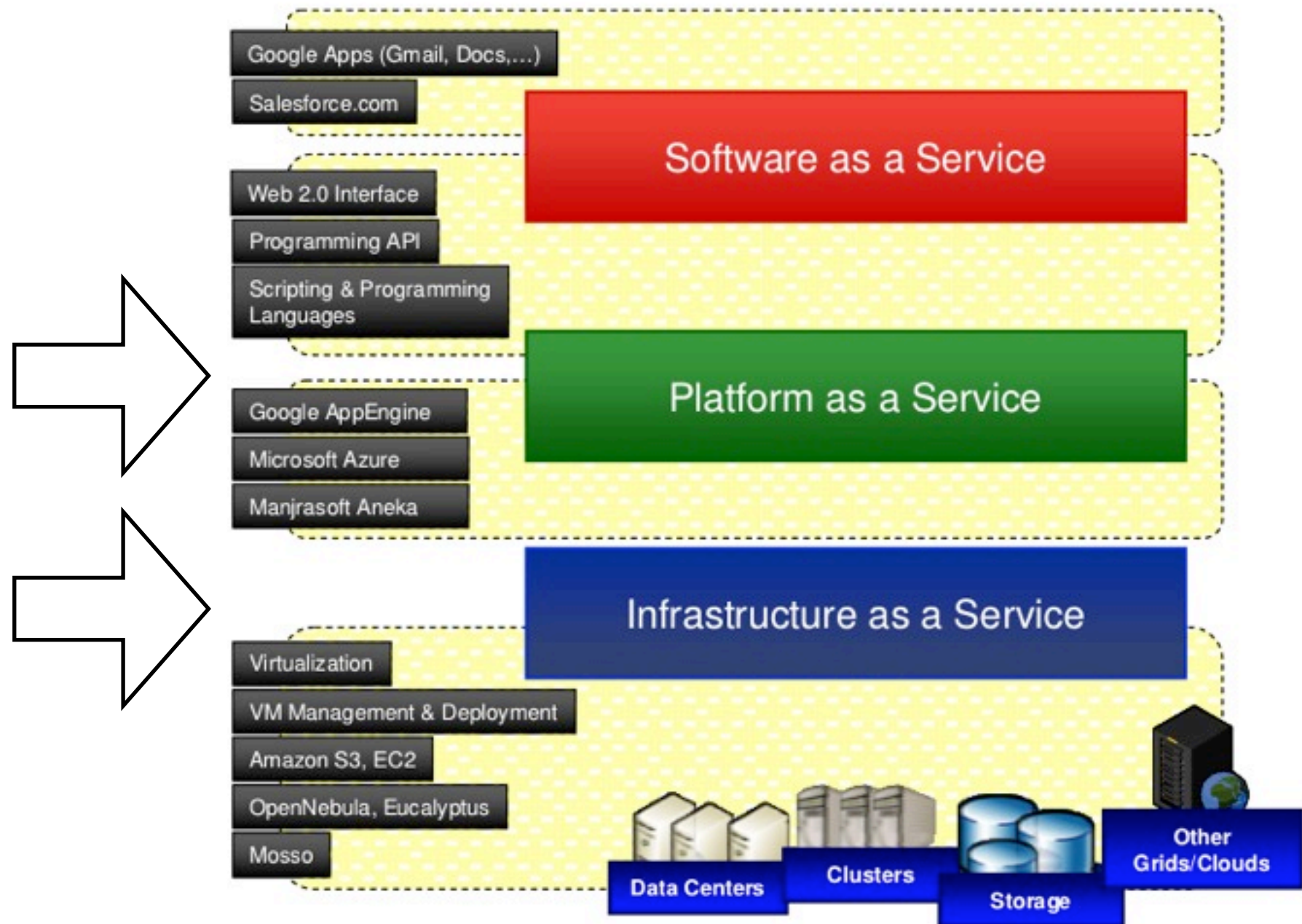
Very Scalable - Robust Distributed File System

New model - Dynamic Provisioning, Easy Access



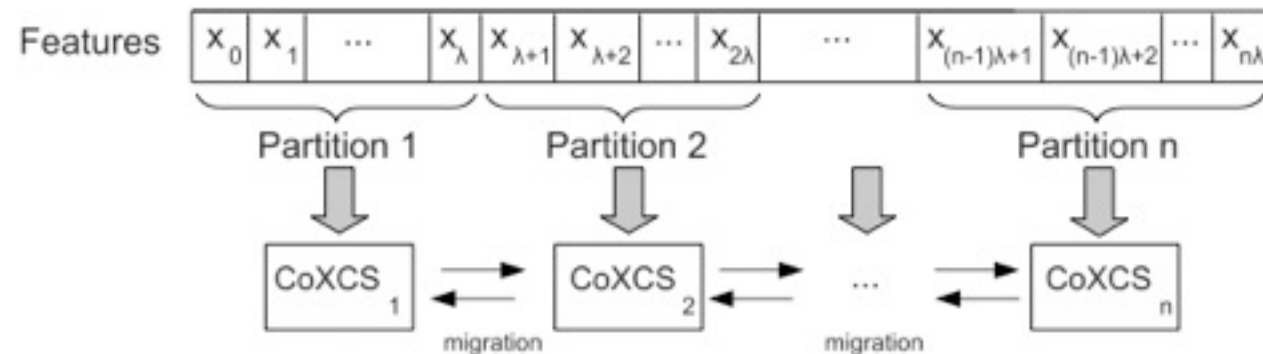
The Reality

Insert
Science
Here



[Christian Vecchiola, Suraj Pandey, Rajkumar Buyya, High-Performance Cloud Computing: A View of Scientific Applications, Keynote, I-SPAN 2009]

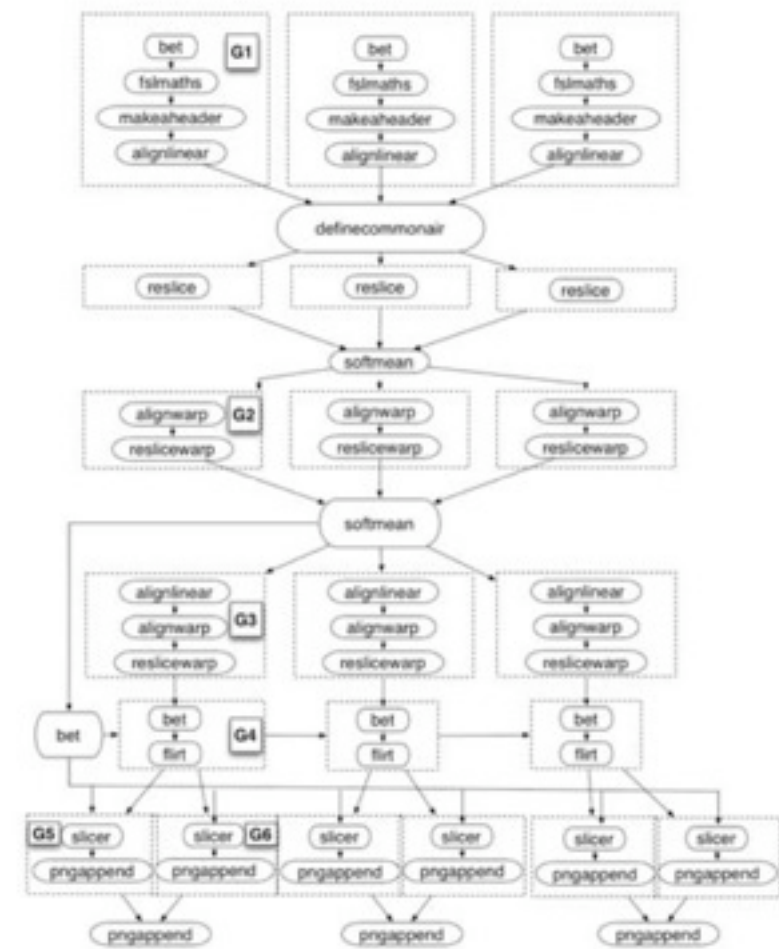
To do what?



Classifier	Mode	BRCA	Prostate
J48	Train	0.92 ± 0.06	1.00
	Test	0.35 ± 0.01	0.60 ± 0.10
NBTree	Train	1.00	1.00
	Test	0.65 ± 0.12	0.46 ± 0.04
Random Forest	Train	1.00	1.00
	Test	0.51 ± 0.01	0.60 ± 0.09
Logistic Regression	Train	1.00	0.50
	Test	0.85 ± 0.17	0.50
Naïve Bayes Classifier	Train	0.99 ± 0.01	1.00
	Test	0.90 ± 0.05	0.35 ± 0.04
SVM	Train	1.00	1.00
	Test	0.53 ± 0.04	0.51 ± 0.07
XCS	Train	0.50	0.50
	Test	0.50	0.50
CoXCS	Train	1.00	1.00
	Test	0.98 ± 0.02	0.70 ± 0.02

Cloud CoXCS for classifying gene expression data.

[M. Abedini and M. Kirley, "CoXCS: A Coevolutionary Learning Classifier Based on Feature Space Partitioning," Proc. The 22nd Australasian Joint Conference on Artificial Intelligence (AI'09), Melbourne, Australia, December 1-4, 2009.]



fMRI image registration workflows.

[Second IEEE International Scalable Computing Challenge (SCALE 2009)]

MapReduce



- A software framework introduced by Google
- Actually, Map-Groupby-Reduce
- Re-implemented by Apache Hadoop
- In Java, but with support for “Streaming”

map: $(k1, v1) \rightarrow \text{list}(k2, v2)$
reduce: $(k2, \text{list}(v2)) \rightarrow \text{list}(v3)$

[<http://wiki.apache.org/hadoop/HadoopPresentations>]

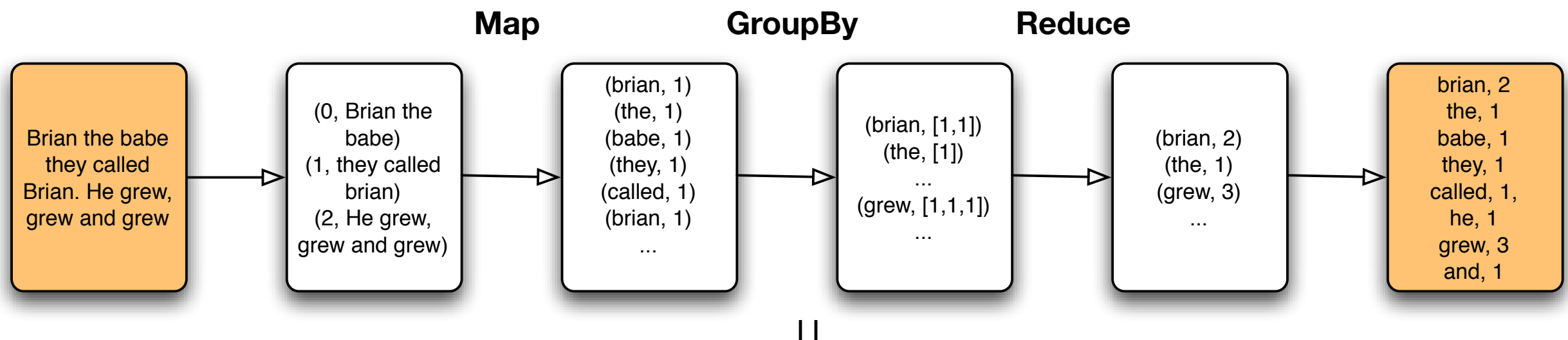
Counting words

```
import dumbo
```

```
def mapper(key,value):  
    for word in value.split(): yield word,1
```

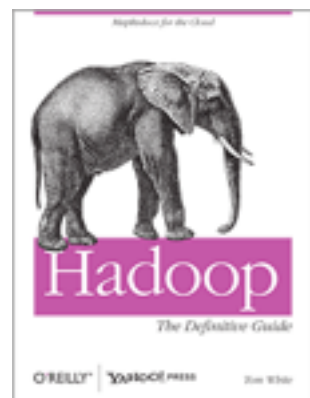
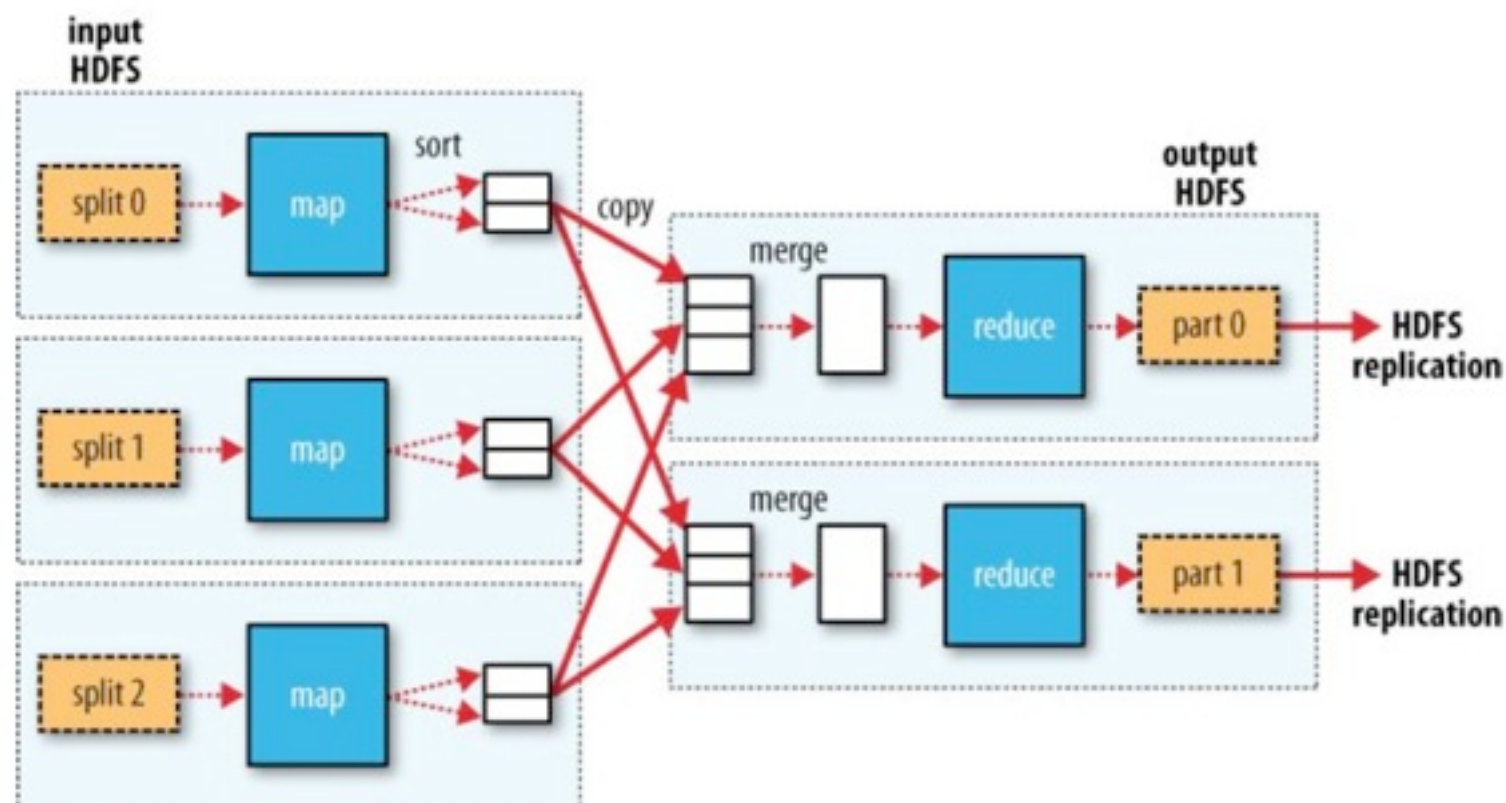
```
def reducer(key,values):  
    yield key,sum(values)
```

```
if __name__ == "__main__":  
    dumbo.run(mapper, reducer, combiner=reducer)
```



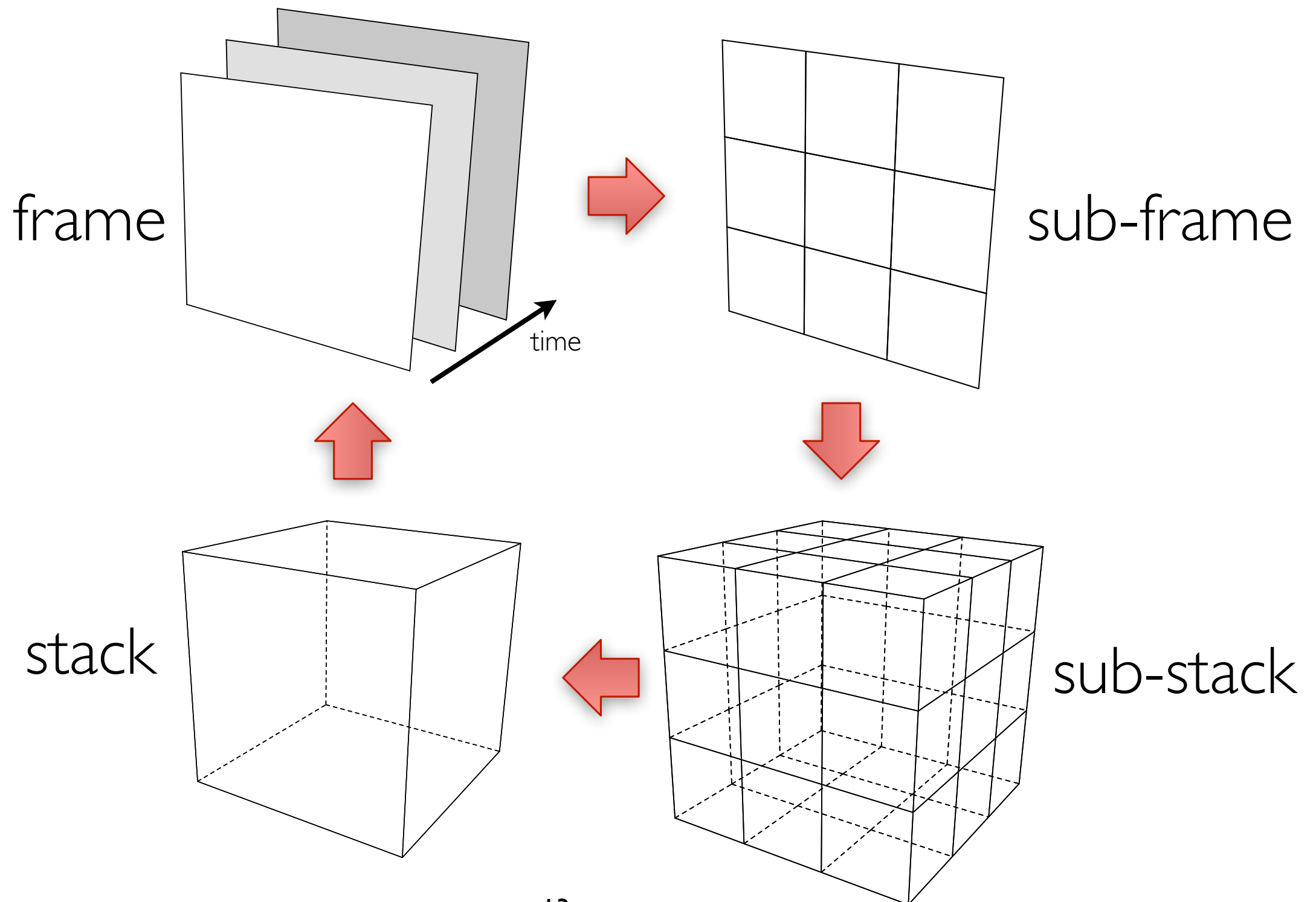
Generating the result...

```
> dumbo put brian.txt brian.txt -hadoop /usr/lib/hadoop/  
> dumbo start wordcount.py -input brian.txt -output brianwc -hadoop /usr/lib/hadoop/  
> dumbo cat brianwc -hadoop /usr/lib/hadoop/  
brian, 2  
the, 1  
babe, 1  
they, 1  
called, 1,  
he, 1  
grew, 3  
and, 1
```



[Hadoop: The Definitive Guide, Tom White, 2009]

Image/Video splitting



Input and process

- Override InputFormat and RecordReader
- Map function accepts stack/image
- Use OpenCV methods + Python to process
- Reduce function collates/sums

```
public class ImageFileInputFormat extends  
FileInputFormat<Text, TypedBytesWritable>
```

```
public class ImageFileRecordReader implements  
RecordReader<Text, TypedBytesWritable>
```



[<http://opencv.willowgarage.com>]

An example

```
import dumbo
from opencv import *

def mapper(key,value):
    data = cvInitMatHeader(1, key, CV_8UC3, value)
    size = cvGetSize(data)
    gray = cvCreateImage(size,8,1)
    cvConvertImage(data,gray)
    hist = cvCreateHist([255], CV_HIST_ARRAY, [[0,256]], 1)
    cvCalcHist([gray], hist, 0, None)
    for i in range(255):
        yield i,cvRound(cvGetReal1D(hist.bins[0],i))

def reducer(key,values):
    yield key,sum(values)

if __name__ == "__main__":
    dumbo.run(mapper, reducer, combiner=reducer)
```



```
> dumbo cat lena -
hadoop /usr/lib/
hadoop/
...
23 0
24 1
25 7
26 22
27 28
28 63
29 93
30 135
...
```

Another example

```
import dumbo
from opencv import *

# key is frame number, width & height are options
def mapper(key,value):
    data = cvInitMatHeader(width,height, CV_8UC3, value)
    size = cvGetSize(data)
    gray = cvCreateImage(size,8,1)
    cvConvertImage(data,gray)
    x,y = find(gray,background,mask) # NOTE: from cache file
    yield key,[x,y]

def reducer(key,values):
    yield key,collapse(values) # collapse separates list

if __name__ == "__main__":
    dumbo.run(mapper,reducer,combiner=reducer)
```



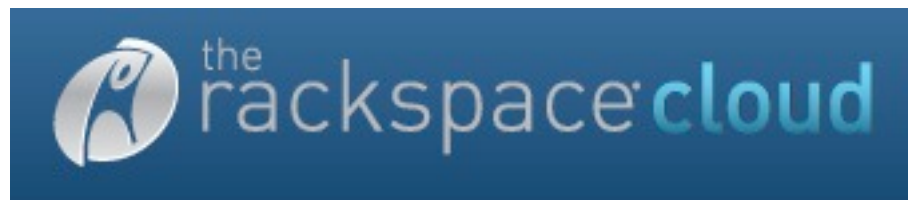
```
> dumbo cat
mousemove -
hadoop /usr/lib/
hadoop/
...
134 560 450
135 560 453
136 559 454
138 557 552
139 557 550
140 557 550
...
```

Infrastructure & platforms

Pig, Hive, HBase, Cascading



disco
massive data - minimal code



Up and running

The screenshot displays the AWS Management Console for Amazon Elastic MapReduce. The browser address bar shows the URL <https://console.aws.amazon.com/elasticmapreduce/home>. The console header includes navigation tabs for Amazon EC2, Amazon Elastic MapReduce (selected), and Amazon CloudFront. The main content area is titled 'Your Elastic MapReduce Job Flows' and features a 'Create New Job Flow' button. Below this, a section titled 'How do I create one?' provides a three-step guide: 1. Upload data to Amazon S3 Bucket, 2. Create a job flow on Amazon Elastic MapReduce, and 3. Get results from Amazon S3 Bucket. The footer contains copyright information for 2008-2009 and links to Feedback, Support, Privacy Policy, and Terms of Use.

© 2008 - 2009, Amazon Web Services LLC or its affiliates. All right reserved. | [Feedback](#) | [Support](#) | [Privacy Policy](#) | [Terms of Use](#) | An [amazon.com](#) company

[aws.amazon.com]

Apps: Machine vision



- The use of a Hierarchical Temporal Memory (HTM) “web-service”.
- Adding “meta-data” layers ontop of video.

[Jeff Hawkins, On Intelligence: How a New Understanding of the Brain will Lead to the Creation of Truly Intelligent Machines, 2004]

Apps: Machine learning

	single	multi
LWLR	$O(mn^2 + n^3)$	$O(\frac{mn^2}{P} + \frac{n^3}{P'} + n^2 \log(P))$
LR	$O(mn^2 + n^3)$	$O(\frac{mn^2}{P} + \frac{n^3}{P'} + n^2 \log(P))$
NB	$O(mn + nc)$	$O(\frac{mn}{P} + nc \log(P))$
NN	$O(mn + nc)$	$O(\frac{mn}{P} + nc \log(P))$
GDA	$O(mn^2 + n^3)$	$O(\frac{mn^2}{P} + \frac{n^3}{P'} + n^2 \log(P))$
PCA	$O(mn^2 + n^3)$	$O(\frac{mn^2}{P} + \frac{n^3}{P'} + n^2 \log(P))$
ICA	$O(mn^2 + n^3)$	$O(\frac{mn^2}{P} + \frac{n^3}{P'} + n^2 \log(P))$
k-means	$O(mnc)$	$O(\frac{mnc}{P} + mn \log(P))$
EM	$O(mn^2 + n^3)$	$O(\frac{mn^2}{P} + \frac{n^3}{P'} + n^2 \log(P))$
SVM	$O(m^2n)$	$O(\frac{m^2n}{P} + n \log(P))$

- Algorithms that fit the Statistical Query model can be written in “summation form”.
- E.g. for Taste recommendation filter.

[Chu et al, Map-Reduce for Machine Learning on Multicore, NIPS, 2006]

<http://lucene.apache.org/mahout/>



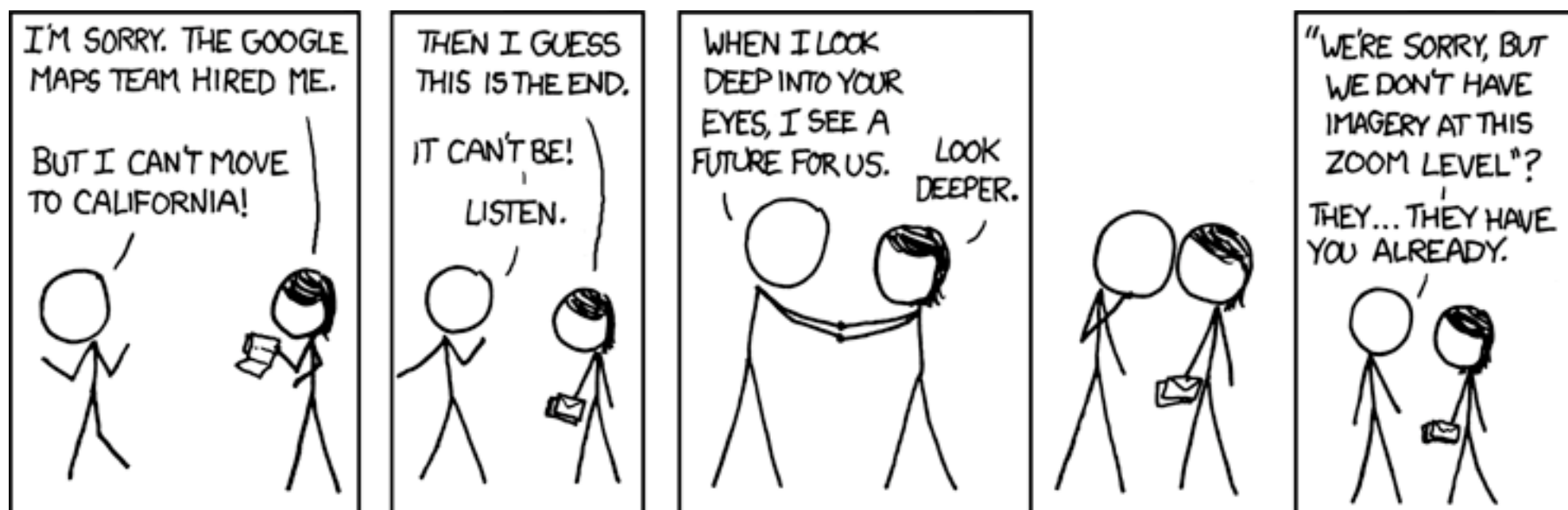
Apps: Next?

- Registration
- Convolution
- Filtering
- = Framework
(e.g. Yahoo Pipes)



Conclusions

- Basic intro to cloud computing.
- Writing and deploying scientific code.
- The peculiarities of handling images.
- Where next?



[xkcd.com]

Clear Skies Beyond!

