

On Low Dimensional Embeddings & Similarity Search

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The Problem

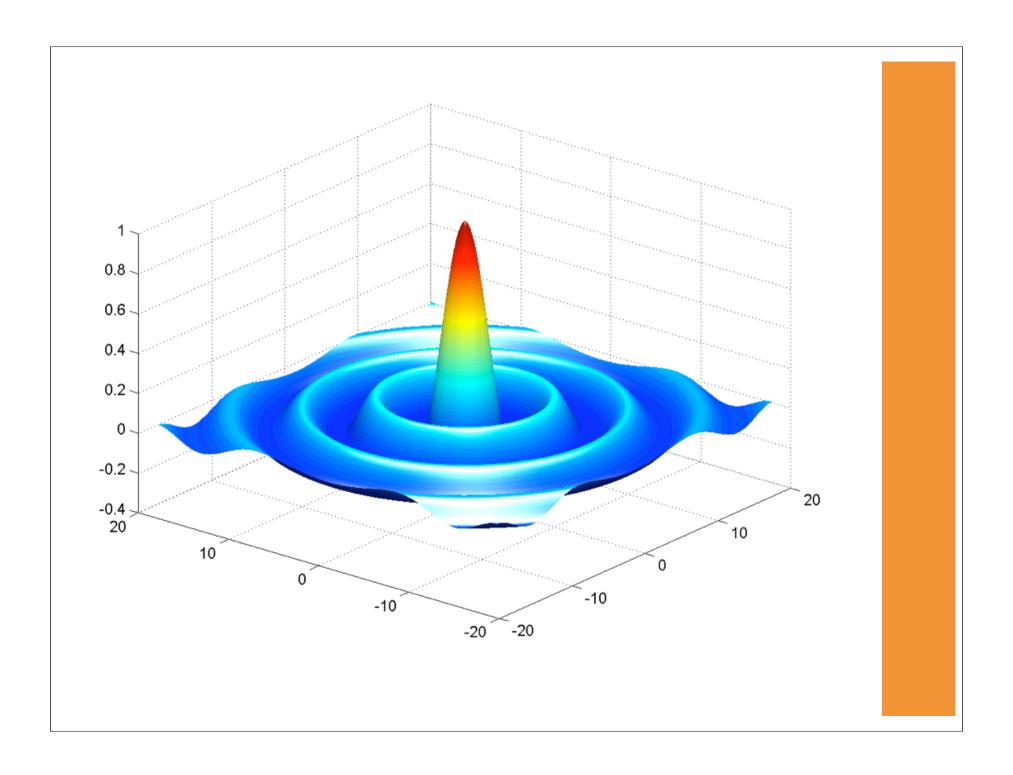
- Given n points in d-dimensional space equipped with L_2 norm, find:
 - A image of \$k\$ dimensions such that:
 - pair-wise distances are largely preserved in the image

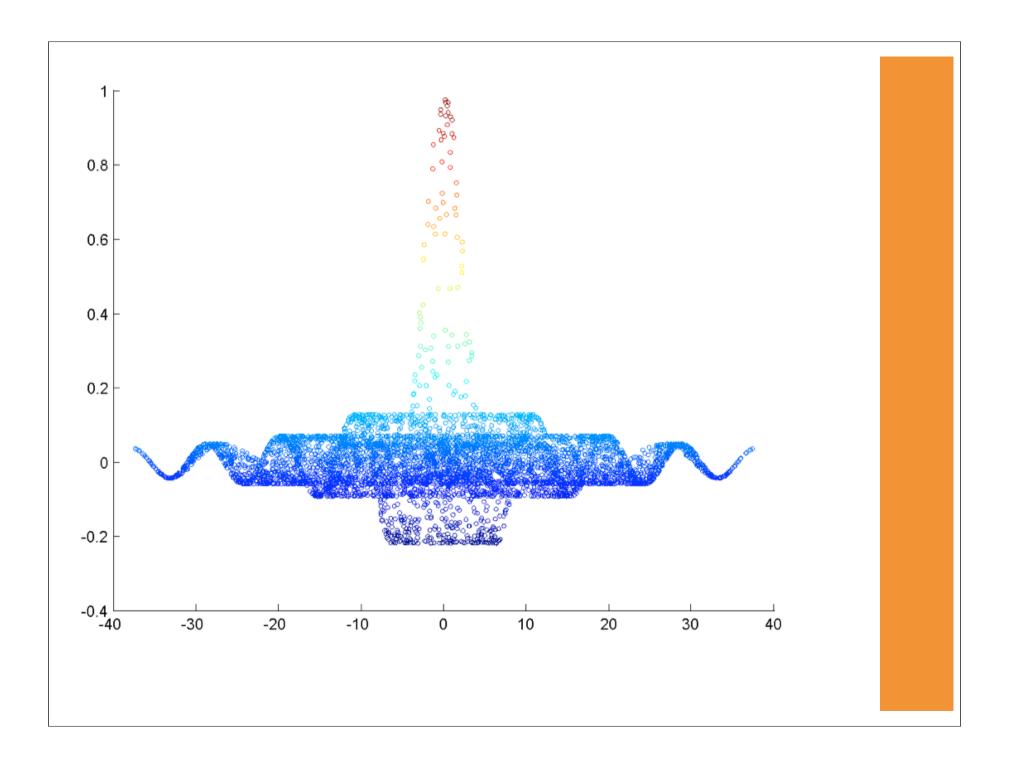


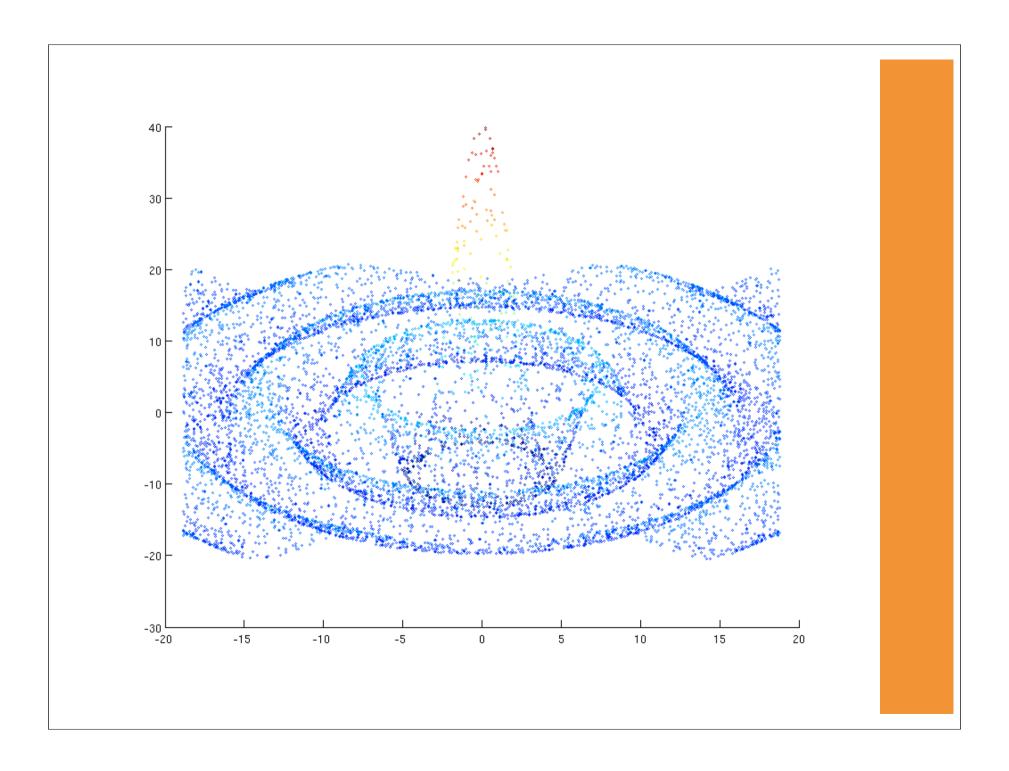
Why this matters

- Nearest neighbor queries: poly(n,d) computation/storage complexity
- The tale of Qube- a multi-dimensional hypercubic overlay
- Similarity queries are fundamental primitives of any search engine









Projection: Matrix View

$$\sqrt{\frac{d}{k}} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix} \times \begin{bmatrix} v_{\cdot 1} & v_{\cdot 2} & \cdots & v_{\cdot n} \end{bmatrix}$$

v_{* i}: n points in R^d
a_{i *}: k vectors of cardinality n

- Matrix A serve as the estimation vectors for V
- obviously picks of a_i crucial to projections

Random Projection Story

- First by Johnson & Lindenstrauss in 80s
- Indyk98 showed N_d(0,1) can do the trick (Gaussian ensembles)
- Achlioptas01 used mildly sparse distributions (1/3 computation only)
- Li05 said very sparse ones can do too!

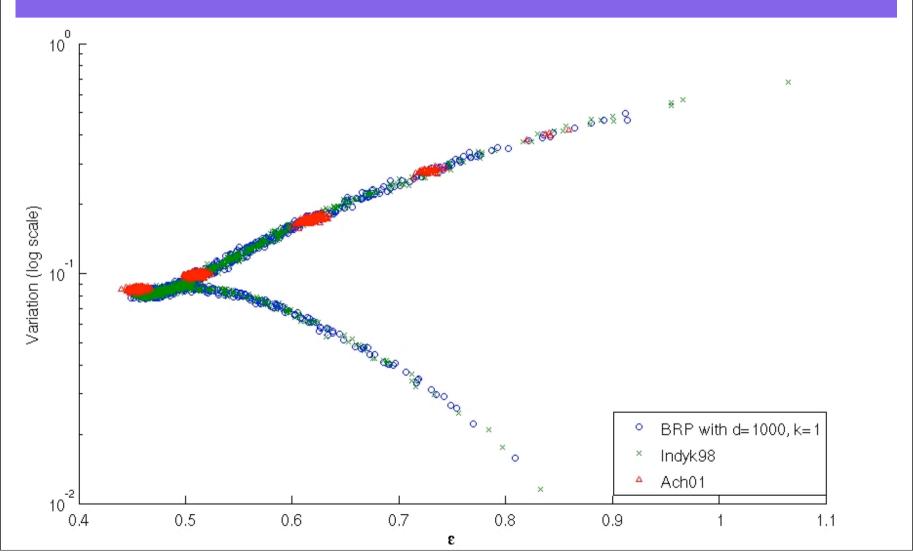


This Talk in 1 Slide

- Sparse is not good for you
- The devil is in the O(.)
- Up to 40% reduction in that O(.) is possible for the same distortion
- And that's not just L_2, cosine too!
- Show this on TREC (130K/170K corpus) & Flickr images (250K corpus)



? Simplify != Neglect ¿



The Formal Bits

Theorem 2.1. For any $u, v \in S \subset \mathbb{R}^d$ and |S| = n, an random instance of H_A in equation 1 where each row A_i is a random vector from the unit d-sphere yield distortion

$$(1 - \epsilon)|u - v|^2 \le |H_A(u) - H_A(v)|^2 \le (1 + \epsilon)|u - v|^2$$

with probability at least $1 - n^{-1}$, when

$$k \geq \begin{cases} \frac{8\log n - 2\log 4\pi}{\epsilon^2} & \text{for } k \geq 30, \sqrt{k}\epsilon \geq 2\\ & \text{for } 30 > k > 0, k(1-\epsilon) \geq 1,\\ \frac{6\log n}{\epsilon^2(1-2/3\epsilon)} & 0 \leq \epsilon \leq 1, n \geq 10 \end{cases}$$

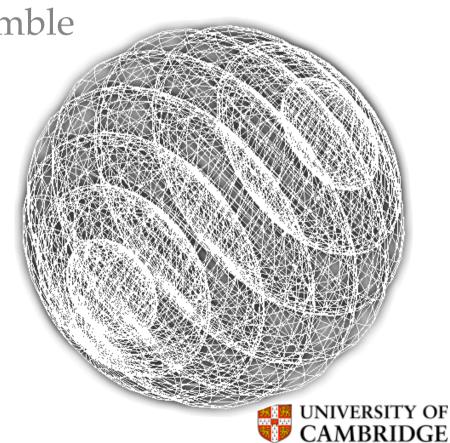


The Main Theorem

• If we pick a random matrix from the unit circular ensemble

Then with probability1-1/n

 you get a "good" projection with distortion ε

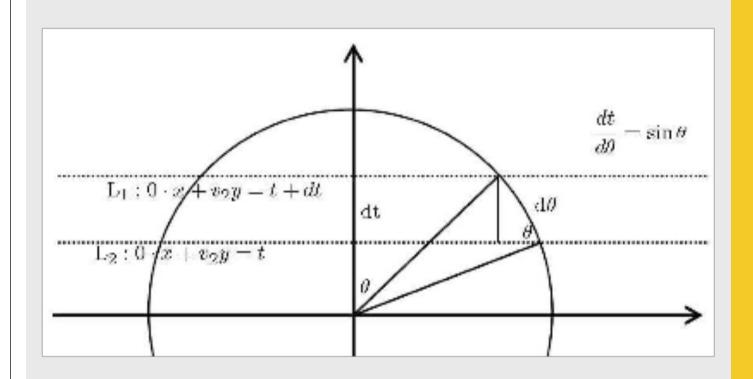


Proof Strategy

- For each a_i · v: show that distortion obeys a Beta distribution
- For k<30, use Beta approximation due to Johannesson & Giri
- For k>30, invoke Central Limit Thm



How we get Beta



How we get Beta

Lemma 3.1. Let X be an uniformly random point on the surface of the unit d-dimension sphere and $v \in \mathbb{R}^d$. Then, we have

$$\frac{(X\cdot v)^2}{|v|^2}\sim \beta(\frac{1}{2},\frac{d-1}{2})$$

where $\beta(\alpha, \beta)$ is the beta distribution.

$$\Pr[|X \cdot v| \le t] = \Pr[|X \cdot v| \le \cos \rho_1]$$

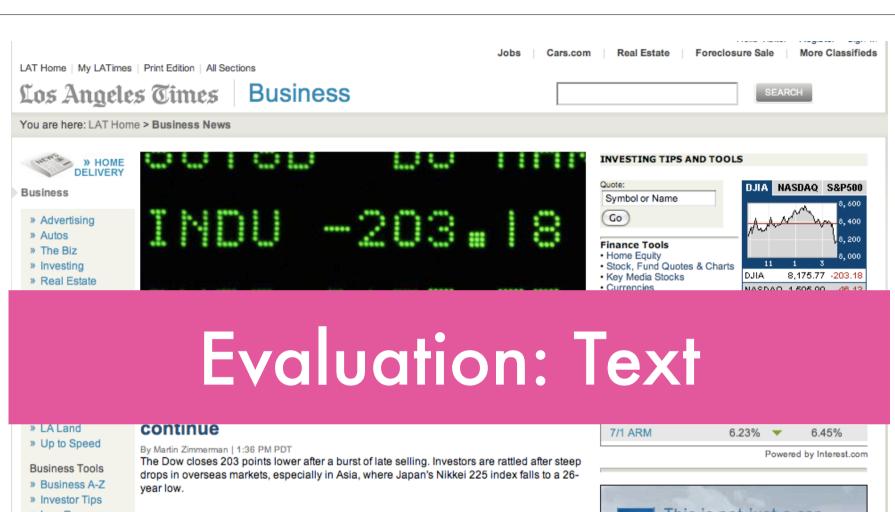
$$= \frac{\frac{\Gamma(d/2)}{\sqrt{\pi}\Gamma(\frac{d-1}{2})} 2 \int_0^{\rho_1} \sin^{d-2}(\rho_1) d\rho_1}{\sqrt{\pi}\Gamma(\frac{d-1}{2})}$$

$$= \frac{\frac{1}{\beta(\frac{1}{2}, \frac{d-1}{2})} \int (1 - \cos^2 \rho_1)^{\frac{d-3}{2}} d\cos \rho_1}{\frac{1}{\beta(\frac{1}{2}, \frac{d-1}{2})} 2t \cdot_2 F_1(\frac{1}{2}, -\frac{d-3}{2}; \frac{3}{2}; t^2)}$$

$$= \frac{\frac{1}{\beta(\frac{1}{2}, \frac{d-1}{2})} \beta_{t^2}(\frac{1}{2}, \frac{d-1}{2})}{\frac{1}{\beta(\frac{1}{2}, \frac{d-1}{2})} \beta_{t^2}(\frac{1}{2}, \frac{d-1}{2})}$$

$$= I_{t^2}(\frac{1}{2}, \frac{d-1}{2})$$





» Law Resources

» Money Library

» Money Q & A

Blog: IHOP, Applebee's parent gets a lift from move to sell stores

move to sell stores BUSINESS: LATEST AP NEWS





TREC Corpus



- TFIDF extraction via LEMUR toolkit
- Foreign Broadcast Information Service
- LA Times

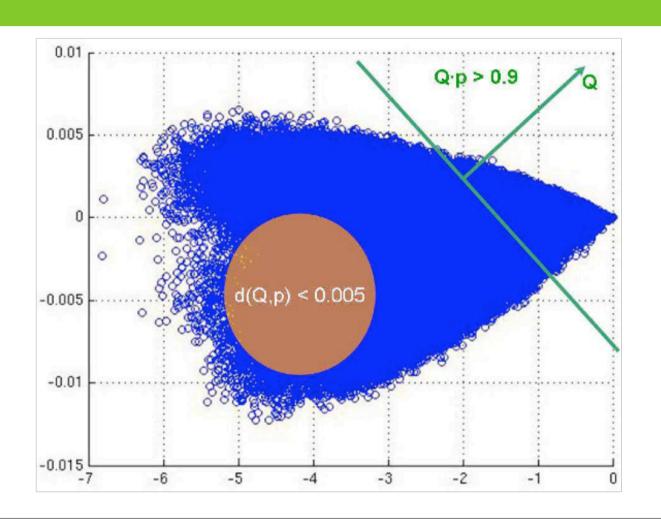


Evaluation Method

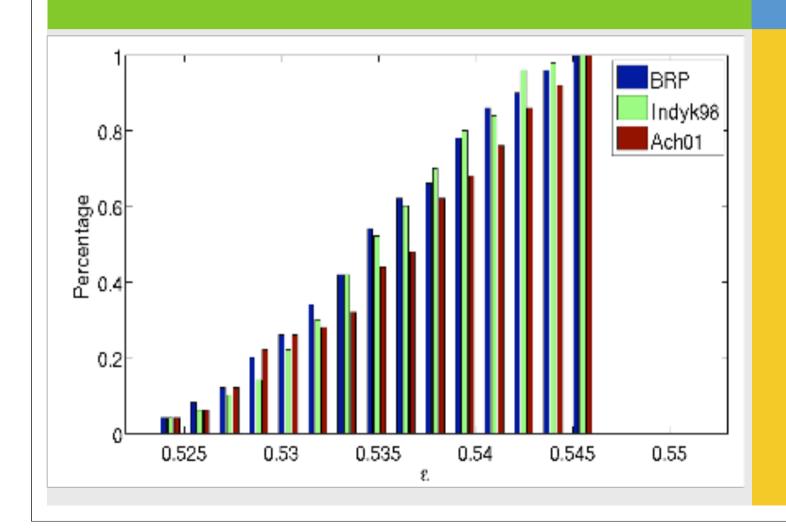
- Instanciate 10K instances of projections for both LA Times and FBIS, check mean and variance of:
 - L2 distance distortion
 - Cosine distortion (with SVD)
 - Agreement with latent semantic indexing (LSI)



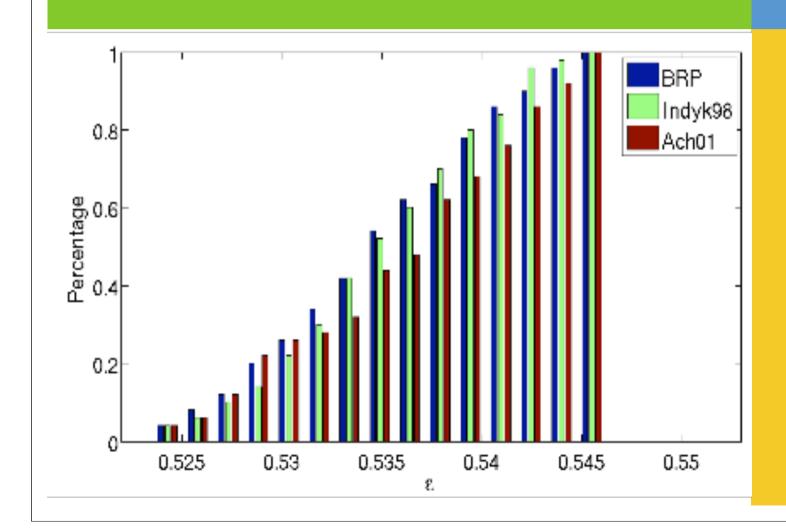
LA Times by LSI



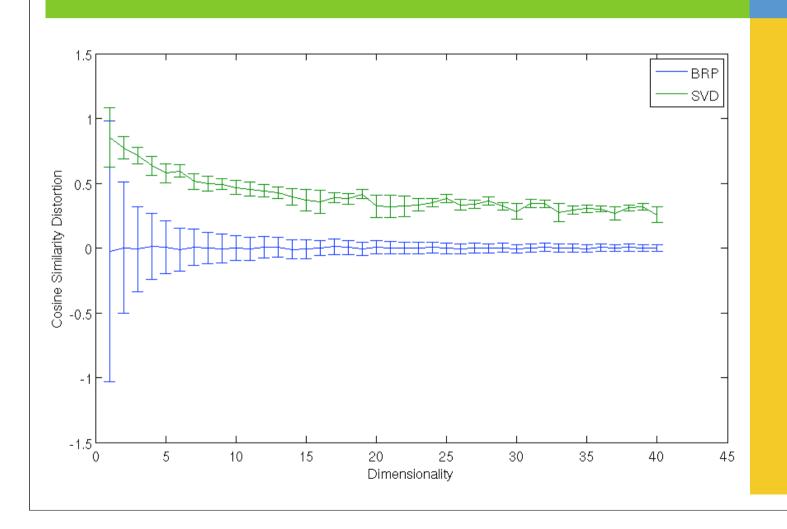
FBIS: L2 distance



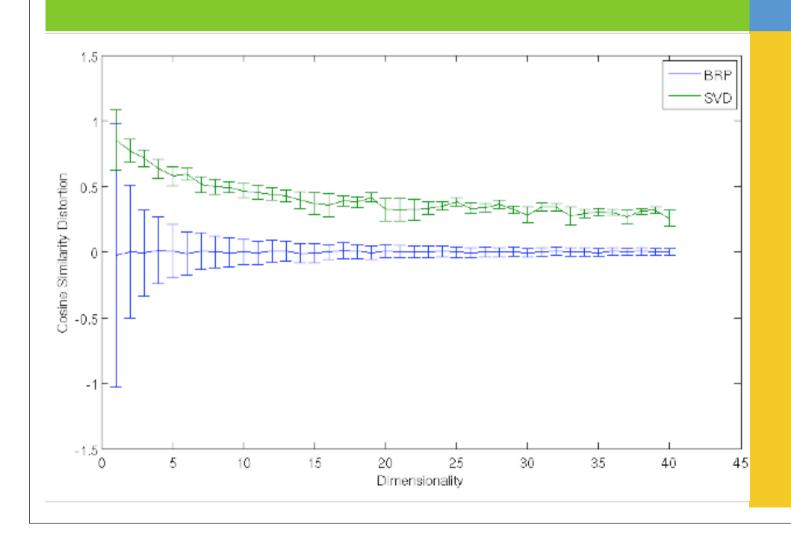
LA Times: L2 dist



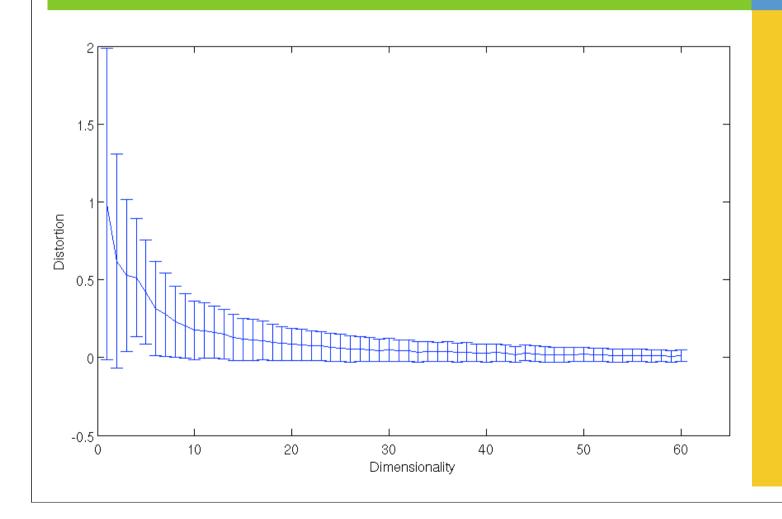
FBIS: Cosine



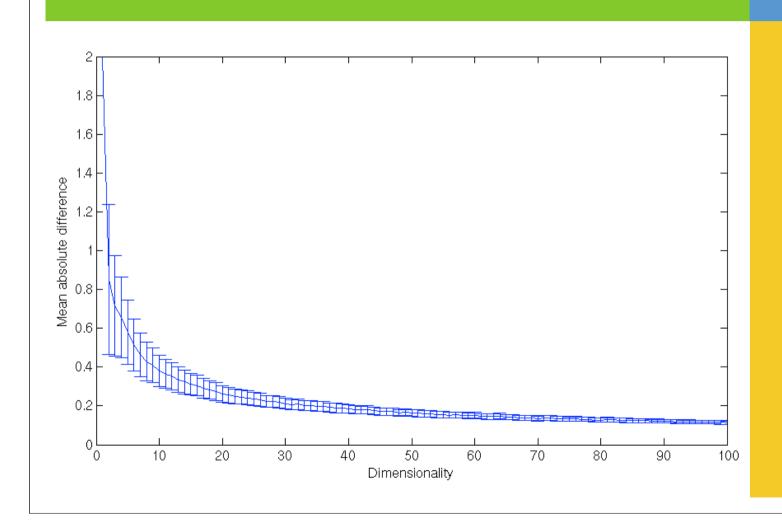
LA Times: Cosine

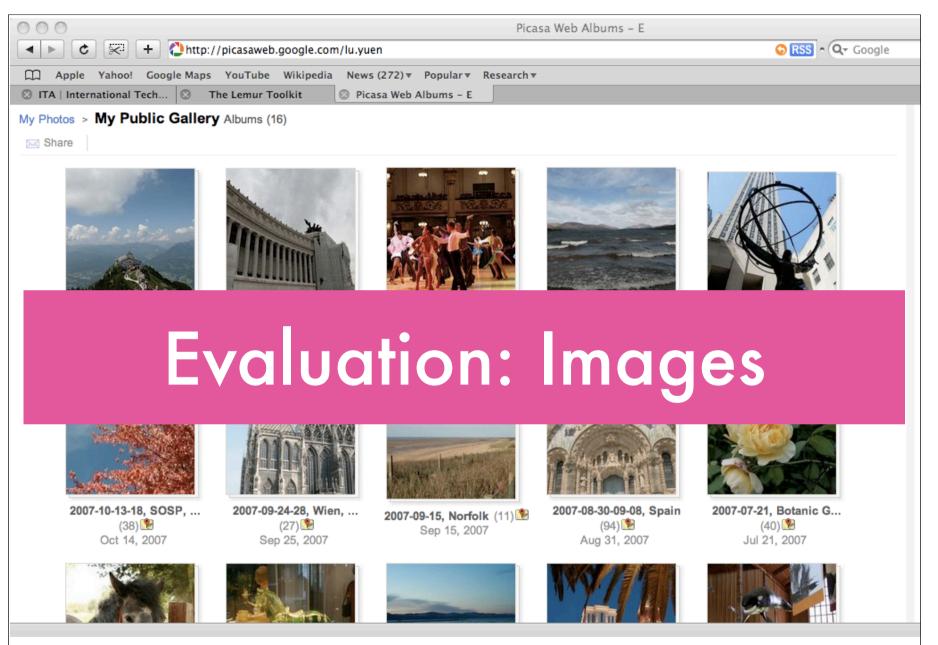


LA Times: LSI



FBIS: LSI





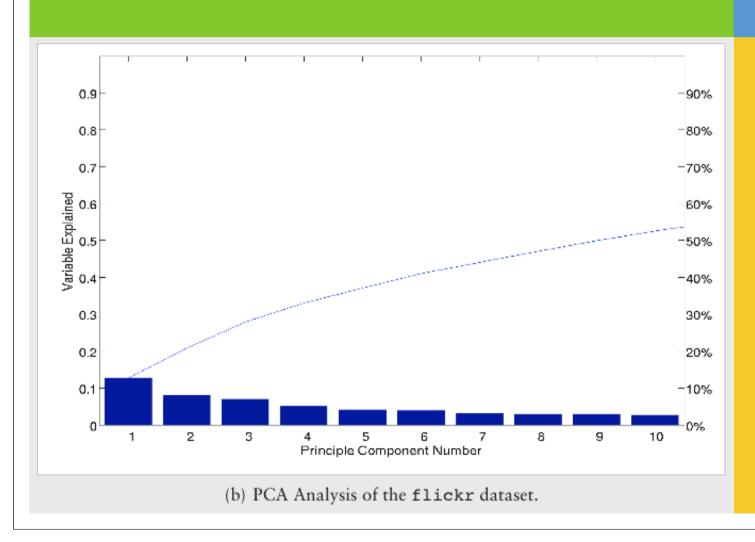


Evaluation Method

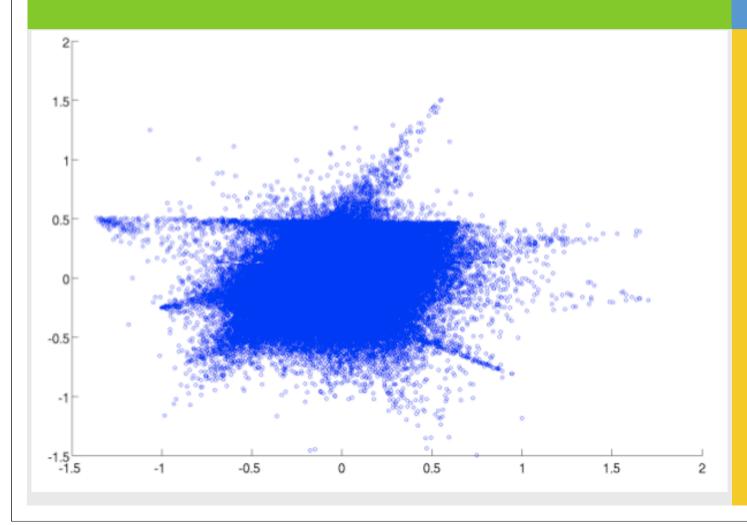
- Again, measure cosine and L2 distance distortions to features of images from:
 - The author's fotos (color histogram)
 - A flickr.com crawl of 250K images with 166 standard features: saturation, texture...etc.



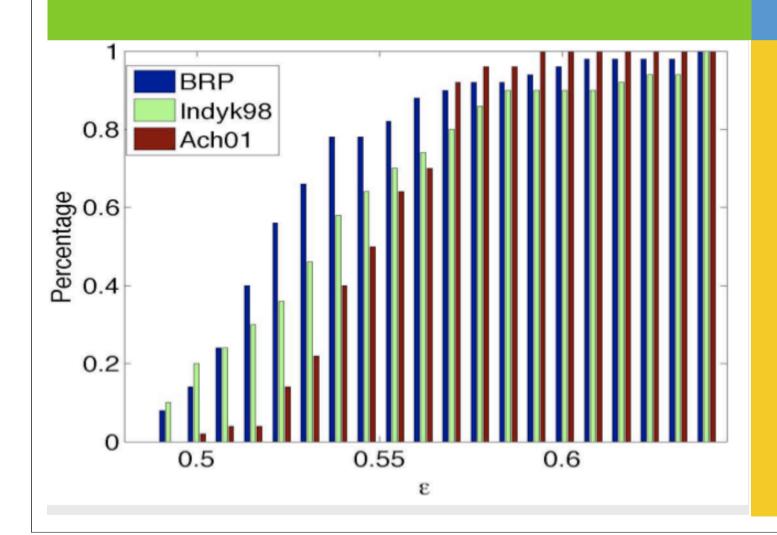
PCA of Images



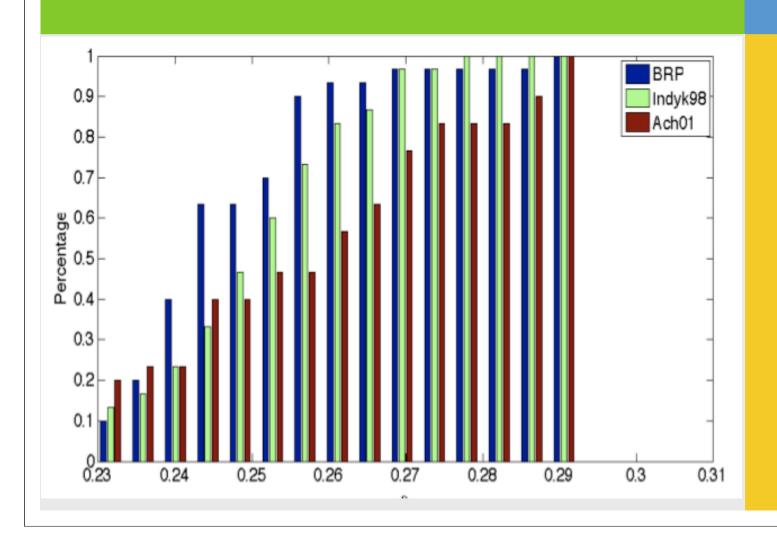
An Image of Images



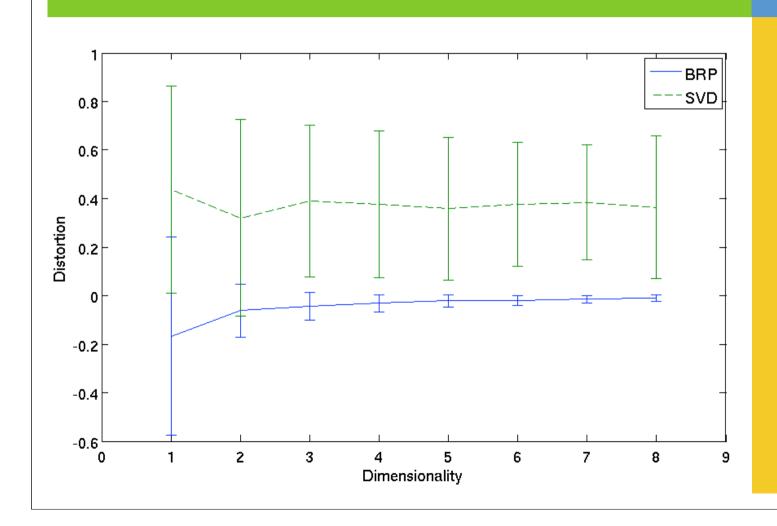
Distortion k=1



Distortion: k=5



BRP vs SVD



Conclusion

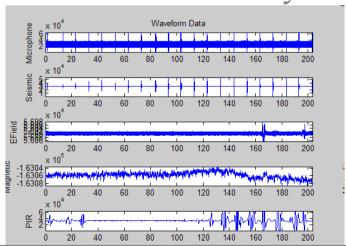
- Random projections are sharp up to L2 and cosine similarity measures
- Beta random projection
 - Picking circular ensembles from random matrices would suffice
 - consistently good performance!



Future Work

- Multi-dimensional sensory fusion
- Streaming DBs
- Curious results in computational

chemistry







Acknowledgements

Cambridge NLP group

(N1/n1_n (N1/n1_n1-coord (N1/n1 (N1/ap_n1 (AP/a1 (A1/a Natural_JJ)) (N1/n Language_NN1))) (N1/cj-end_n1 and_CC (N1/n Information_NN1))) Processing_NN11)



US-UK ITA for partly sponsoring this research

Anonymous referees for useful comments and feedbacks





Thank you! Questions?

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Introduction

