Self Organization of a Massive Document Collection

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Their Goal

- Organize large document collections according to textual similarities
  - Search engine
- Create a useful tool for searching and exploring large document collections

Their Solution

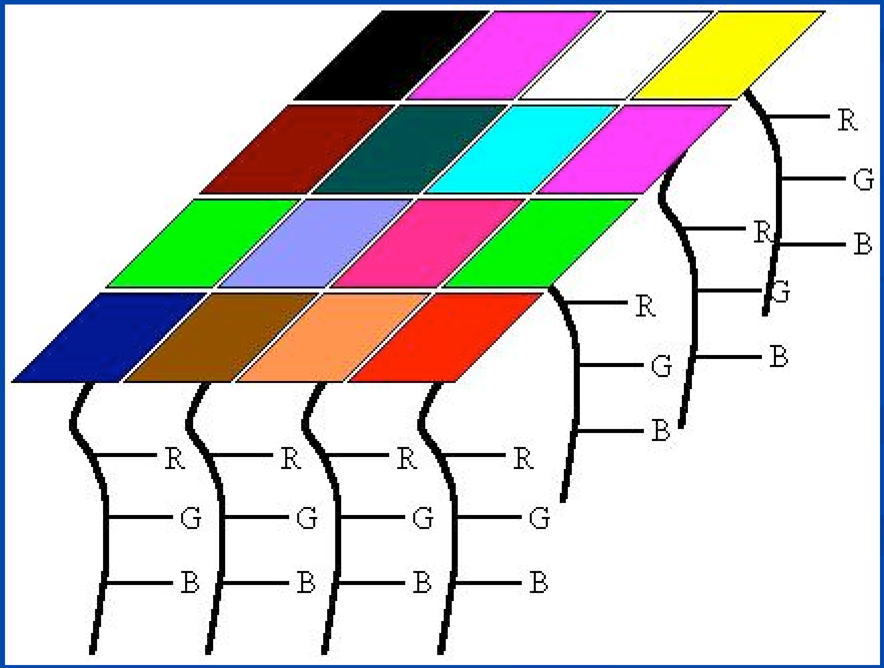
- Self-organizing maps
  - Groups similar documents together
  - Interactive and easily interpreted
  - Facilitates data mining

Self-organizing maps

- Unsupervised learning neural network
- Maps multidimensional data onto a 2 dimensional grid
- Geometric relations of image points indicate similarity

Self-organizing map algorithm

- Neurons arranged in a 2 dimensional grid
- Each neuron has a vector of weights
  - Example: R, G, B values



Self-organizing map algorithm (cont)

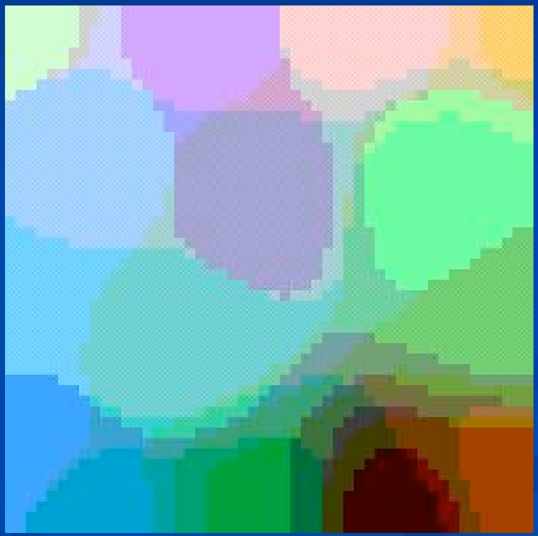
- Initialize the weights
- For each input, a "winner" is chosen from the set of neurons
- The "winner" is the neuron most similar to the input
  - Euclidean distance:

    $\text{sqrt}\ ((r_1 - r_2)^2 + (g_1 - g_2)^2 + (b_1 - b_2)^2 + \ldots)$

Self-organizing map algorithm (cont)

- Learning takes place after each input
- $n_i(t + 1) = n_i(t) + h_{c(x),i}(t) * [x(t) – n_i(t)]$
  - $n_i(t)$ weight vector of neuron i at regression step t
  - $x(t)$ input vector
  - $c(x)$ index of “winning” neuron
  - $h_{c(x),i}$ neighborhood function / smoothing kernel
    - Gaussian
    - Mexican hat

Self-organizing map example



6 shades of red, green, and blue used as input

500 iterations

The Scope of This Work

- Organizing massive document collections using a self-organizing map
- Researching the up scalability of self-organizing maps

Original Implementation

- WEBSOM (1996)
- Classified ~5000 documents
- Self-organizing map with "histogram vectors"
  - Weight vectors based on collection of words whose vocabulary and dimensionality were manually controlled

Problem

- Large vector dimensionality required to classify massive document collections
  - Aiming to classify ~7,000,000 patent abstracts

Goals

- Reduce dimensionality of histogram vectors
- Research shortcut algorithms to improve computation time
- Maintain classification accuracy

Histogram Vector

- Each component of the vector corresponds to the frequency of occurrence of a particular word
- Words associated with weights that reflect their power of discrimination between topics

Reducing Dimensionality

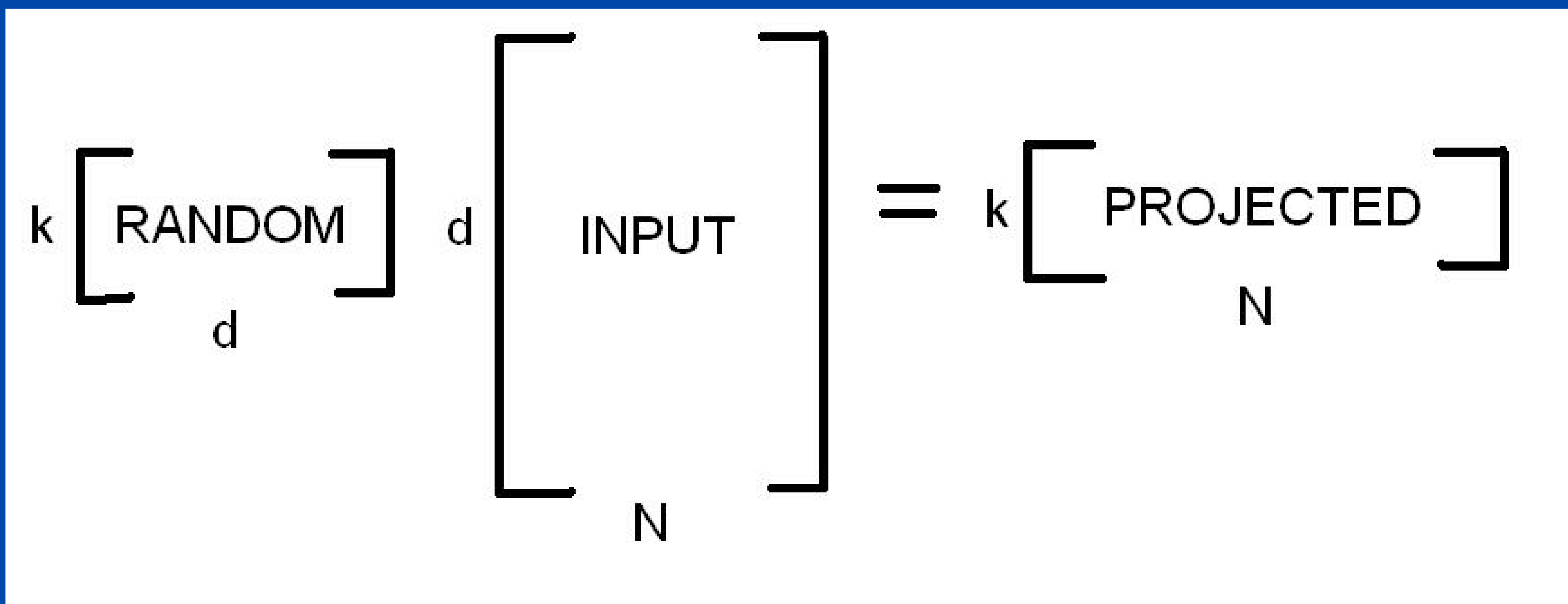
- Find a suitable subset of words that accurately classifies the document collection
  - Randomly Projected Histograms

Randomly Projected Histograms

- Take original d-dimensional data X and project to a k-dimensional (k << d) subspace through the origin
- Use a random k x d matrix R, the elements in each column of which are normally distributed vectors having unit length:

$R_{k \times d} X_{d \times N}$ => new matrix $X_{k \times N}$

Random Projection Formula



Why Does This Work?

- Johnson – Lindenstrauss lemma:

  "If points in a vector space are projected onto a randomly selected subspace of suitably high dimension, then the distances between the points are approximately preserved"
- If the original distances or similarities are themselves suspect, there is little reason to preserve them completely

In Other Words

- The similarity of a pair of projected vectors is the same on average as the similarity of the corresponding pair of original vectors
  - Similarity is determined by the dot product of the two vectors

Why Is This Important?

- We can improve computation time by reducing the histogram vector's dimensionality

Loss in Accuracy

	Accuracy
Vector space model	60.6
Normally distributed $\mathbf{R}$	59.1

Optimizing the Random Matrix

- Simplify the projection matrix R in order to speed up computations
- Store permanent address pointers from all the locations of the input vector to all locations of the projected matrix for which the matrix element of R is equal to one

	Accuracy	Standard deviation due to different randomization of $\mathbf{R}$
Normally distributed $\mathbf{R}$	59.1	0.4
Thresholding to $+1$ or -1	59.4	0.2
5 ones in each column	58.2	0.3
3 ones in each column	56.8	0.2
2 ones in each column	55.4	0.3

So…

- Using randomly projected histograms, we can reduce the dimensionality of the histogram vectors
- Using pointer optimization, we can reduce the computing time for the above operation

Map Construction

- Self-organizing map algorithm is capable of organizing a randomly initialized map
- Convergence of the map can be sped up if initialized closer to the final state

Map Initialization

- Estimate larger maps based on the asymptotic values of a much smaller map
  - Interpolate/extrapolate to determine rough values of larger map

Optimizing Map Convergence

- Once the self-organized map is smoothly ordered, though not asymptotically stable, we can restrict the search for new winners to neurons in the vicinity of the old one.
- This is significantly faster than performing an exhaustive winner search over the entire map
- A full search for the winner can be performed intermittently to ensure matches are global bests

Final Process

- Preprocess text
- Construct histogram vector for input
- Reduce dimensionality by random projection
- Initialize small self-organizing map
- Train the small map
- Estimate larger map based on smaller one
- Repeat last 2 steps until desired map size reached

Performance Evaluation

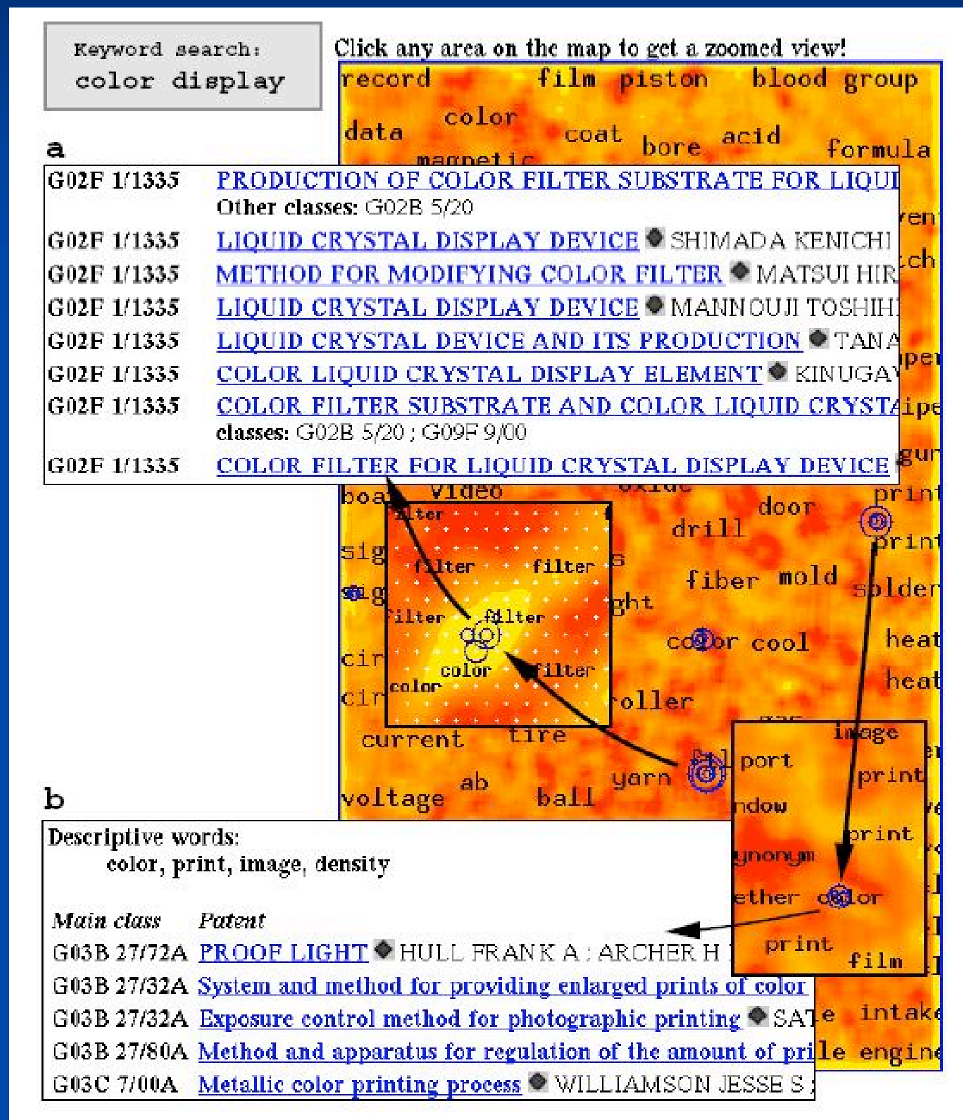
- Reduced dimensionality
- Pointer optimization
- Non-random initialization of the map
- Optimized map convergence
- Multiprocessor parallelism

	Classification accuracy (%)	Quantization error	Time (s)
Traditional SOM	58.2 ± 0.2	0.799 ± 0.001	2550 ± 40
Shortcut methods	58.0 ± 0.2	0.798 ± 0.002	241 ± 3.5

Largest Map So Far

- 6,840,568 patent abstracts written in English
- Self-organizing map composed of 1,002,240 neurons
- 500-dimension histogram vectors (reduced from 43,222)
- 5 ones in each column of the random matrix

What It Looks Like



Conclusions

- Self-organizing maps can be optimized to map massive document collections without losing much in classification accuracy

Questions?