CS109 – Data Science

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Announcements

- Grades for HW2 are getting out tonight
- Final Projects:
  - 3-4 persons per team

(10/12-10/18)	JB	Similarities, recommendations - VK	telecom churn dataset		
Week 8 (10/19-10/25)	Amazon EC2, AWS Datastore, MapReduce - VK	Spark. - RD	Ensemble Methods	HW4	HW3
	Act 3: Bayes, Clustering & Text Analysis				
Week 9 (10/26-11/1)	Bayesian thinking and methods. Prior distributions, likelihood. Naive Bayes. - JB	Advanced Bayesian Thinking. - JB	EC2 and Spark		
Week 10 (11/2-11/8)	Text Analysis. LDA. Topic Modeling. - JB	Interactive Visualizations. Vega. - HP	Bayesian Thinking	HW5	HW4
Week 11 (11/9-11/15)	Clustering. k-means. Mean Shift. Hierarchical Clustering. - VK	Effective Presentations. - HP / JB	Text Analysis: From Naive Bayes to LDA		PROJECT PROPOSALS DUE
Week 12 (11/16-11/22)	Experimental Design. A/B testing. Tirthankar Dasgupta	Deep Learning. - VK	Wrapup: Completely worked example: Chicago Inspections Dataset		HW5, PROJECT REVIEW WEEK
Week 13	**No class**		**No class**		

Next Topics

- ML best practices
  - imbalanced data
  - missing values

- Recommender systems
  - collaborative filtering
  - content-based filtering

- Map Reduce

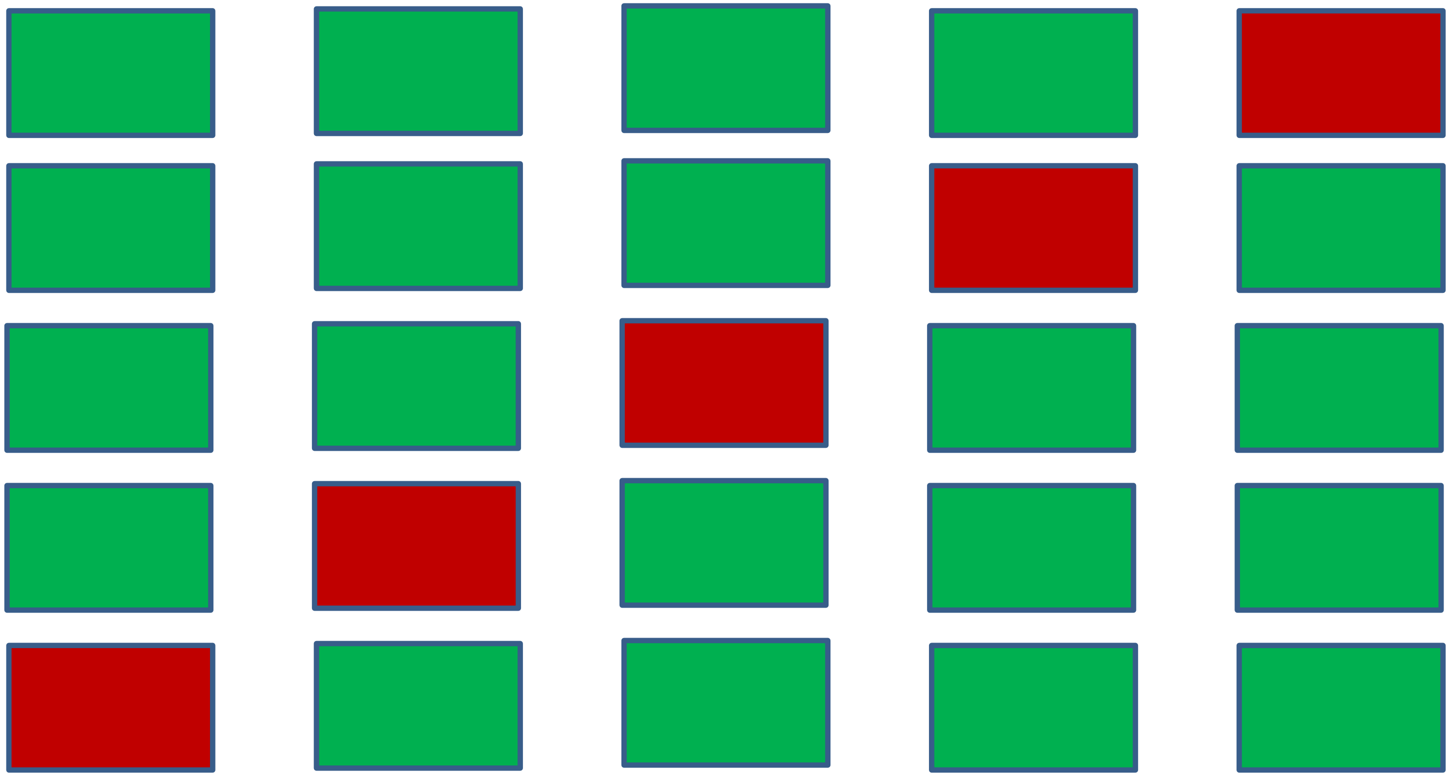
Cross Validation

training data | validation data | test data

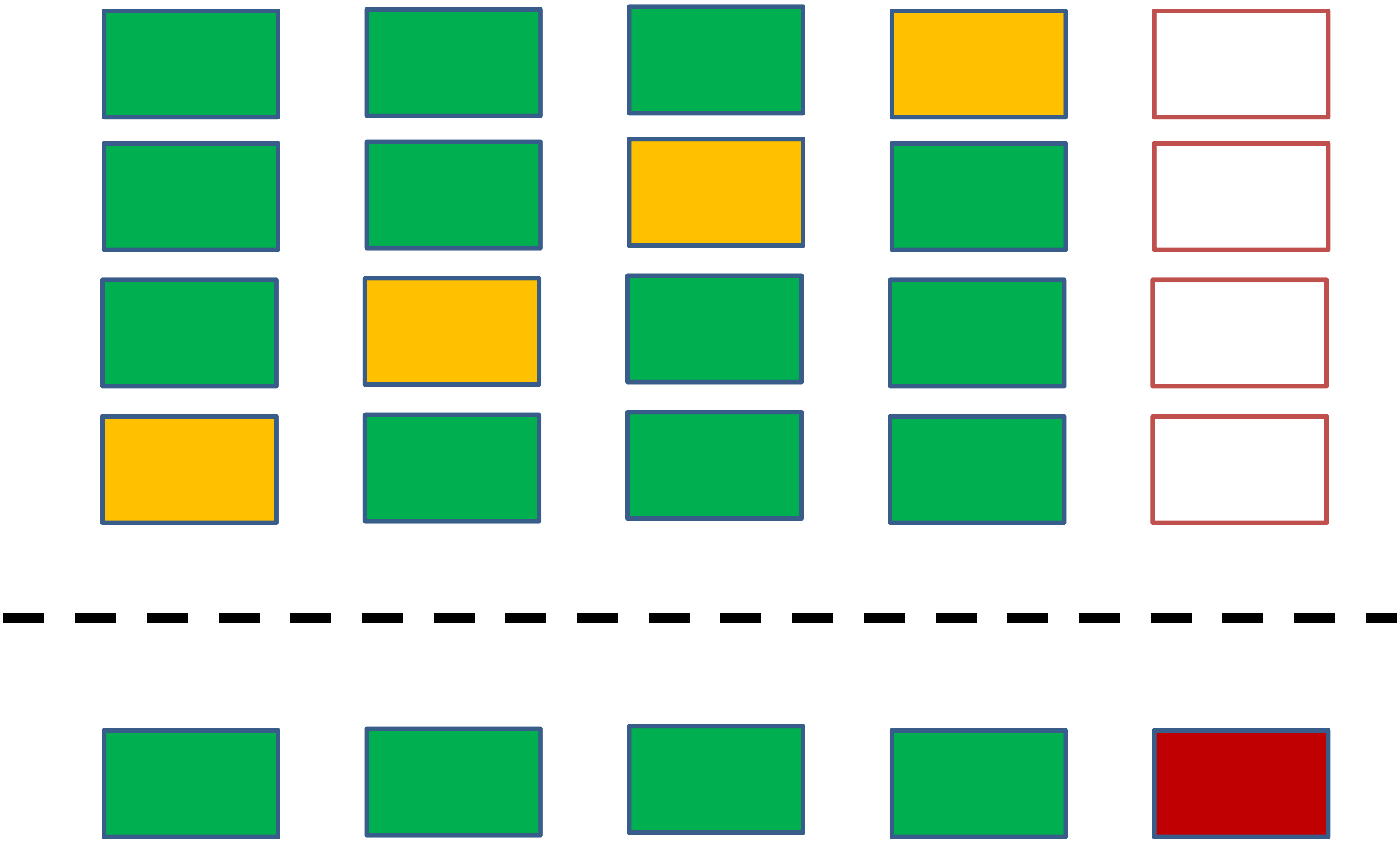
- Training data: train classifier
- Validation data: estimate hyper parameters
- Test data: estimate performance

- Be mindful of validation and test set, validation set might refer to test set in some papers.

5 – Fold Cross Validation



5 – Fold Cross Validation



Last Step of Each Fold

1. Take best parameters
2. Train on training data and validation data together
3. Test performance on test data

This is the **final** result of your method.

Things to Keep in Mind

- How do you aggregate the parameters?
- What if the hyperparameters are all over the place?
- What if the hyperparameters are at the border of your grid search window?

Scenario - 1

- 1. Screen the predictors: find a subset of "good" predictors that show fairly strong (univariate) correlation with the class labels
- 2. Using just this subset of predictors, build a multivariate classifier.
- 3. Use cross-validation to estimate the unknown tuning parameters and to estimate the prediction error of the final model.

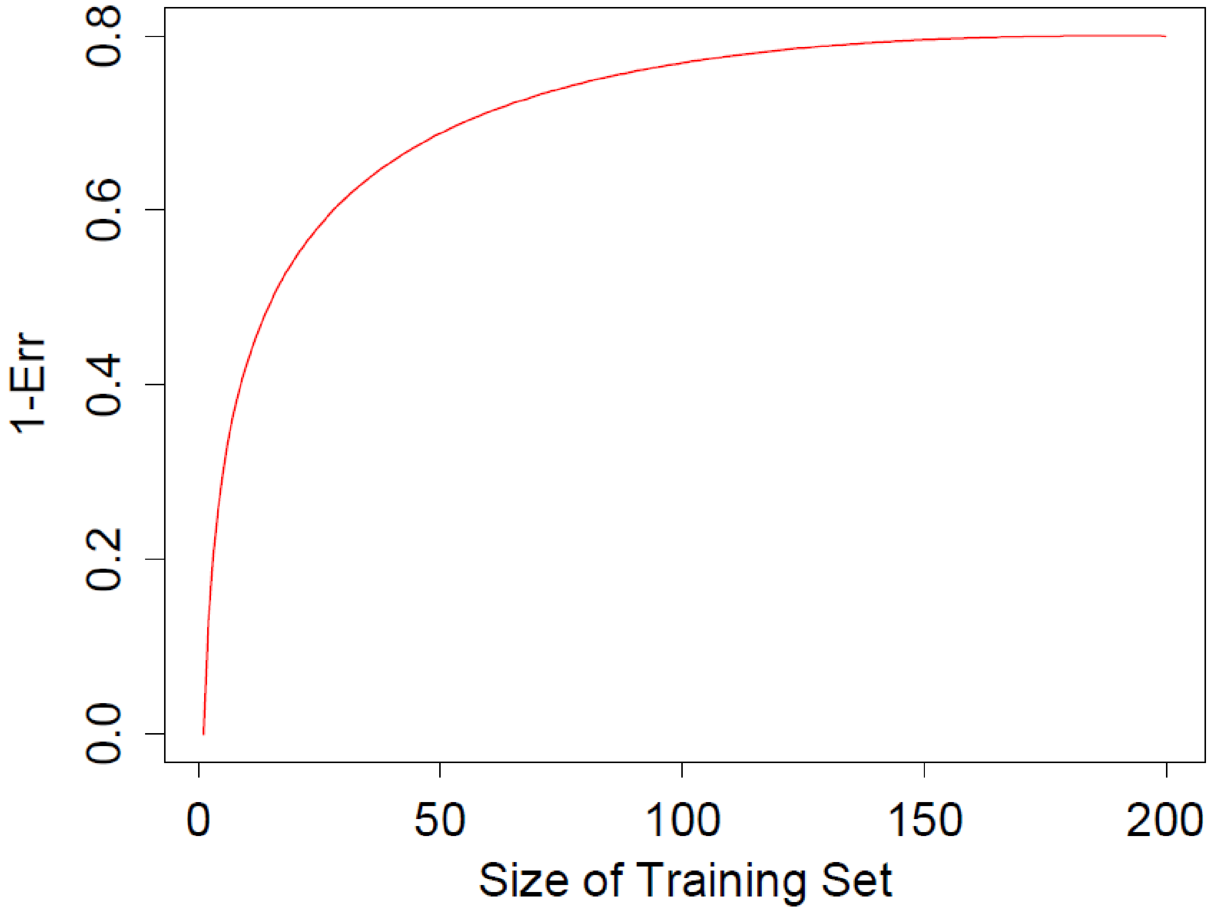
Hastie-Tibsherani_Friedman, "The Elements of Statistical Learning"

Scenario - 2

- 1. Divide the samples into K cross-validation folds (groups) at random.
- 2. For each fold k = 1, 2, . . . ,K
  - Find a subset of “good” predictors that show fairly strong (uni-variate) correlation with the class labels, using all of the samples except those in fold k.
  - Using just this subset of predictors, build a multivariate classifier, using all of the samples except those in fold k.
  - Use the classifier to predict the class labels for the samples in fold k.

Hastie-Tibsherani_Friedman, “The Elements of Statistical Learning”

Effect of Sample Size

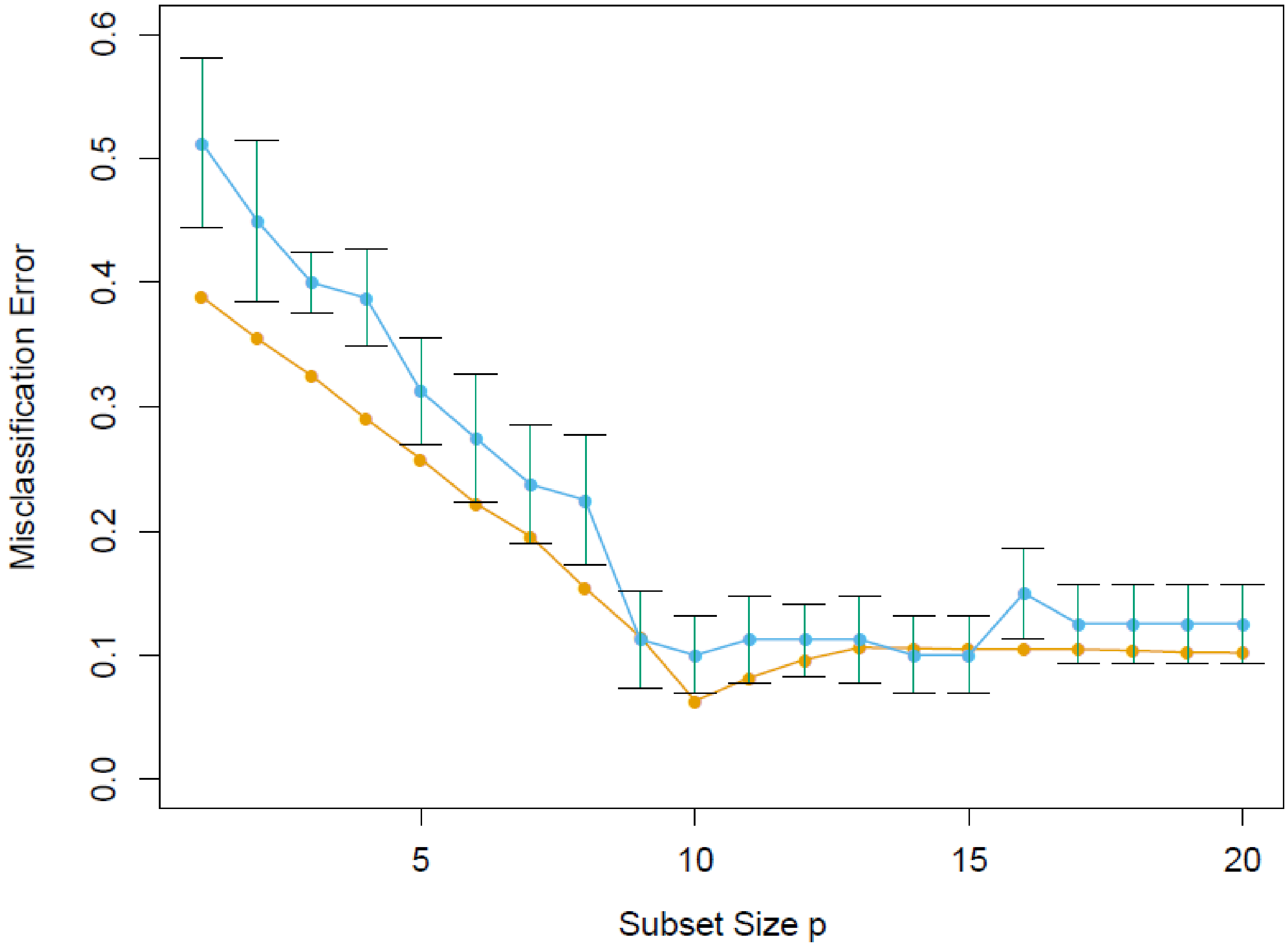


5-fold cross validation:

- n=200 => 160 samples
- n=50 => 40 samples

Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction"

Cross Validation Over Estimates Error

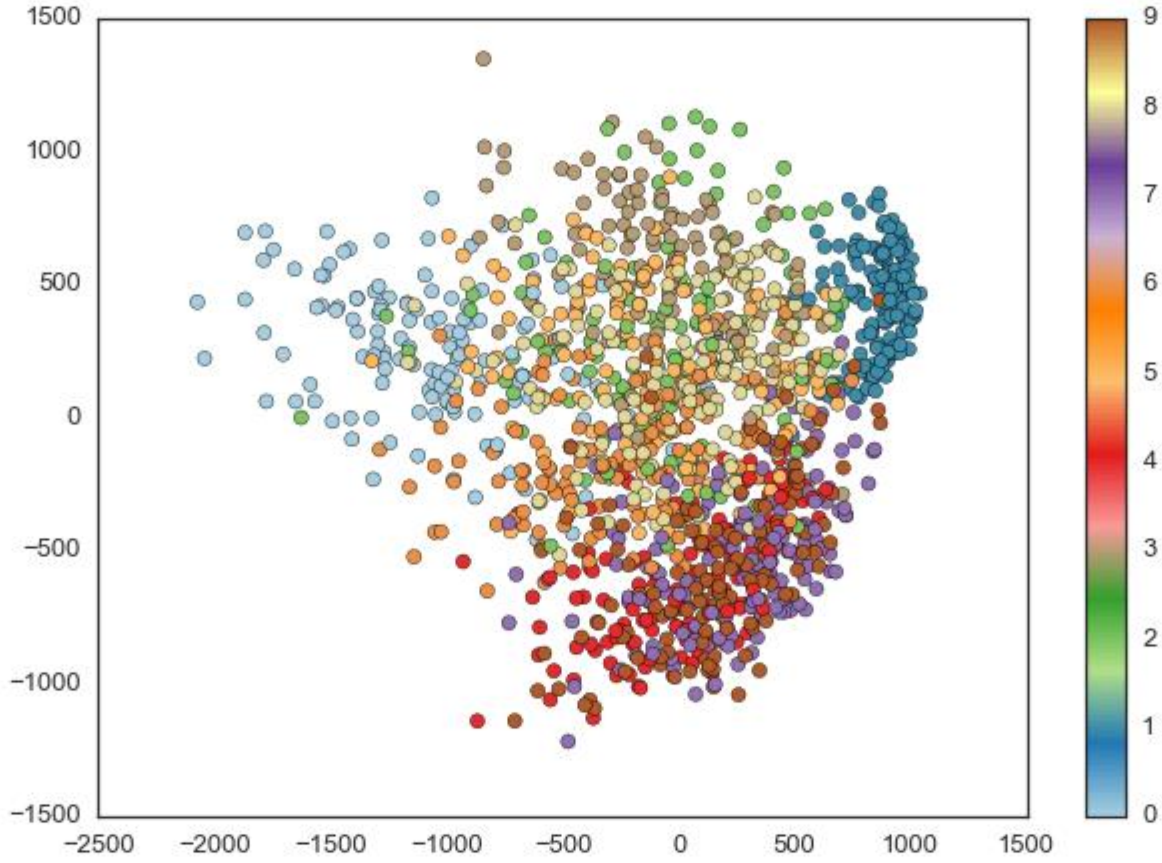


Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction"

Normalization

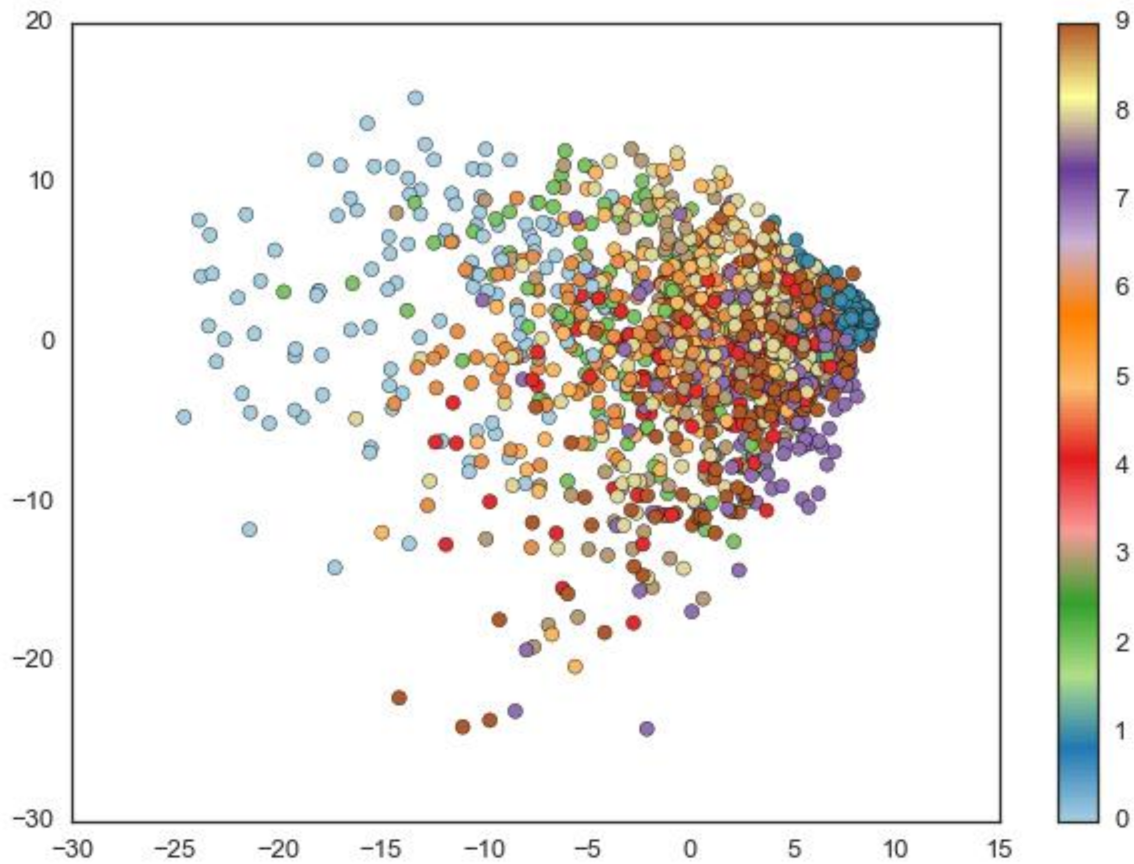
- Be very careful.
- Do not leak into the test data.
- Think about what is useful.

Example PCA on MNIST



standard PCA

Example PCA on MNIST



PCA with normalized std dev

Normalization - 1

training

Estimate mean values and normalize.

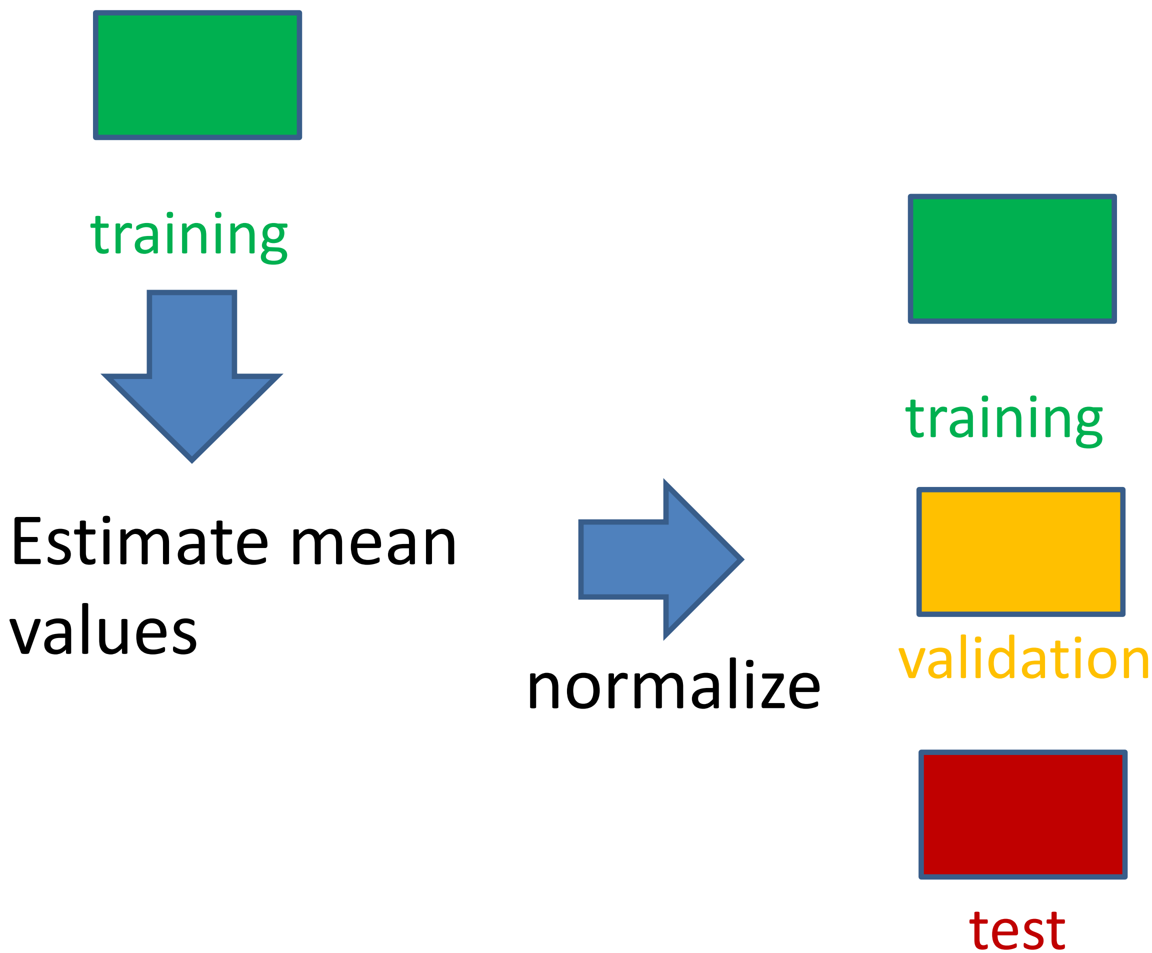
validation

Estimate mean values and normalize.

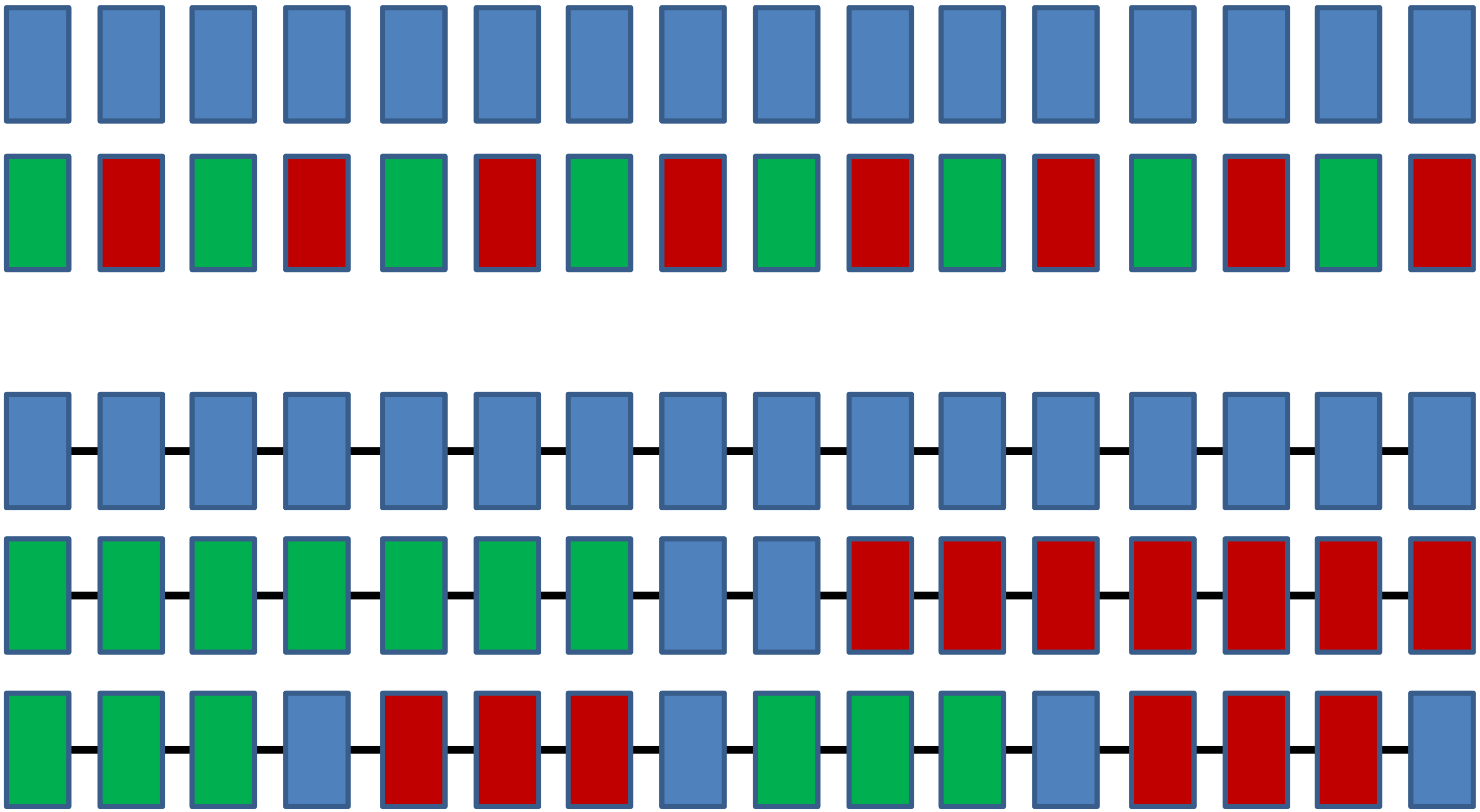
test

Estimate mean values and normalize.

Normalization - 2



Know Your Data



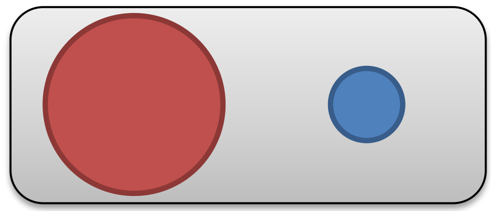
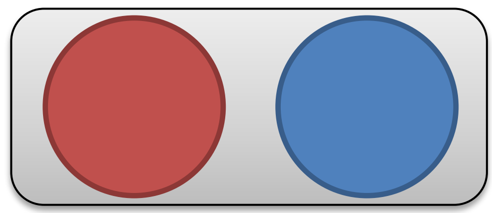
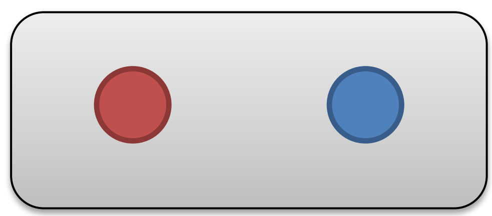
Imbalanced Data

- subsample
- oversample
- re-weight sample points
- use clustering to reduce majority class

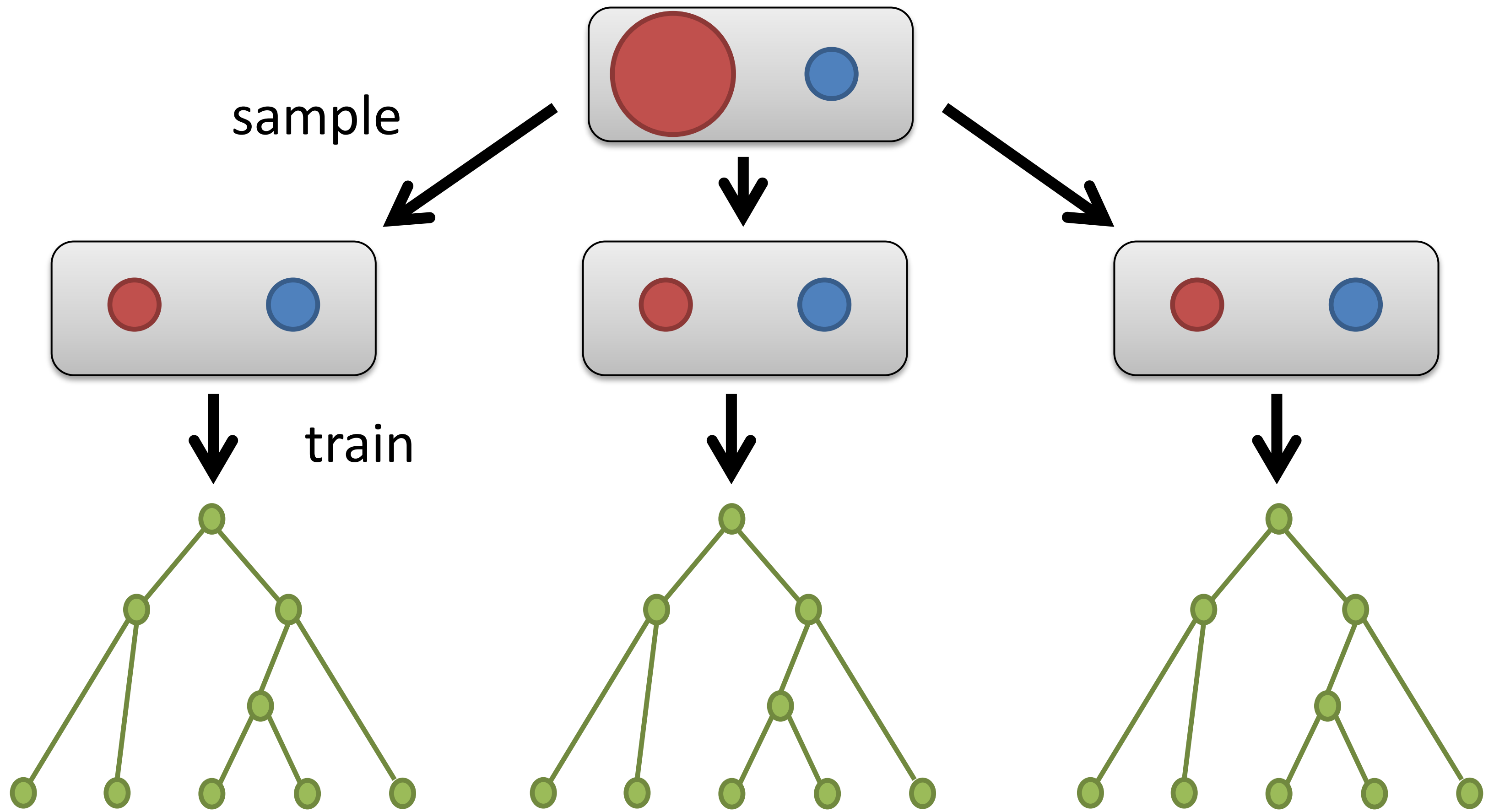
- re-calibrate classifier output

- Beware the easy true negatives

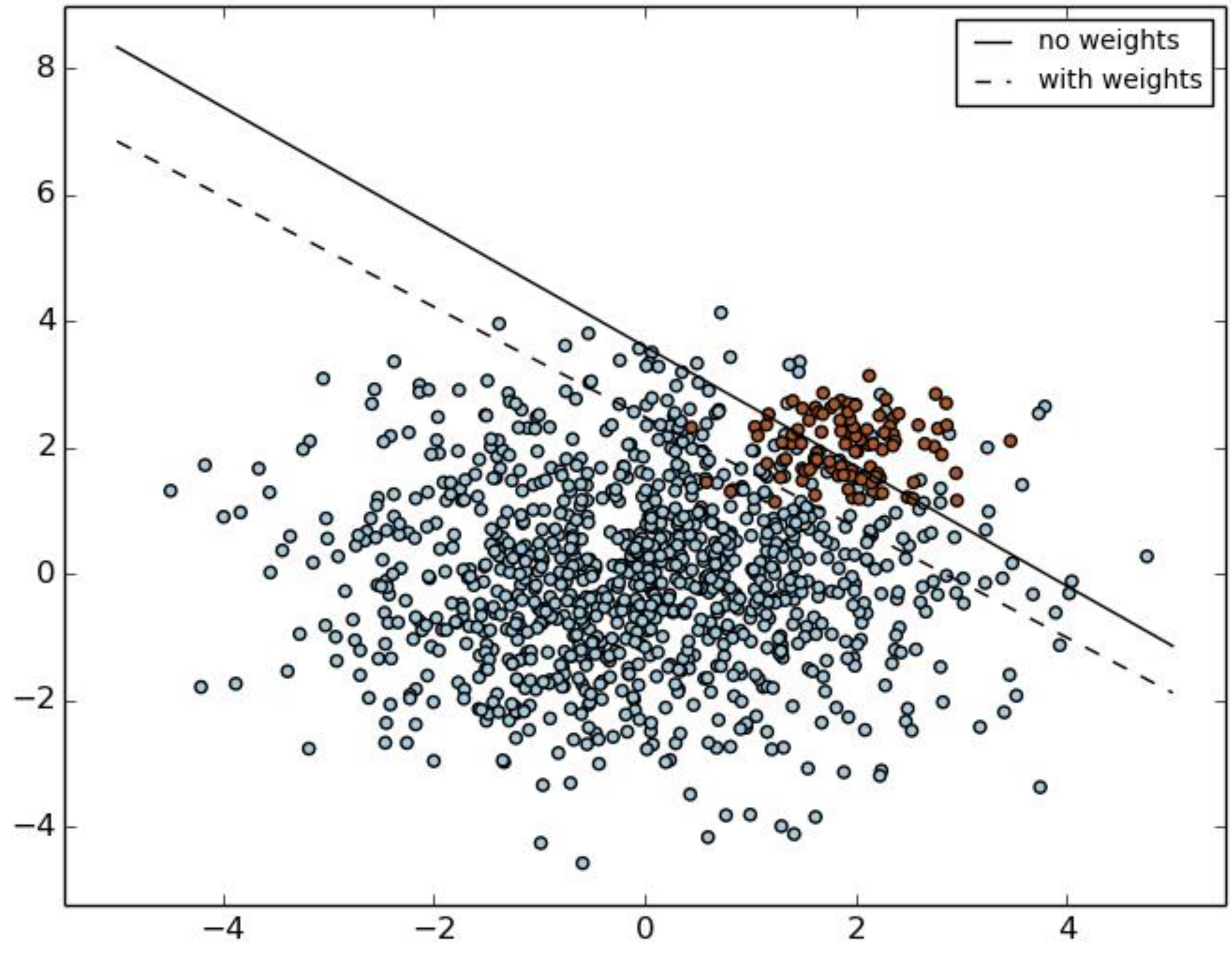
Imbalanced Classes

- The Problem: 
- Oversample: 
- Subsample: 
- Subsample for each tree in a random forest

Example: Random Forest Subsampling



Class Weights



http://scikit-learn.org/stable/_images/plot_separating_hyperplane_unbalanced_0011.png

Cross Validation with Imbalanced Classes

- Think about using stratified sampling to generate the folds
- The goal is to have the same class ratio in training, validation and test set.

Missing data

- Delete data points
  – Can cause sample size to be way too small
- Use the mean of the feature
  – Does not change the sample mean, but is independent of the other features.
- Use regression to estimate the value
  – Values will be deterministic

Recommender Systems

- We are already surrounded by them

NETFLIX

amazon®

PANDORA®

Good Resources (also for this lecture)

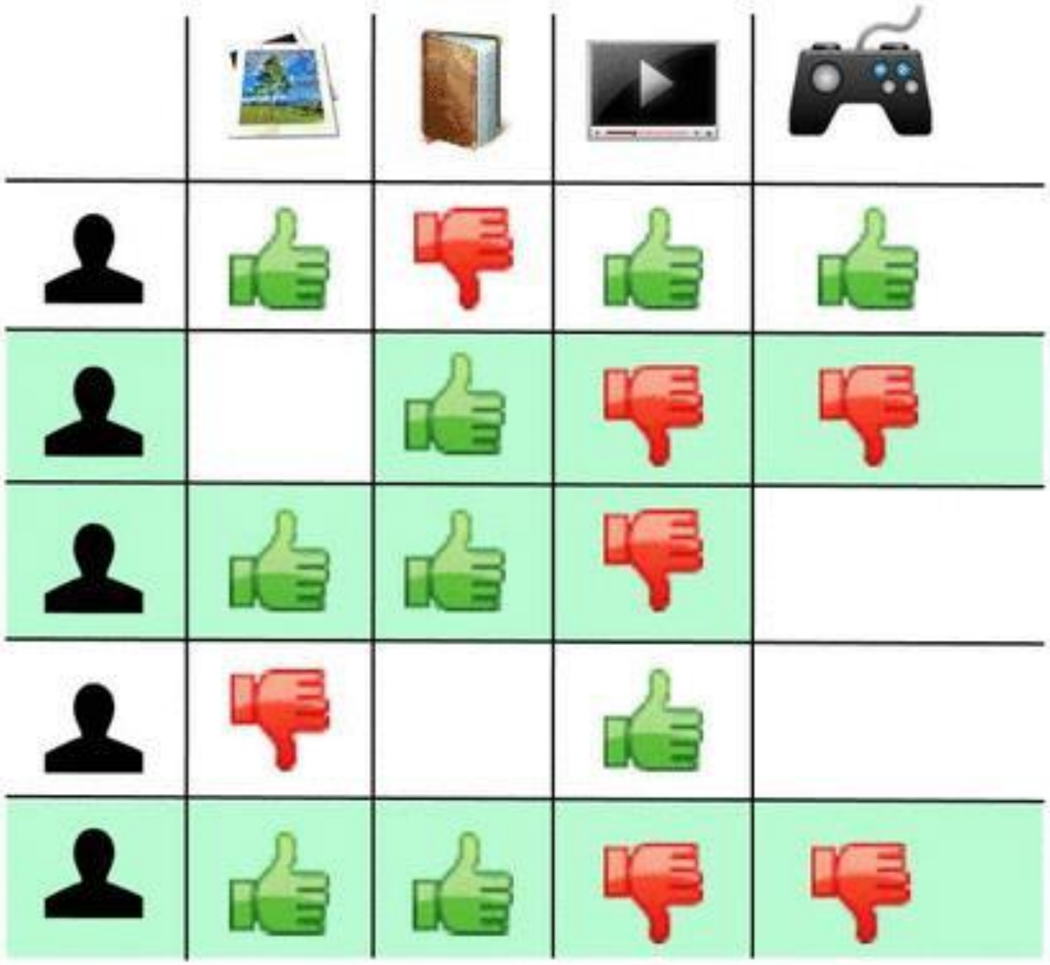
Survey on recommender systems by Michael D. Ekstrand et al.

- http://files.grouplens.org/papers/FnT%20CF%20Recsys%20Survey.pdf

Good slides from Stanford lecture by Lester Mackey

- http://web.stanford.edu/~lmackey/papers/cf_slides-pml09.pdf

Rating Matrix Completion Problem



https://en.wikipedia.org/wiki/Collaborative_filtering

Collaborative Filtering

Insight: Personal preferences are correlated

- If Jack loves A and B, and Jill loves A, B, and C, then Jack is more likely to love C

- Does not rely on item or user attributes (e.g. demographic info, author, genre)

Content-based Filtering

- Each item is described by a set of features
- Measure similarity between items
- Recommend items that are similar to the items the User liked

Comparison

- Collaborative filtering:
  - Items entirely described by user ratings
  - Good for new discoveries
  - People who like SciFi maybe also like Fantasy
- Content-based filtering:
  - Predictions are in users comfort zone
  - Can start with a single item
- Can do a hybrid approach

User Based Collaborative Filtering

Intuition:

- I like what people similar to me like
- Users give ratings
- People with similar ratings in the past assumed to have similar ratings in the future

Item-based Collaborative Filtering

- Similar to user-based, but looks at the items instead of the users
- Useful if the user base is way larger than the number of items.
- More useful: Items are relatively stable in their rating, users vary more.

We Could Use Missing Data Strategies

All that we talked about earlier:

- Omitting samples
- Using the mean rating of an item
- Doing regression

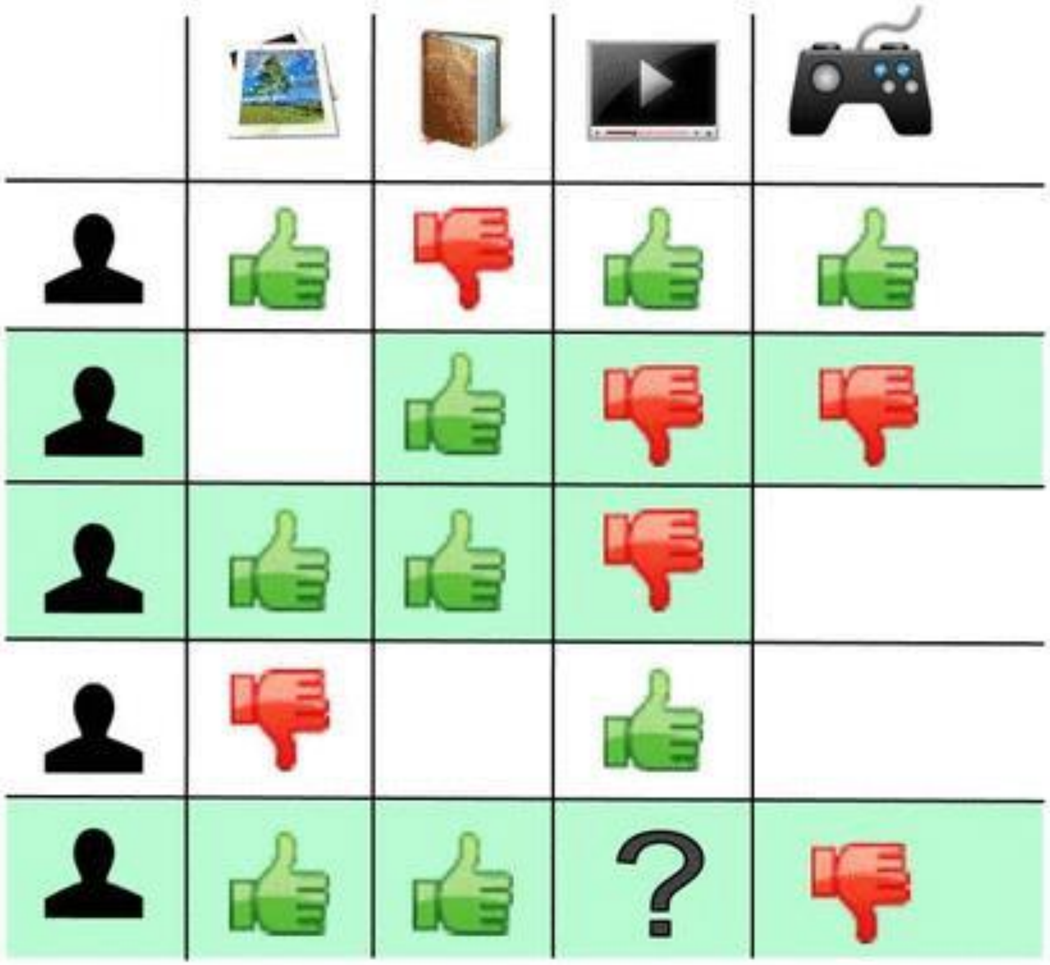
CF as Regression

- Choose favorite regression algorithm
- Train a predictor for each item
- Each user who rated that item provides one sample
- To predict rating of an item A, apply predictor for A to the user’s incomplete ratings vector.

Recommendation by Regression

- **Pros:**
  - Reduces recommendations to a well-studied problem
  - Many good prediction algorithms available
- **Cons:**
  - Have to handle tons of missing data
  - Training M predictors is expensive

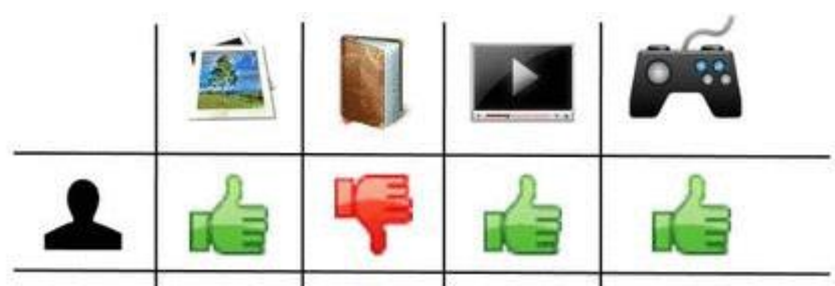
KNN



https://en.wikipedia.org/wiki/Collaborative_filtering

KNN for Collaborative Filtering

- Widely used
- Item-based and User-based focus
- Represent each user as incomplete vector of item ratings
- Compute similarity between query user and all other users
- Find K most similar users who rated the query item
- Predict weighted average of ratings



Similarity Measures

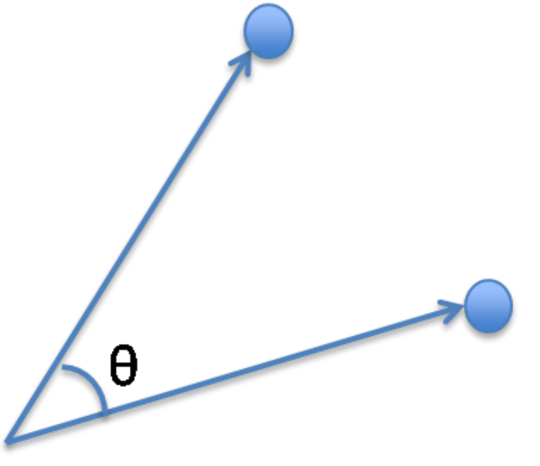
- Pearson Correlation Coefficient
  - bound between 1 and -1
  - suffers from computing high similarity between users with few ratings in common
  - set threshold for minimum number of co-rated itemssuffers from computing high similarity between users with few ratings in common

$$s(u,v) = \frac{\sum_{i \in I_u \cap I_v} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in I_u \cap I_v} (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{i \in I_u \cap I_v} (r_{v,i} - \bar{r}_v)^2}}$$

Similarity Measures

- Cosine similarity
  - vector-space approach based on linear algebra
  - Unknown ratings are considered to be 0
  - this causes them to effectively drop out of the numerator

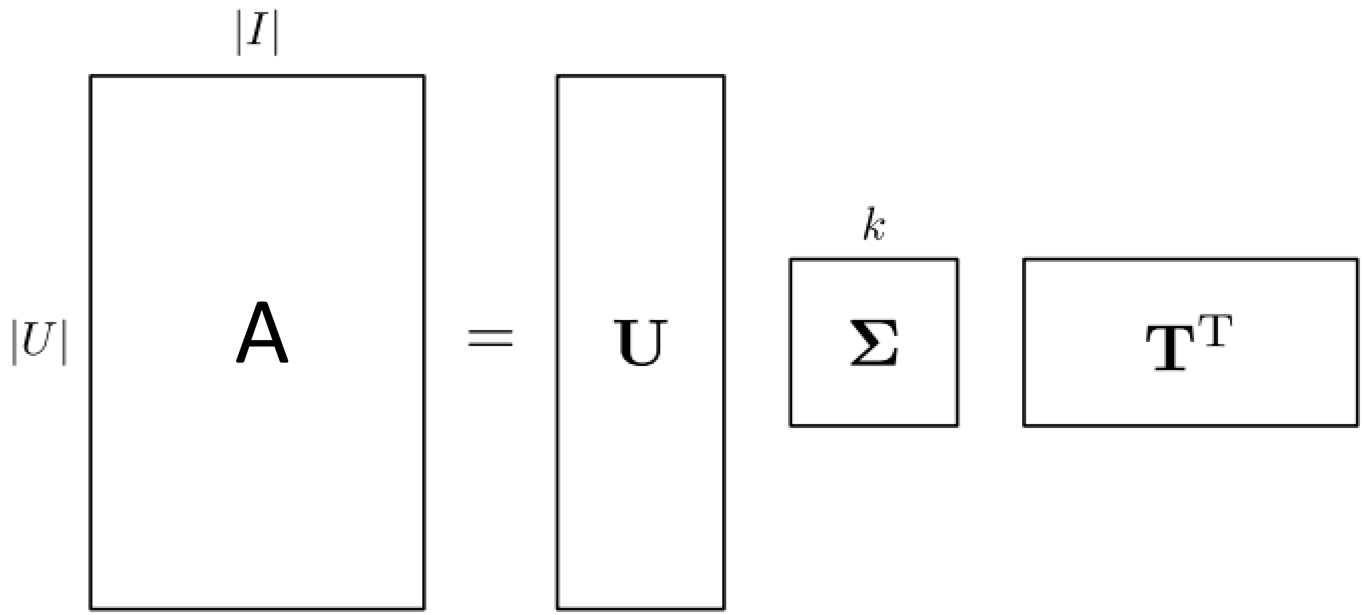
$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$



Netflix Prize

- Remember when we saw the Netflix prize video they mentioned SVD
- SimonFunk did this publicly on his blog with the title “Try this at home”
- http://sifter.org/~simon/journal/20061027.2.html

Singular Value Decomposition



- If we know the SVD, we could compute the missing values in R.
- Try to infer SVD from matrix with missing data, and reconstruct full matrix R

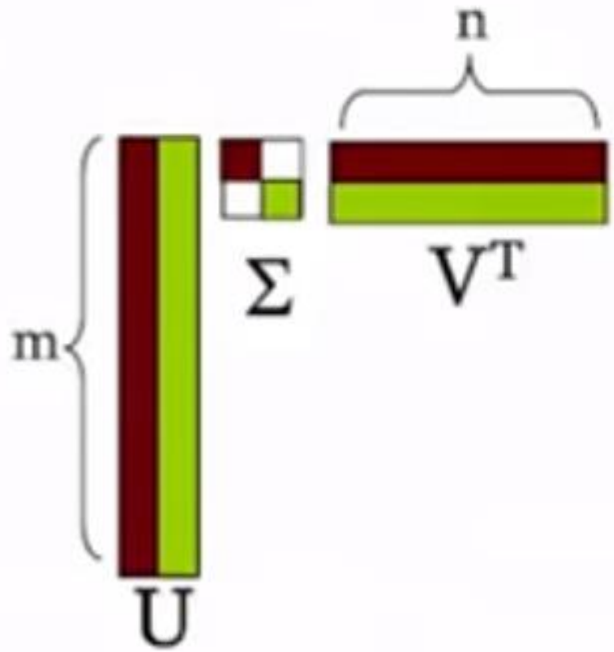
Best SVD Explanation I have seen!

- Leskovec, Rajaraman, Ullman

- https://www.youtube.com/watch?v=YKmkAoIUxkU

▪ $A = U\,\Sigma\,V^T$ - example: Users to Movies

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{array} \\
\begin{array}{c} \\ \text{:i} \\ \\ \\ \\ \text{nce} \\ \\ \end{array} & \left[\begin{array}{ccccc}
1 & 1 & 1 & 0 & 0 \\
3 & 3 & 3 & 0 & 0 \\
4 & 4 & 4 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 2 & 0 & 4 & 4 \\
0 & 0 & 0 & 5 & 5 \\
0 & 1 & 0 & 2 & 2
\end{array}\right]
\end{array}
=
$$



https://www.youtube.com/watch?v=YKmkAoIUxkU

$A = U \Sigma V^T$ - example: Users to Movies

U: Users x Topics

Σ: Topics x Topics

$$
\begin{array}{c}
\begin{array}{ccccc} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{array} \\
\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
3 & 3 & 3 & 0 & 0 \\
4 & 4 & 4 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 2 & 0 & 4 & 4 \\
0 & 0 & 0 & 5 & 5 \\
0 & 1 & 0 & 2 & 2
\end{bmatrix}
\end{array}
=
\begin{bmatrix}
\mathbf{0.13} & 0.02 & -0.01 \\
\mathbf{0.41} & 0.07 & -0.03 \\
\mathbf{0.55} & 0.09 & -0.04 \\
\mathbf{0.68} & 0.11 & -0.05 \\
0.15 & \mathbf{-0.59} & \mathbf{0.65} \\
0.07 & \mathbf{-0.73} & \mathbf{-0.67} \\
0.07 & \mathbf{-0.29} & \mathbf{0.32}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{12.4} & 0 & 0 \\
0 & \mathbf{9.5} & 0 \\
0 & 0 & \mathbf{1.3}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}
$$

V^T: Topics x Movies

https://www.youtube.com/watch?v=YKmkAoIUxkU

SVD for Recommender Systems

- Not only good for estimating missing data
- We might actually care about the topics more

What is Map Reduce

- programming model
- addressing large data sets
- parallel and distributed algorithms
- cluster framework

- It also is a way of thinking!

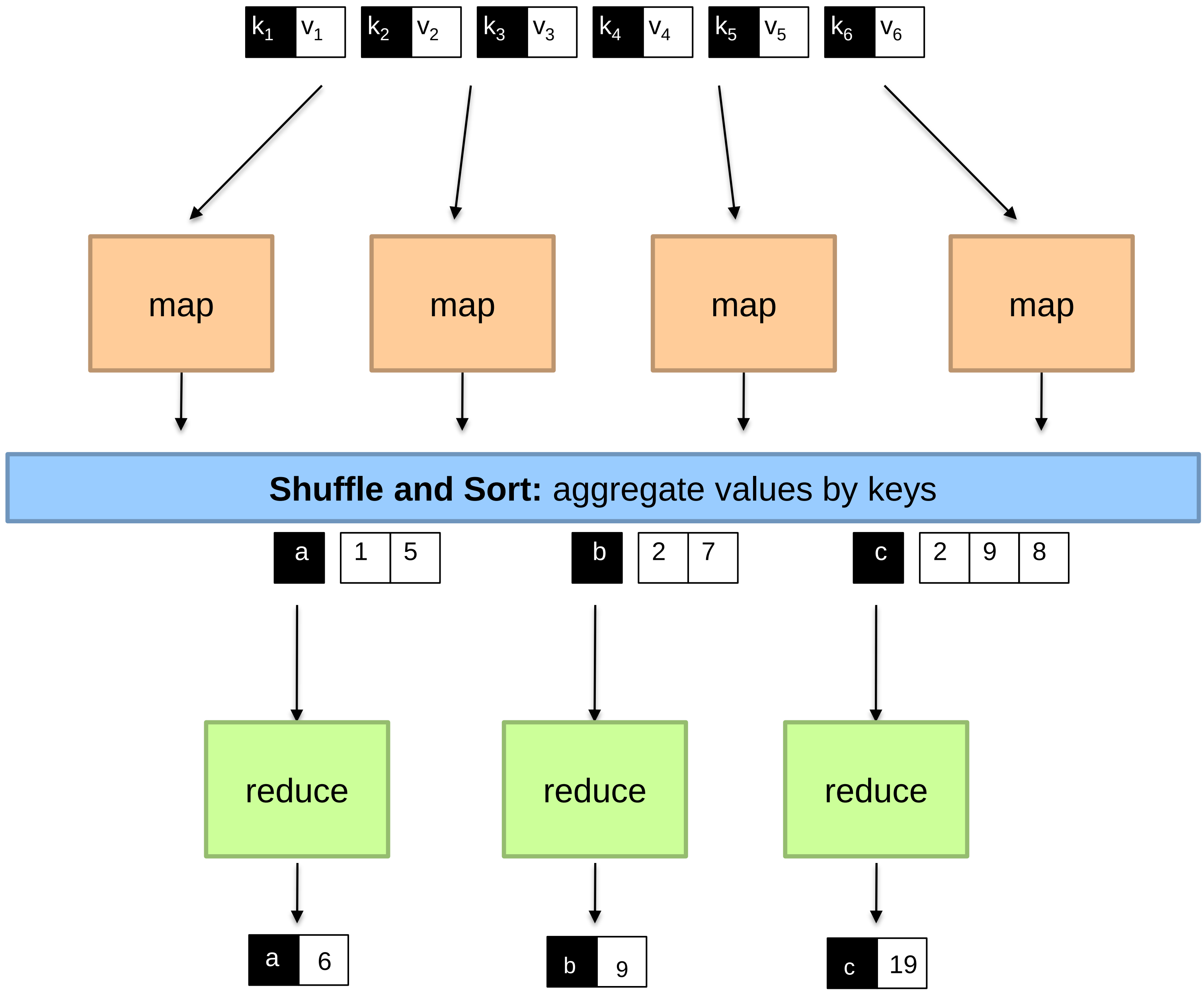
Map Reduce Background

- Originally developed by Google
- Apache Hadoop is open source implementation in Java
- MrJob is a Python interface to Hadoop

The Map and the Reduce

- Map:
  - performs filtering and sorting

- Reduce:
  - summary operation



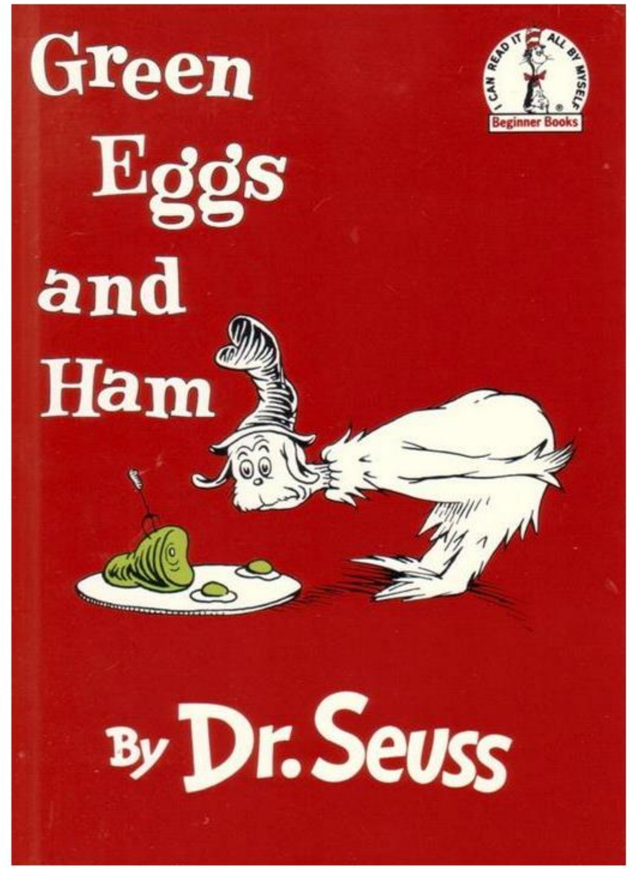
k_1 v_1
k_2 v_2
k_3 v_3
k_4 v_4
k_5 v_5
k_6 v_6
map
map
map
map
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
a 6
b 9
c 19

The Famous Word Count Example

```
from mrjob.job import MRJob

class mrWordCount(MRJob):

    def mapper(self,key,line):
        for word in line.split(' '):
            yield word.lower(),1

    def reducer(self, word, occurrences):
        yield word, sum(occurrences)

if __name__ == '__main__':
    mrWordCount.run()
```

Green Eggs and Ham

- Result of a bet:
- Can Dr. Seuss write a book using only 50 words?
- Bennett Cerf (Dr. Seuss's publisher) lost.
- It is the fourth best selling English-language children's hardcover book of all time.



Example Input File

```
I am Sam

I am Sam
Sam I am

That Sam I am
That Sam I am
I do not like
that Sam I am

Do you like
green eggs and ham

I do not like them
Sam I am
I do not like
green eggs and ham
```

```python
from mrjob.job import MRJob

class mrWordCount(MRJob):

    def mapper(self,key,line):
        for word in line.split(' '):
            yield word.lower(),1

    def reducer(self, word, occurrences):
        yield word, sum(occurrences)

if __name__ == '__main__':
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```
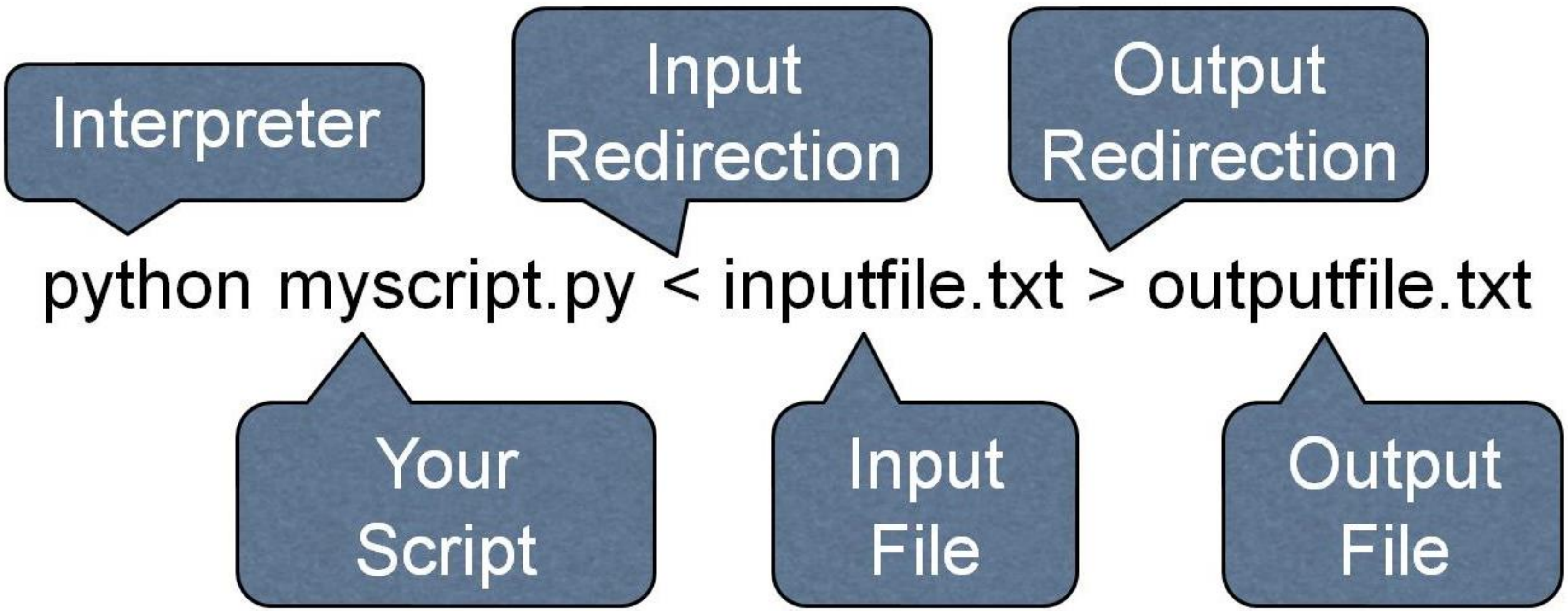

Launching the Job



Output File

```
""        36
"a"       60
"am"      16
"and"     24
"anywhere"        8
"are"     2
"be"      4
"boat"    3
"box"     7
"car"     7
"could"   14
"dark"    7
"do"      36
"eat"     24
"eggs"    10
"fox"     7
"goat"    4
"good"    2
"green"   10
"ham"     10
"here"    11
"house"   8
"i"       84
"if"      1
"in"      41
"let"     4
"like"    44
```

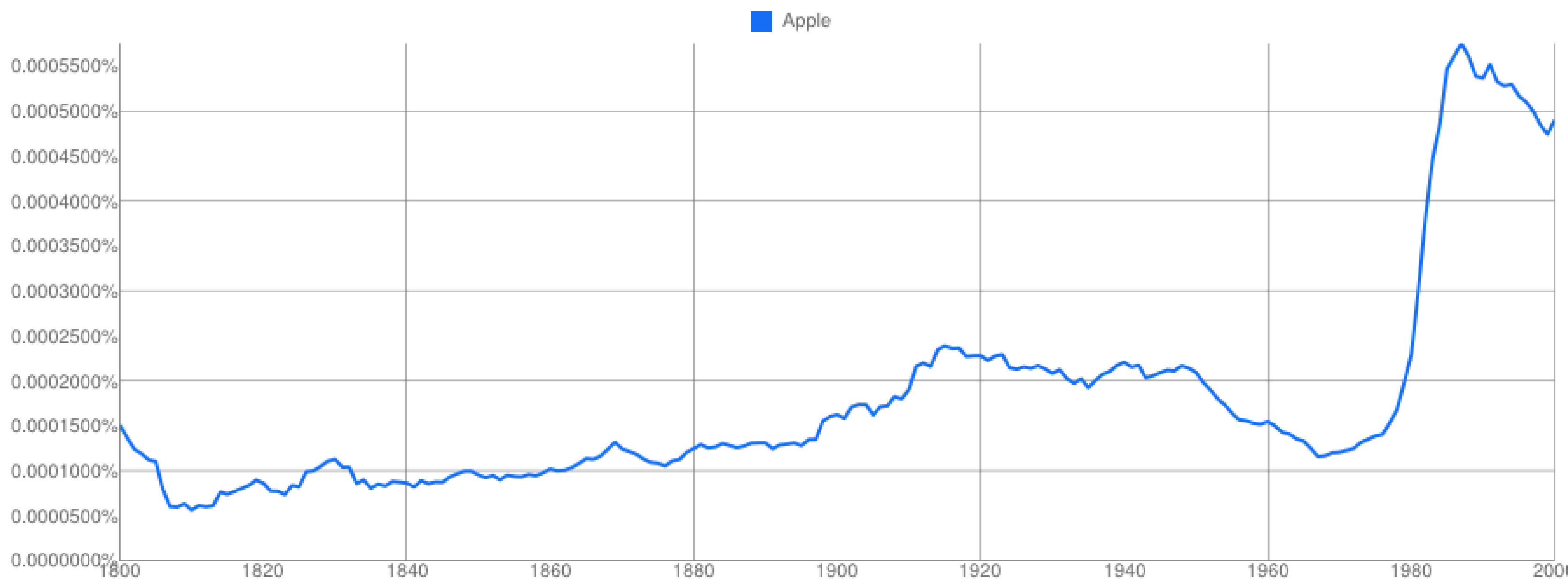
Culturomics

Google books Ngram Viewer

Graph these ***case-sensitive*** *comma-separated phrases:* Apple

between 1800 *and* 2000 *from the corpus* English *with smoothing of* 3.

Search lots of books



Search in Google Books:

1800 - 1839	1840 - 1978	1979 - 1987	1988 - 1993	1994 - 2000	Apple (English)

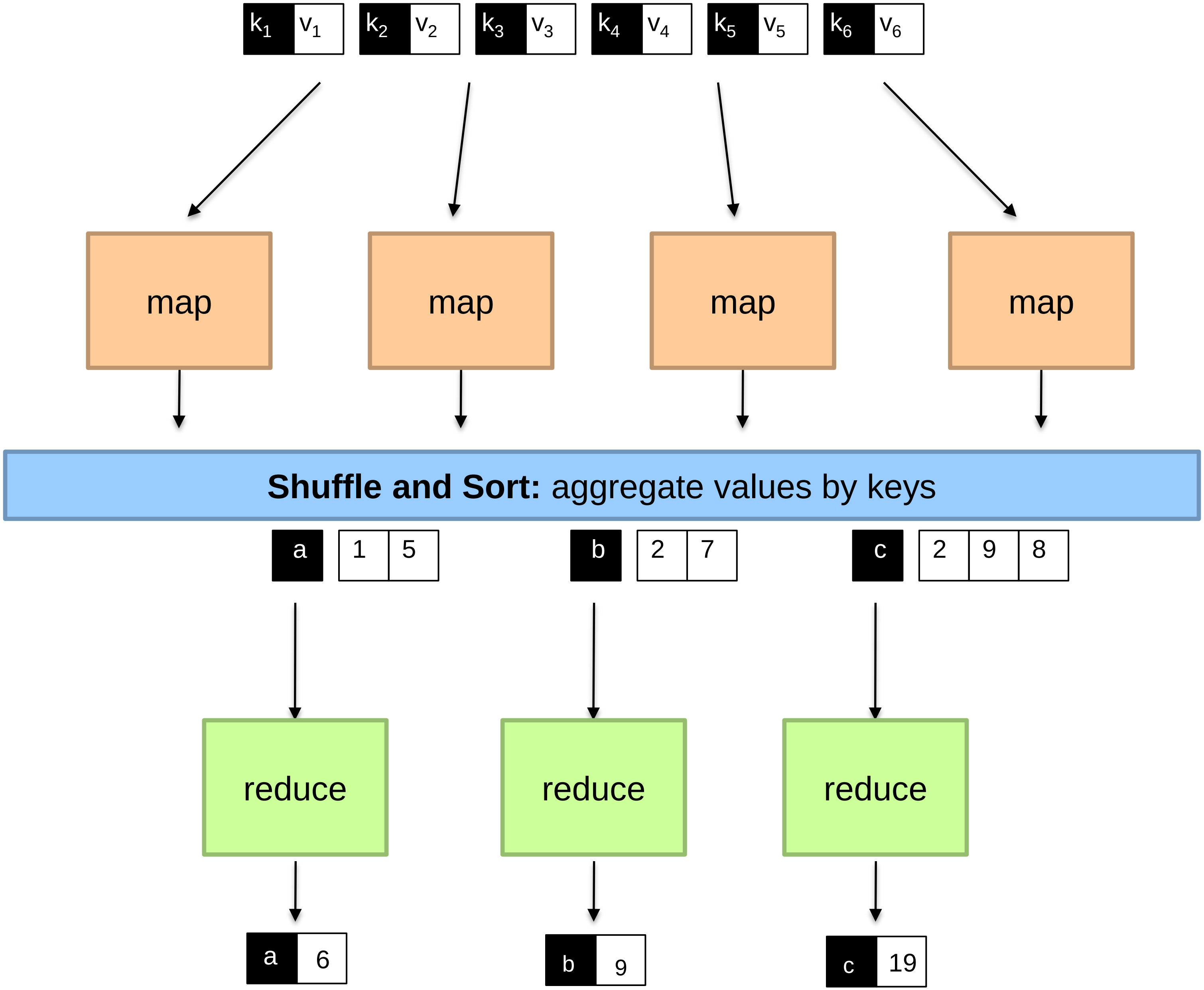
Run your own experiment! Raw data is available for download here.

Anagram Finder

- Anagram: Words or phrases consisting of the same letters
- Examples:
  - Dormitory – Dirty room
  - Astronomer – Moon starer
  - Election results – Lies let’s recount

- Verifying anagrams with map reduce
- Input: file with one word per line

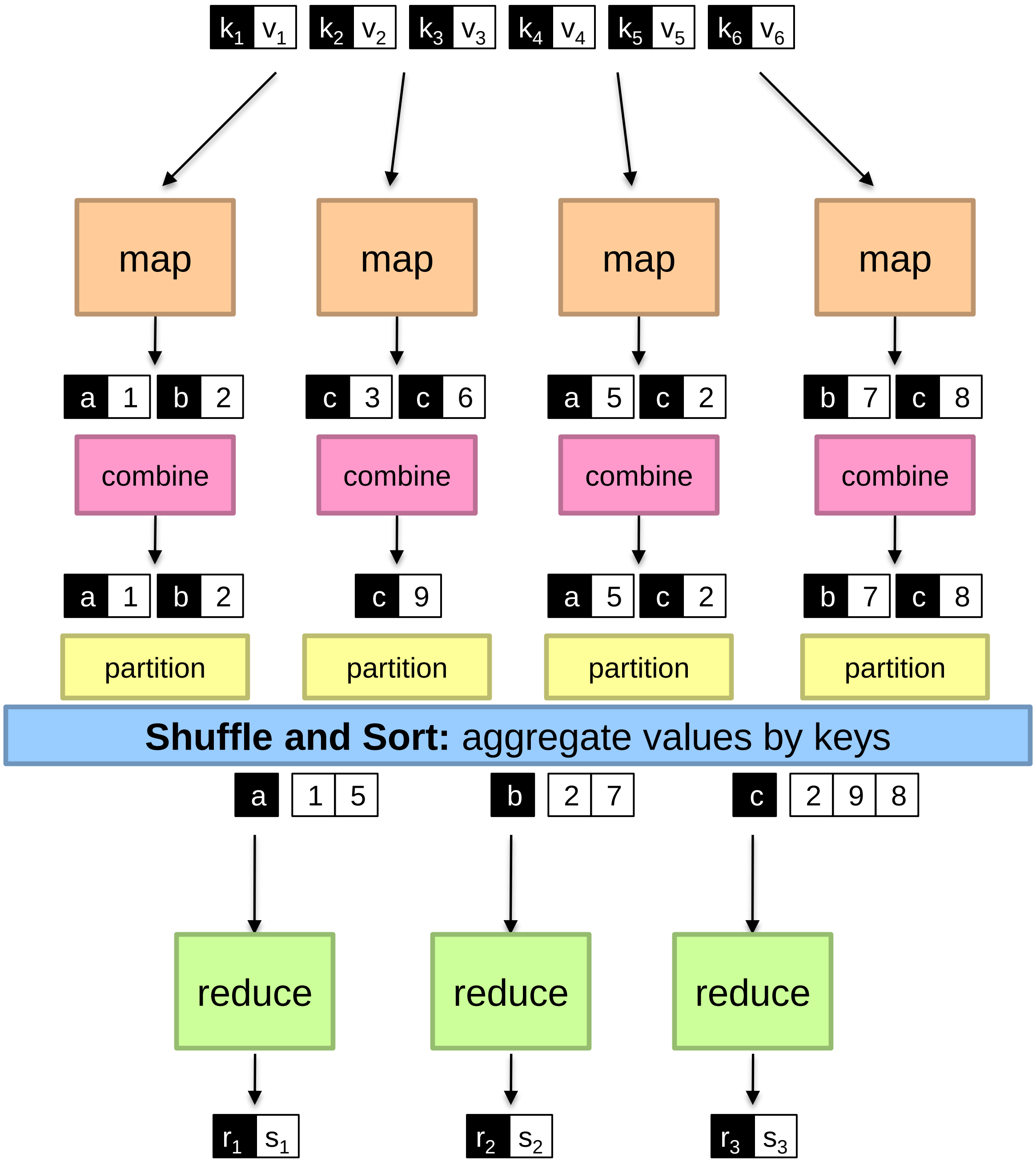
```python
from mrjob.job import MRJob

class MRAnagram(MRJob):

    def mapper(self, _, line):
        # Convert word into a list of characters, sort them, and convert
        # back to a string.
        letters = list(line)
        letters.sort()

        # Key is the sorted word, value is the regular word.
        yield letters, line

    def reducer(self, _, words):
        # Get the list of words containing these letters.
        anagrams = [w for w in words]

        # Only yield results if there are at least two words which are
        # anagrams of each other.
        if len(anagrams) > 1:
            yield len(anagrams), anagrams


if __name__ == "__main__":
    MRAnagram.run()
```



k_1 v_1
k_2 v_2
k_3 v_3
k_4 v_4
k_5 v_5
k_6 v_6
map
map
map
map
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
a 6
b 9
c 19

Importance of Local Aggregation

- Ideal scaling characteristics:
  – Twice the data, twice the running time
  – Twice the resources, half the running time
- Why can’t we achieve this?
  – Synchronization requires communication
  – Communication kills performance
- Thus… avoid communication!
  – Reduce intermediate data via local aggregation
  – Two possibilities:
    - Combiners
    - In-mapper combining


k1 v1 k2 v2 k3 v3 k4 v4 k5 v5 k6 v6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
combine
combine
combine
combine
a 1 b 2
c 9
a 5 c 2
b 7 c 8
partition
partition
partition
partition
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

Combiner

- “mini-reducers”
- Takes mapper output before shuffle and sort
- Can significantly reduce network traffic
- No access to other mappers
- Not guaranteed to get all values for a key
- Not guaranteed to run at all!
- Key and value output must match mapper

Why does the key and value output have to match the mapper output?

Word Count with Combiner

```
from mrjob.job import MRJob

class mrWordCount(MRJob):

    def mapper(self,key,line):
        for word in line.split(' '):
            yield word.lower(),1

    def combiner(self,word,occurrences):
        yield word, sum(occurrences)

    def reducer(self, word, occurrences):
        yield word, sum(occurrences)

if __name__ == '__main__':
    mrWordCount.run()
```

Combiner Design

- Combiners and reducers share same method signature
  - Sometimes, reducers can serve as combiners
  - Often, not…
- Remember: combiners are optional optimizations
  - Should not affect algorithm correctness
  - May be run 0, 1, or multiple times
- Example: find average of all integers associated with the same key

Computing the Mean: Version 1

```
class Mapper
    method Map(string t, integer r)
        Emit(string t, integer r)

class Reducer
    method Reduce(string t, integers [r_1, r_2, ...])
        sum ← 0
        cnt ← 0
        for all integer r ∈ integers [r_1, r_2, ...] do
            sum ← sum + r
            cnt ← cnt + 1
        r_avg ← sum/cnt
        Emit(string t, integer r_avg)
```

Why can't we use reducer as combiner?

Computing the Mean: Version 2

```
class Mapper
    method Map(string t, integer r)
        Emit(string t, integer r)

class Combiner
    method Combine(string t, integers [r1, r2, ...])
        sum ← 0
        cnt ← 0
        for all integer r ∈ integers [r1, r2, ...] do
            sum ← sum + r
            cnt ← cnt + 1
        Emit(string t, pair (sum, cnt))                ▷ Separate sum and count

class Reducer
    method Reduce(string t, pairs [(s1, c1), (s2, c2) ...])
        sum ← 0
        cnt ← 0
        for all pair (s, c) ∈ pairs [(s1, c1), (s2, c2) ...] do
            sum ← sum + s
            cnt ← cnt + c
        r_avg ← sum/cnt
        Emit(string t, integer r_avg)
```

Why doesn't this work?

Computing the Mean: Version 3

class Mapper
  method Map(string t, integer r)
    Emit(string t, pair $(r, 1)$)

class Combiner
  method Combine(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
    $sum \leftarrow 0$
    $cnt \leftarrow 0$
    for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
      $sum \leftarrow sum + s$
      $cnt \leftarrow cnt + c$
    Emit(string t, pair (sum, cnt))

class Reducer
  method Reduce(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
    $sum \leftarrow 0$
    $cnt \leftarrow 0$
    for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
      $sum \leftarrow sum + s$
      $cnt \leftarrow cnt + c$
    $r_{avg} \leftarrow sum/cnt$
    Emit(string t, pair (r_{avg}, cnt))

Fixed? What if combiner does not run?

In-Mapper Combining

- “Fold the functionality of the combiner into the mapper by preserving state across multiple map calls

```
class Mapper
    method Initialize
        S ← new AssociativeArray
        C ← new AssociativeArray
    method Map(string t, integer r)
        S{t} ← S{t} + r
        C{t} ← C{t} + 1
    method Close
        for all term t ∈ S do
            Emit(term t, pair (S{t}, C{t}))
```

In-Mapper Combining

- Advantages
  - Speed
  - Why is this faster than actual combiners?
- Disadvantages
  - Explicit memory management required
  - Potential for order-dependent bugs

Word Count with In-Mapper-Comb.

```
from collections import defaultdict
from mrjob.job import MRJob

class mrWordCount(MRJob):
    def __init__(self, *args, **kwargs):
        super(mrWordCount, self).__init__(*args, **kwargs)
        self.localWordCount = defaultdict(int)

    def mapper(self,key,line):
        if False:
            yield
        for word in line.split(' '):
            self.localWordCount[word.lower()]+=1

    def mapper_final(self):
        for (word, count) in self.localWordCount.iteritems():
            yield word, count

    def reducer(self, word, occurrences):
        yield word, sum(occurrences)

if __name__ == '__main__':
    mrWordCount.run()
```

Which is better?

- For large dictionaries?
  - Combiner has no memory problems

- For skewed word distributions (“the”)?
  - In-mapper reduces load on reducer

Word of Caution

```python
from mrjob.job import MRJob
import sys

class SimpleTest(MRJob):

    def __init__(self, *args, **kwargs):
        super(SimpleTest, self).__init__(*args, **kwargs)
        self.test = 1

    def mapper(self,key,value):
        self.test = 2
        yield 1, self.test

    def mapper_final(self):
        yield 1, self.test

    def reducer(self, key, value):
        sys.stderr.write(str(self.test))
        yield 1, value

if __name__ == '__main__':
    SimpleTest.run()
```

1!!

Pairs and Stripes:

- Term co-occurrence matrix for a text collection
  - M = N x N matrix (N = vocabulary size)
  - M_{ij}: number of times *i* and *j* co-occur in some context
  - Context can be a sentence, sequence of m words, etc.
  - In this case co-occurrence matrix is symmetric

MapReduce: Large Counting Problems

- Term co-occurrence matrix for a text collection = specific instance of a large counting problem
  - A large event space (number of terms)
  - A large number of observations (the collection itself)
  - Goal: keep track of interesting statistics about the events
- Basic approach
  - Mappers generate partial counts
  - Reducers aggregate partial counts

First Try: “Pairs”

- Each mapper takes a sentence:
  - Generate all co-occurring term pairs
  - For all pairs, emit (a, b) → count
- Reducers sum up counts associated with these pairs
- Use combiners!

Pairs: Pseudo-Code

```
class Mapper
    method Map(docid a, doc d)
        for all term w ∈ doc d do
            for all term u ∈ Neighbors(w) do
                Emit(pair (w, u), count 1)          ▷ Emit count for each co-occurrence

class Reducer
    method Reduce(pair p, counts [c1, c2, . . .])
        s ← 0
        for all count c ∈ counts [c1, c2, . . .] do
            s ← s + c                                ▷ Sum co-occurrence counts
        Emit(pair p, count s)
```

“Pairs” Analysis

- Advantages
  - Easy to implement, easy to understand
- Disadvantages
  - Lots of pairs to sort and shuffle around
  - Not many opportunities for combiners to work

Another Try: "Stripes"

- Idea: group together pairs into an associative array

(a, b) → 1
(a, c) → 2
(a, d) → 5
(a, e) → 3
(a, f) → 2

a → { b: 1, c: 2, d: 5, e: 3, f: 2 }

- Each mapper takes a sentence:
  - Generate all co-occurring term pairs
  - For each term, emit a → { b: $count_b$, c: $count_c$, d: $count_d$ … }
- Reducers perform element-wise sum of associative arrays

	a → { b: 1, d: 5, e: 3 }
+	a → { b: 1, c: 2, d: 2, f: 2 }
	a → { b: 2, c: 2, d: 7, e: 3, f: 2 }

Key: cleverly-constructed data structure brings together partial results

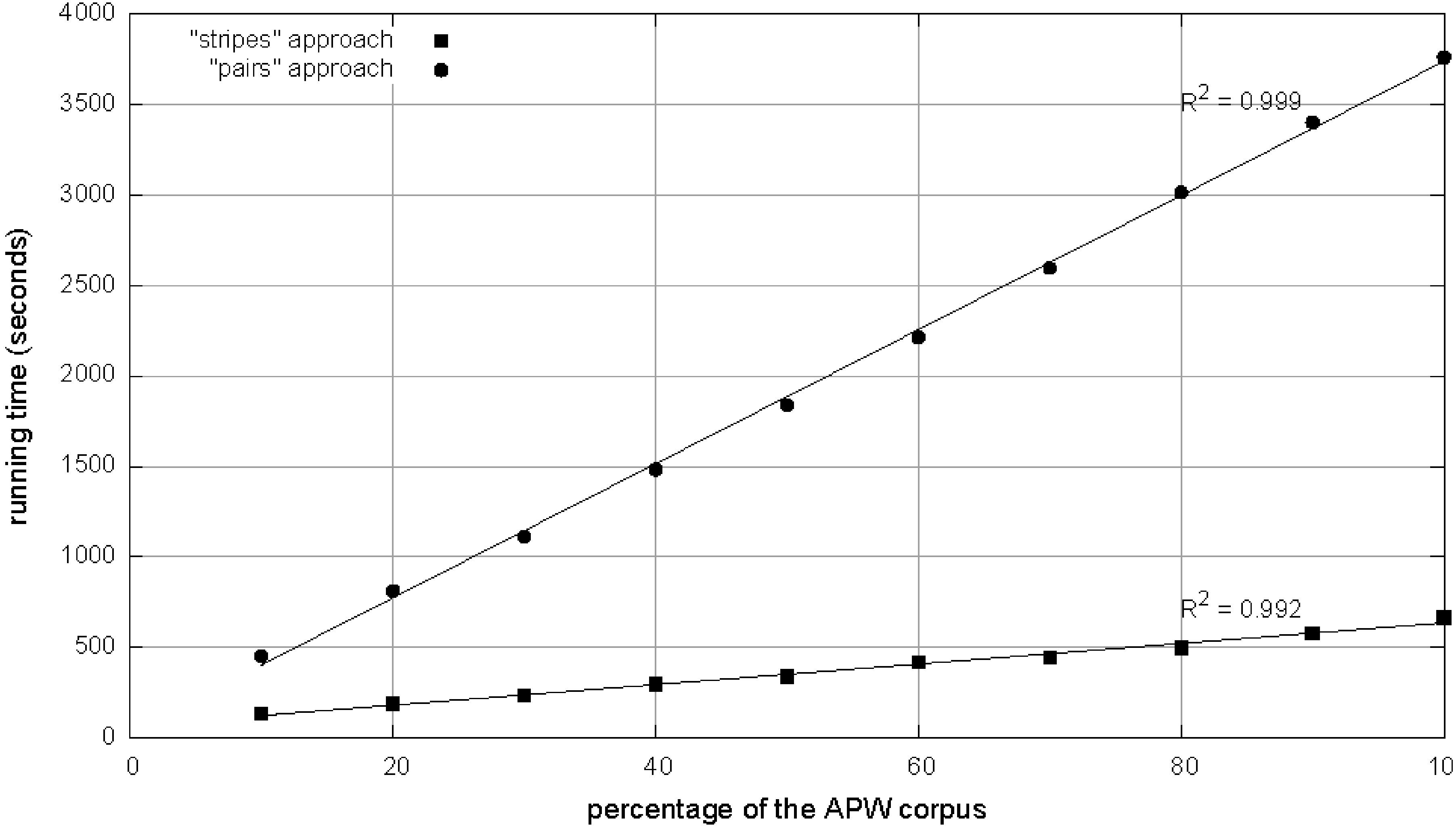
Stripes: Pseudo-Code

```
class Mapper
    method Map(docid a, doc d)
        for all term w ∈ doc d do
            H ← new AssociativeArray
            for all term u ∈ Neighbors(w) do
                H{u} ← H{u} + 1                    ▷ Tally words co-occurring with w
            Emit(Term w, Stripe H)

class Reducer
    method Reduce(term w, stripes [H1, H2, H3, ...])
        Hf ← new AssociativeArray
        for all stripe H ∈ stripes [H1, H2, H3, ...] do
            Sum(Hf, H)                             ▷ Element-wise sum
        Emit(term w, stripe Hf)
```

“Stripes” Analysis

- Advantages
  - Far less sorting and shuffling of key-value pairs
  - Keys are less unique than in pairs approach
  - Can make better use of combiners
- Disadvantages
  - More difficult to implement
  - Underlying object more heavyweight
  - Fundamental limitation in terms of size of event space

Comparison of "pairs" vs. "stripes" for computing word co-occurrence matrices



Cluster size: 38 cores
Data Source: Associated Press Worldstream (APW) of the English Gigaword Corpus (v3), which contains 2.27 million documents (1.8 GB compressed, 5.7 GB uncompressed)

Map Reduce for Machine Learning

- Random Forest?
- SVM?