

Image Metadata Extraction

-- Drain the Data Swamp

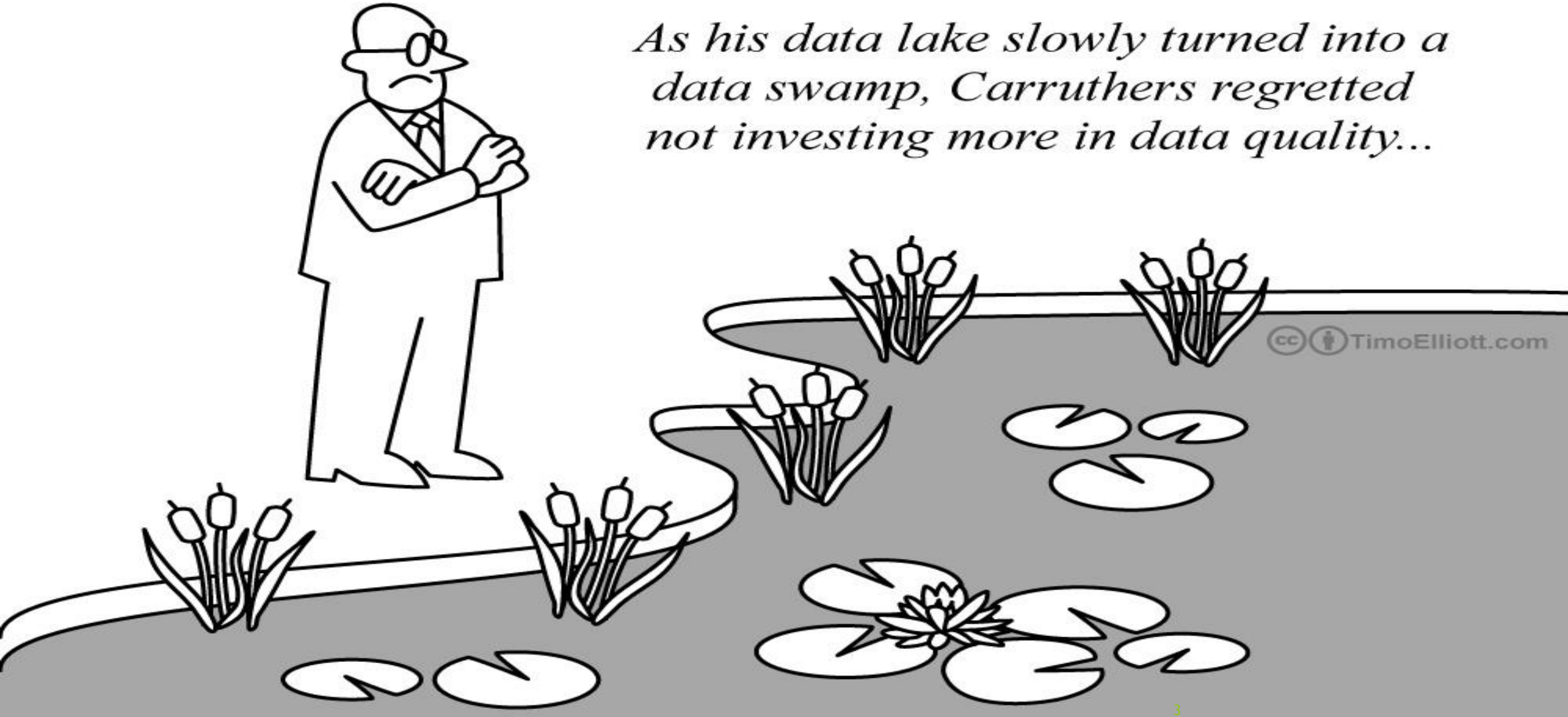
Chaofeng Wu

Advisor: Kyle Chard, Tyler J. Skluzacek, Ian Foster

Computational Institute
The University of Chicago

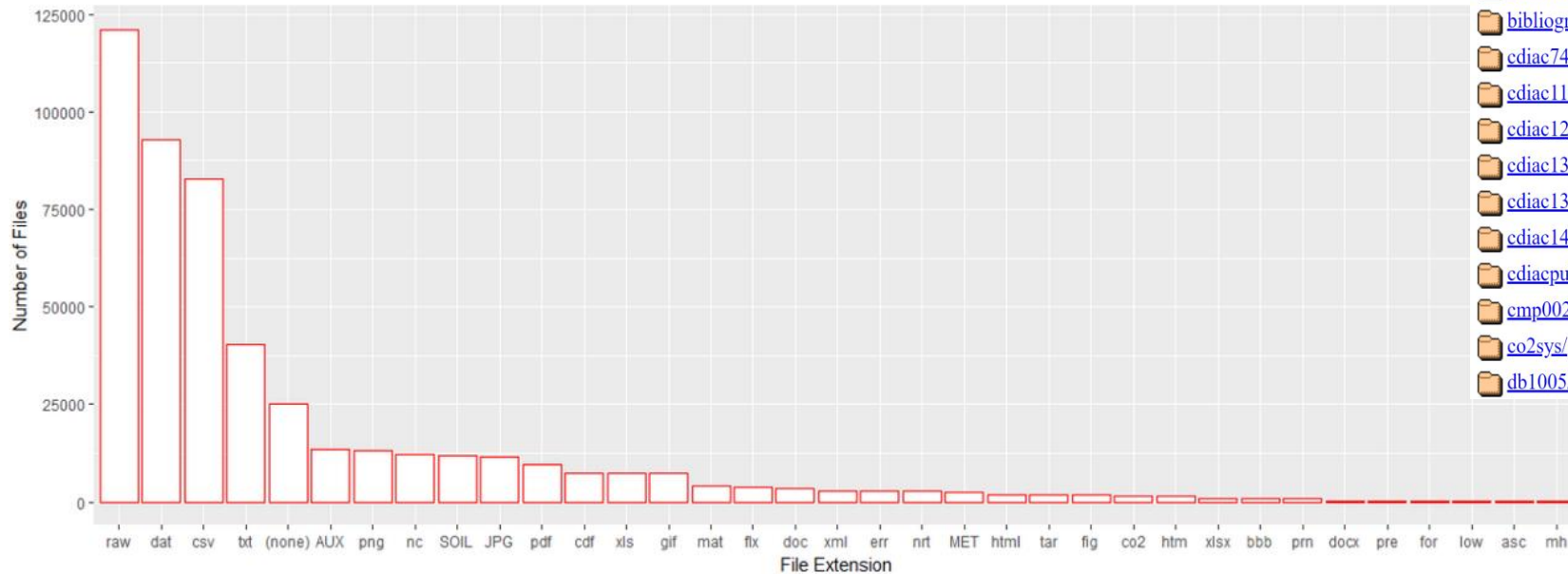
Motivation

As his data lake slowly turned into a data swamp, Carruthers regretted not investing more in data quality...



f23146.dat	06-Nov-2008 00:23 1.1M
f23205.dat	06-Nov-2008 00:23 1.7M
f23219.dat	06-Nov-2008 00:23 1.4M
f23405.dat	06-Nov-2008 00:23 2.4M
f23418.dat	06-Nov-2008 00:23 1.3M
f23472.dat	06-Nov-2008 00:23 944K
f23631.dat	06-Nov-2008 00:23 1.4M
f23711.dat	06-Nov-2008 00:23 2.5M
f23724.dat	06-Nov-2008 00:23 1.4M
f23804.dat	06-Nov-2008 00:23 2.5M
f23849.dat	06-Nov-2008 00:23 2.6M
f23884.dat	06-Nov-2008 00:23 1.4M
f23891.dat	06-Nov-2008 00:23 1.4M
f23921.dat	06-Nov-2008 00:23 1.5M
f23933.dat	06-Nov-2008 00:23 2.4M

Data in,
different formats,
different extensions,
different repositories,
with similar name



Histogram of top files on a scientific Data Lake

cdiac.ess-dive.lbl.gov/ftp/			
Name	Last modified	Size	Description
Parent Directory		-	
ALE_GAGE_AGAGE_deep_archive.tar.gz	25-May-2017 21:10	2.5G	
Atul Jain etal Land Use Fluxes/	16-Apr-2013 18:14	-	
CDIAC_UWG_Presentations_Sept2010/	30-Sep-2010 17:21	-	
CSEQ/	14-Aug-2003 20:46	-	
FACE/	23-Jan-2015 20:49	-	
GISS3-D/	19-Jul-2005 19:45	-	
Global Carbon Project/	25-May-2017 19:46	-	
HIPPO/	19-Dec-2012 21:26	-	
ICRCCM-radiative_fluxes/	04-Aug-2009 17:59	-	
Nassar Emissions Scale Factors/	18-Aug-2014 18:42	-	
README	13-Sep-2017 22:15	17K	
Smith_Rothwell_Land-Use_Change_Emissions/	01-Aug-2014 19:07	-	
Tris West US County Level Cropland C Estimates/	08-Jun-2009 17:45	-	
ale_gage_Agage/	07-Sep-2017 19:37	-	
ameriflux/	09-Mar-2017 20:39	-	
bibliography/	14-Feb-2000 21:27	-	
cdiac74/	19-Jul-2005 19:52	-	
cdiac115/	19-Jul-2005 19:48	-	
cdiac129/	19-Jul-2005 19:49	-	
cdiac130/	19-Jul-2005 19:50	-	
cdiac136/	19-Jul-2005 19:51	-	
cdiac140/	19-Jul-2005 19:51	-	
cdiacpubs/	19-Jul-2005 19:53	-	
emp002/	10-Aug-2009 16:51	-	
co2sys/	28-Oct-2013 13:50	-	
db1005/	04-Aug-2009 18:10	-	

How to deal with all the mess? - Skluma!

Text-based
files



File
metadata



Contextual
relationship

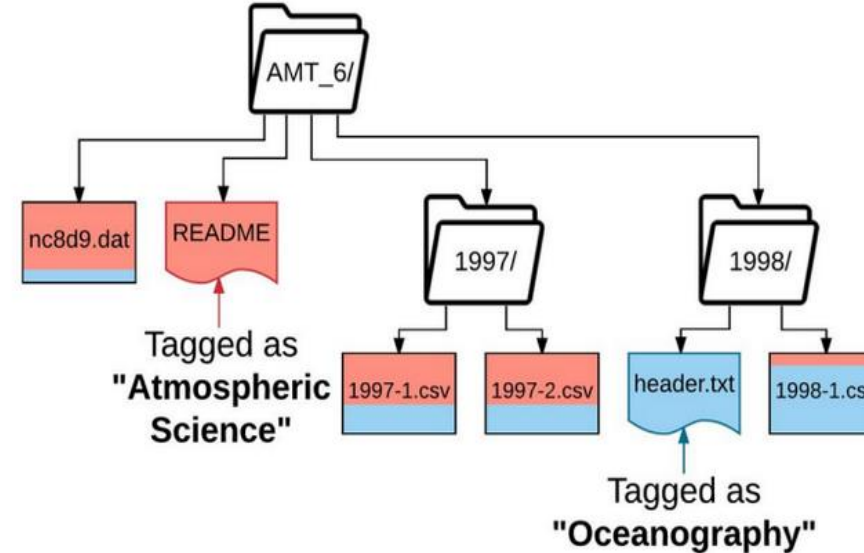


Indexed
searchable
collection

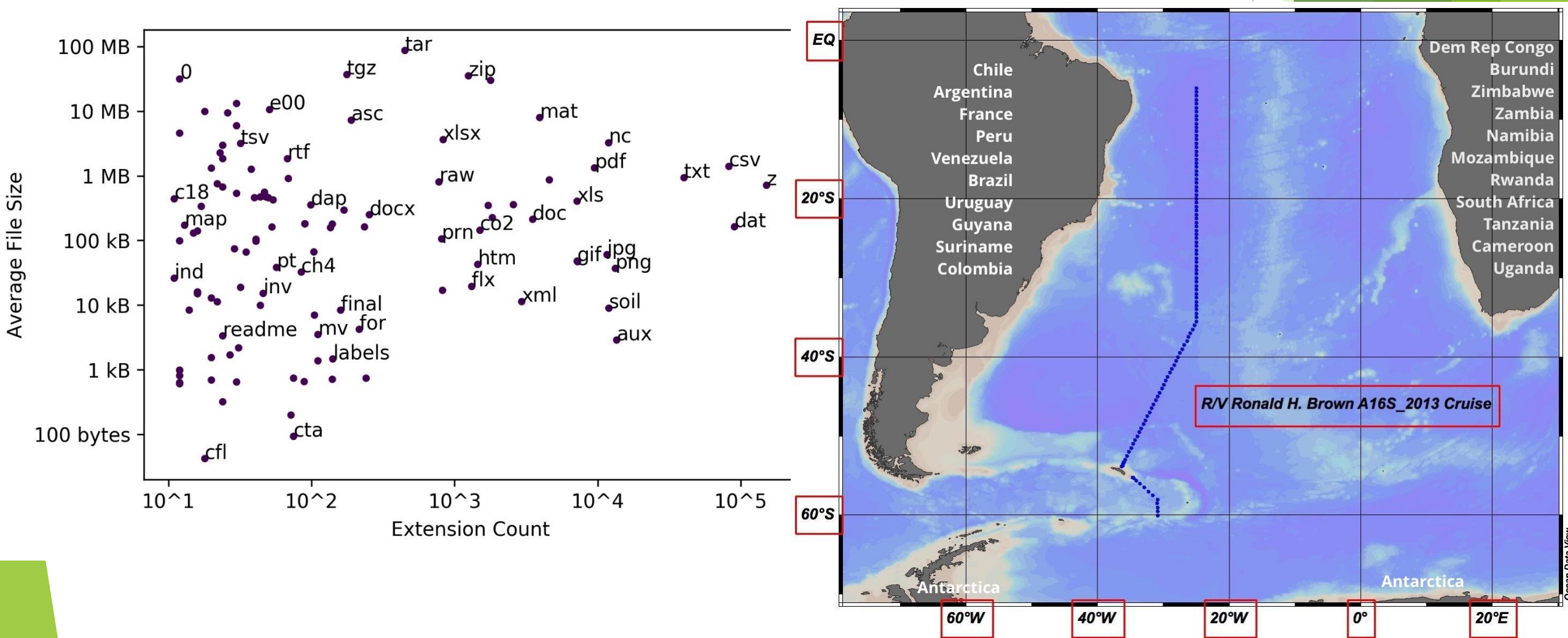
SUMMARY11.MONTHLY.ISOMASS.DAT
DOI: 10.3334/CDIAC/ffe.MonthlyIsomass.2009
All values, except year, should be zero or negative.
Units of minigrd and maxigrd are mass*del.
Units of del 13 C are per mil.

year	minigrd	maxigrd	del13C
1950	-69.75	0.00	-26.16
1951	-72.36	0.00	-26.15
1952	-71.14	0.00	-26.27
1953	-72.29	0.00	-26.33
1954	-72.61	0.00	-26.46
1955	-79.85	0.00	-26.48
1956	-81.25	0.00	-26.36
1957	-80.49	0.00	-26.51
1958	-79.62	0.00	-26.55
1959	-83.20	0.00	-26.62

CDIAC
2009
Year range
Minigrd
Maxigrd
...

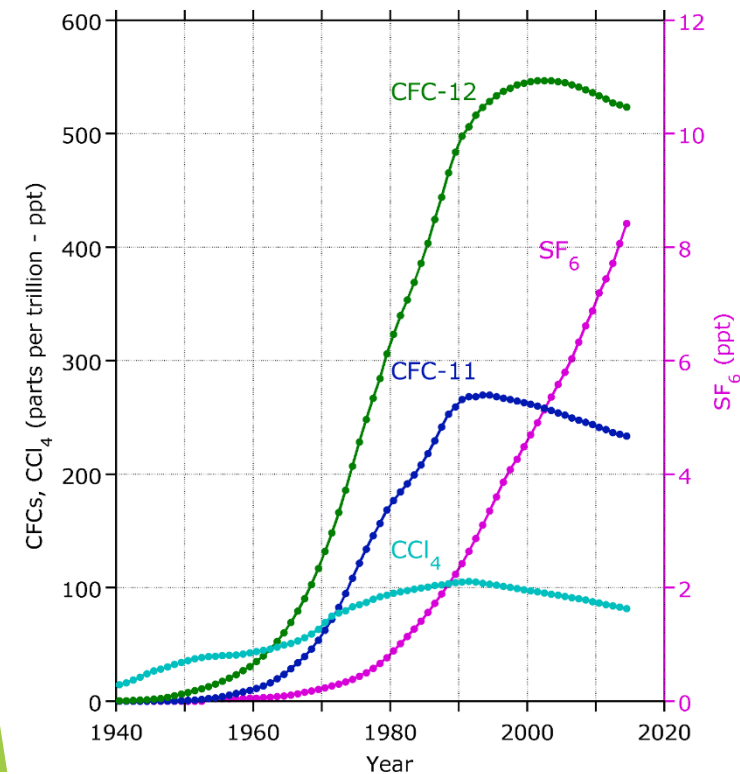


Goal: extract metadata from images

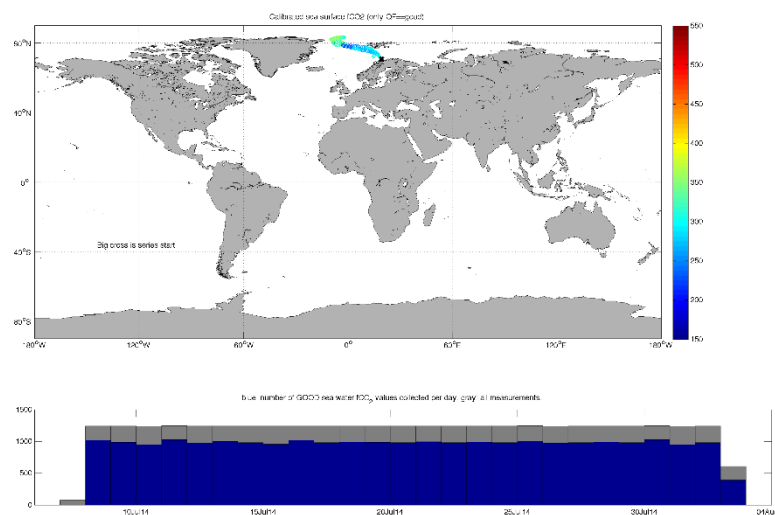
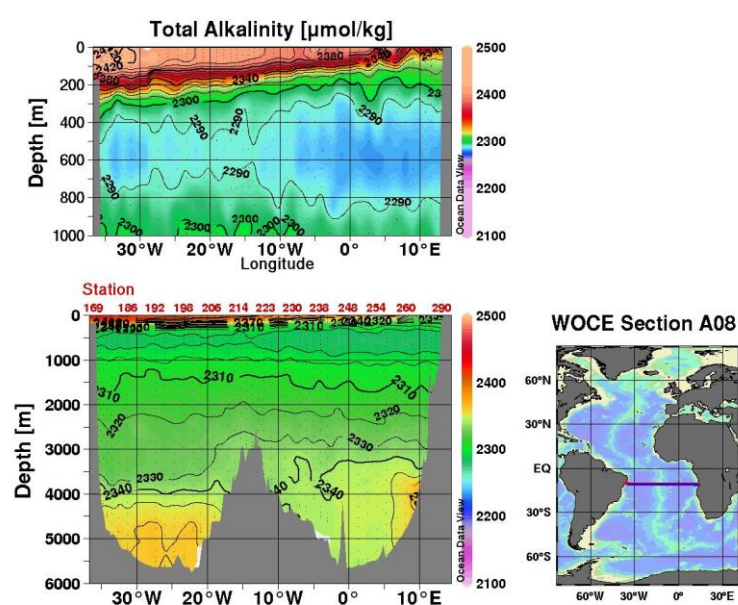
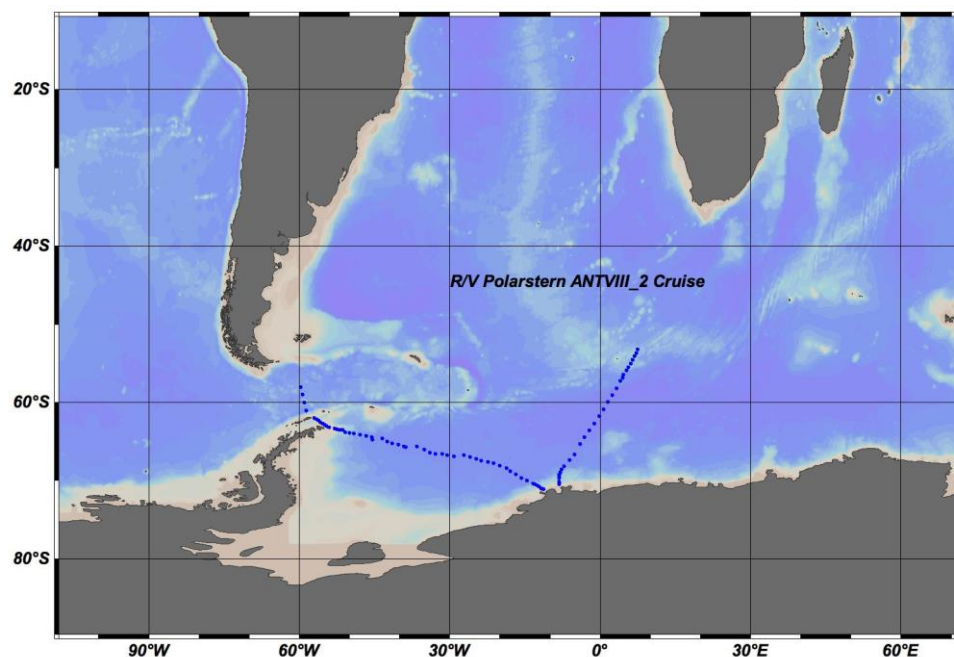
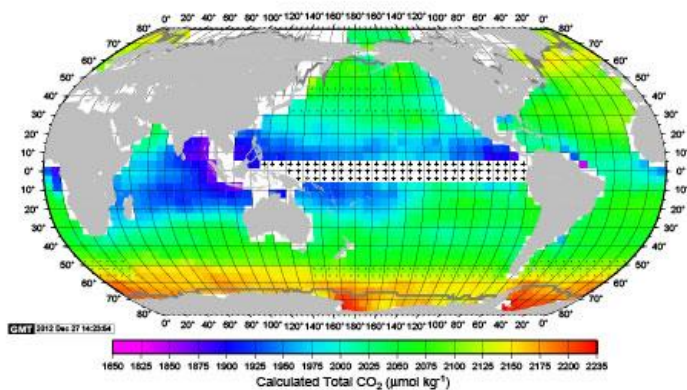


Designed Solution

Northern Hemisphere Atmospheric Concentrations: CFCs, CCl₄ and SF₆



Calculated Total CO₂ for April 2005



Metadata

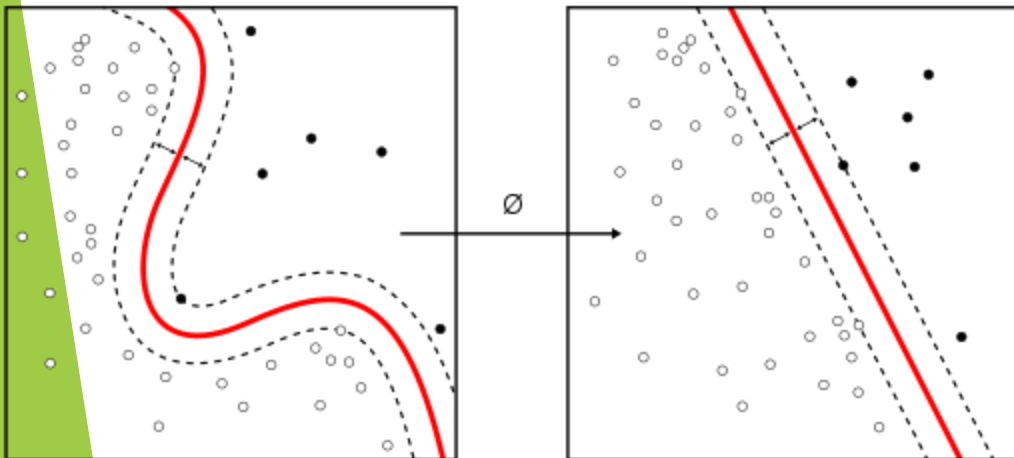
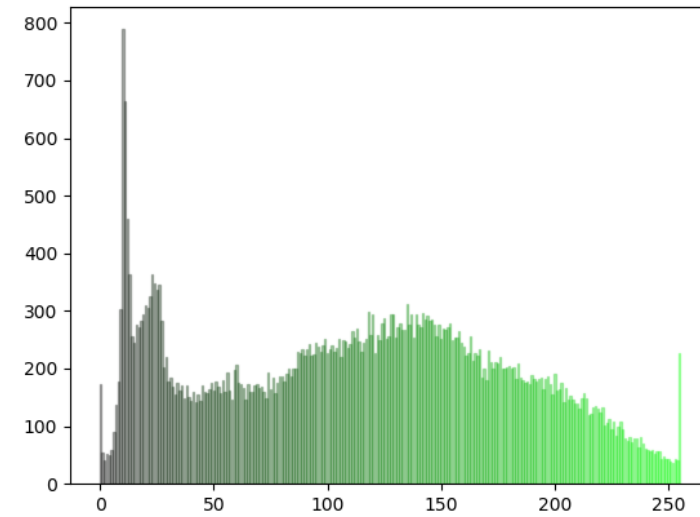
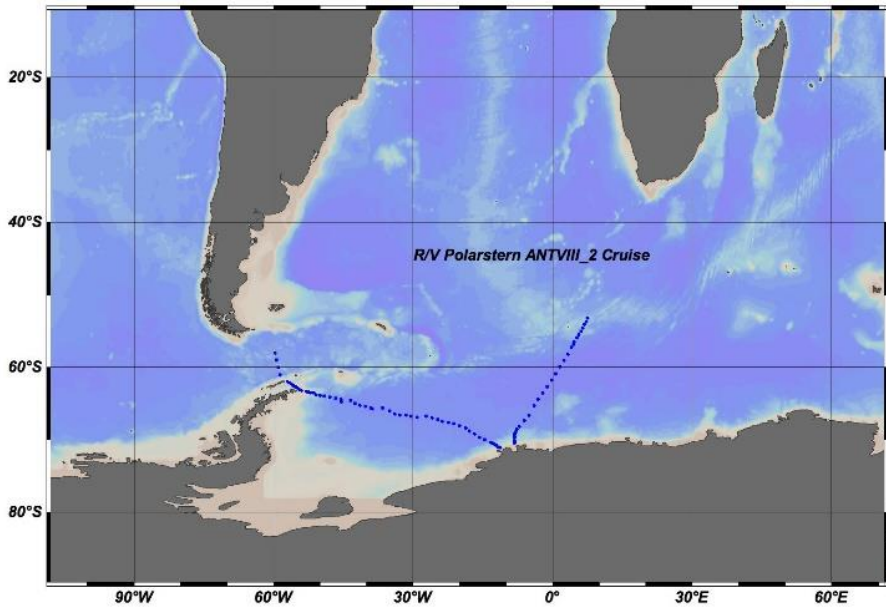
System metadata

- ▶ Image name
- ▶ Image path
- ▶ Image extension (jpg, png...)
- ▶ Image file size (KB, MB...)
- ▶ Image size (1024*768...)
- ▶ Image color mode (RGB...)

Image metadata

- ▶ A map?
- ▶ A plot?
- ▶ A figure?
- ▶ A photo?
- ▶ How to classify the image?

Process

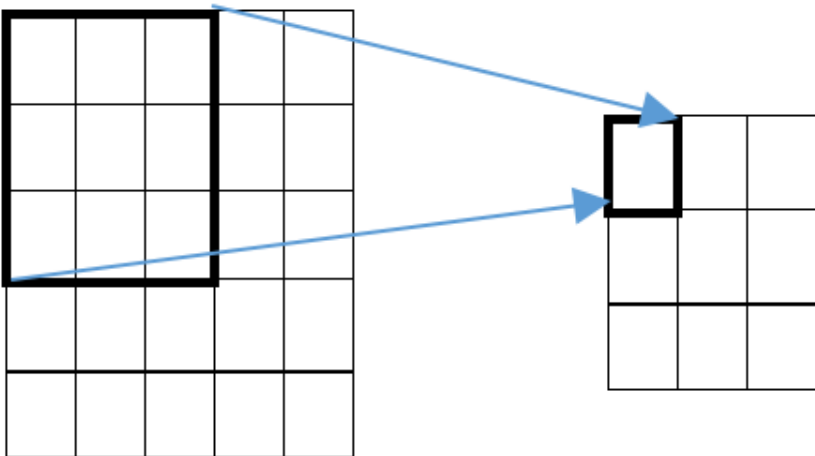


MAP

Features

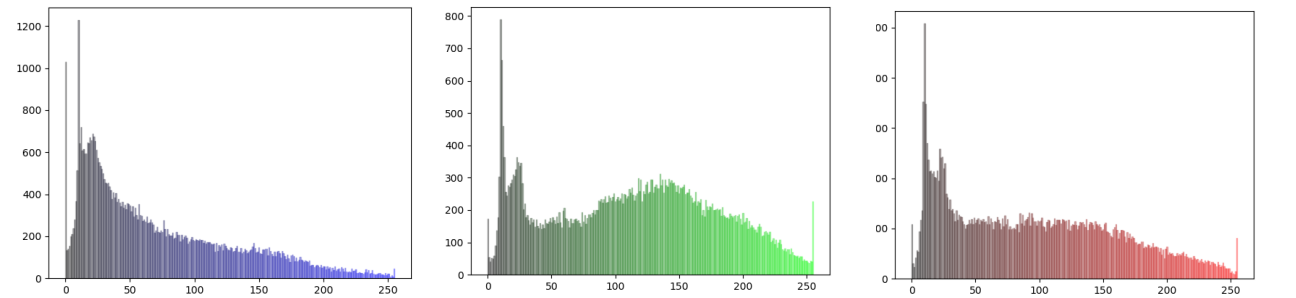
Mean square

- ▶ The average of small blocks in different part of original images
- ▶ Hope this can show some local features of image



Color histogram

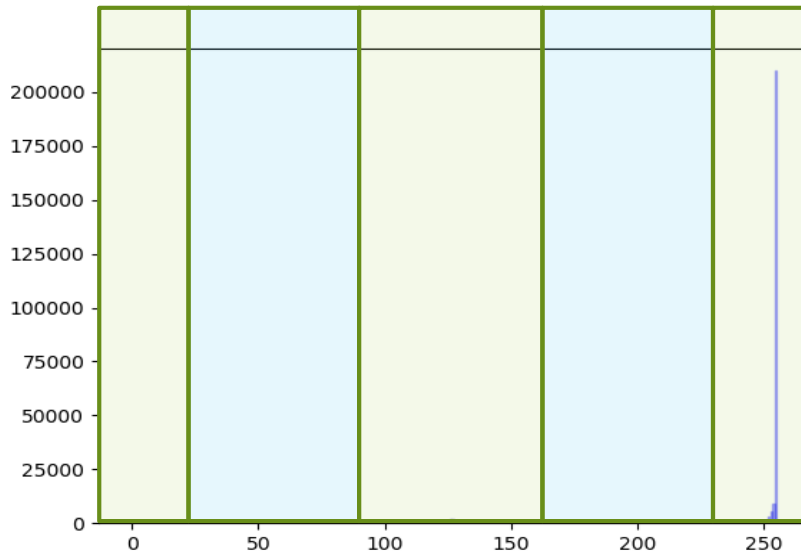
- ▶ The color frequency in the images
- ▶ Hope this can show color features of image



Reducing dimension of features

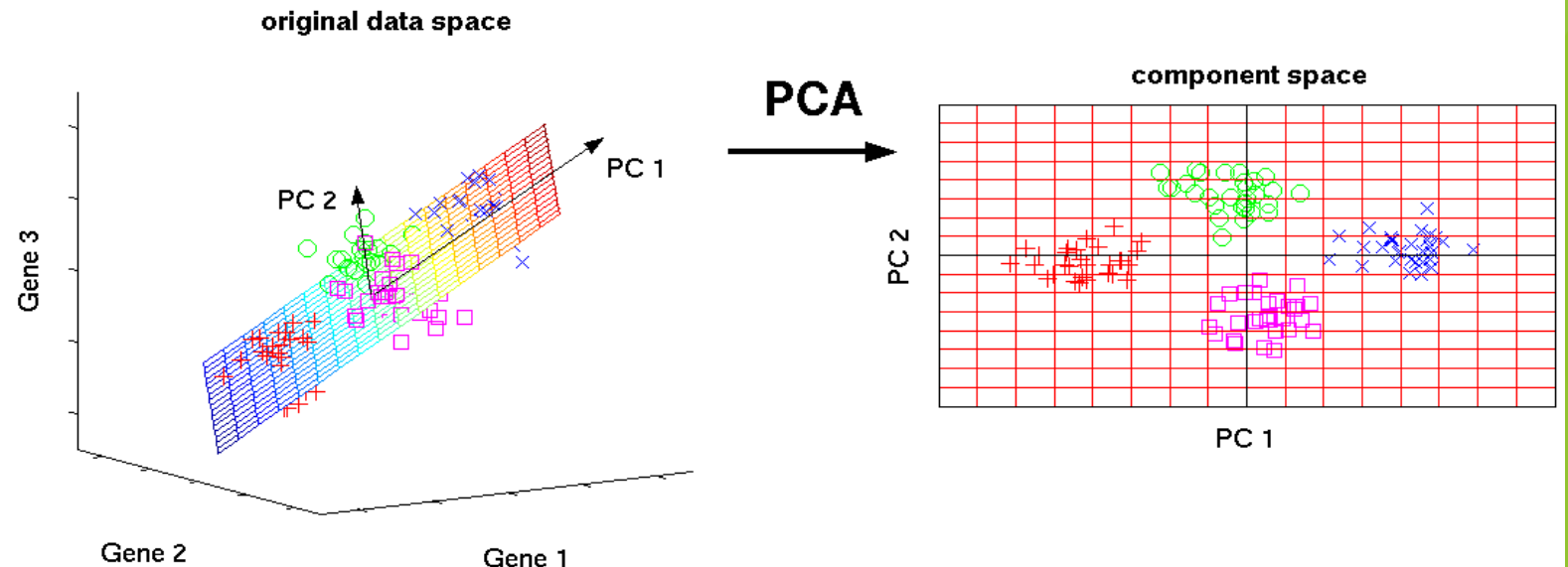
Naïve way

- ▶ Grouping color histogram in to small partitions
- ▶ Repeat the mean square for small square



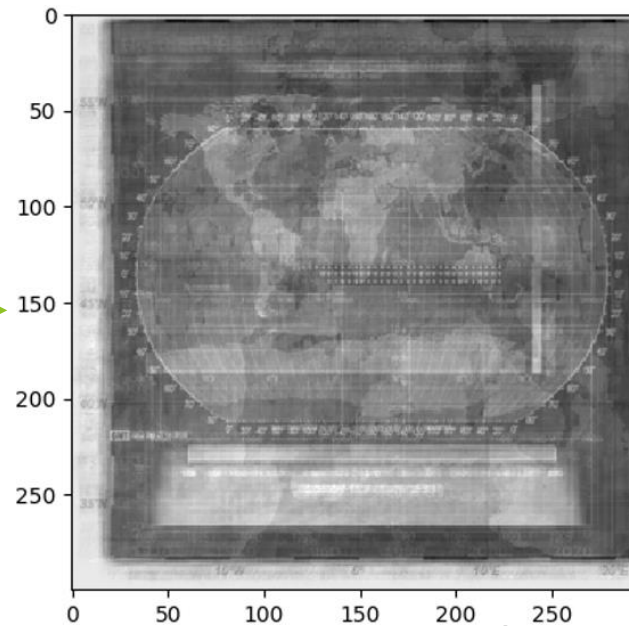
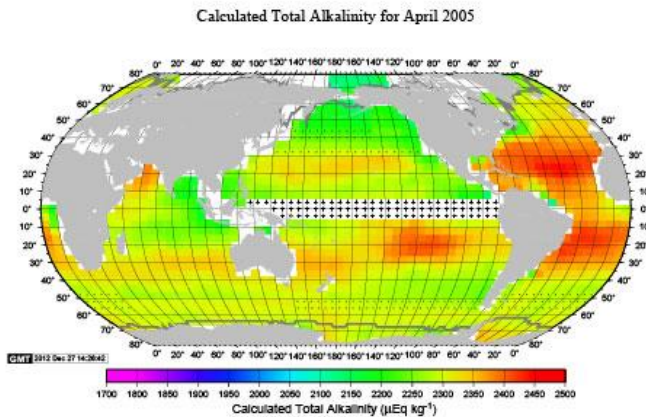
Principal Component Analysis (PCA)

- ▶ Statistical procedure to reduce dimension of variables
- ▶ Keep the variable whose variance is large in result



New feature by PCA

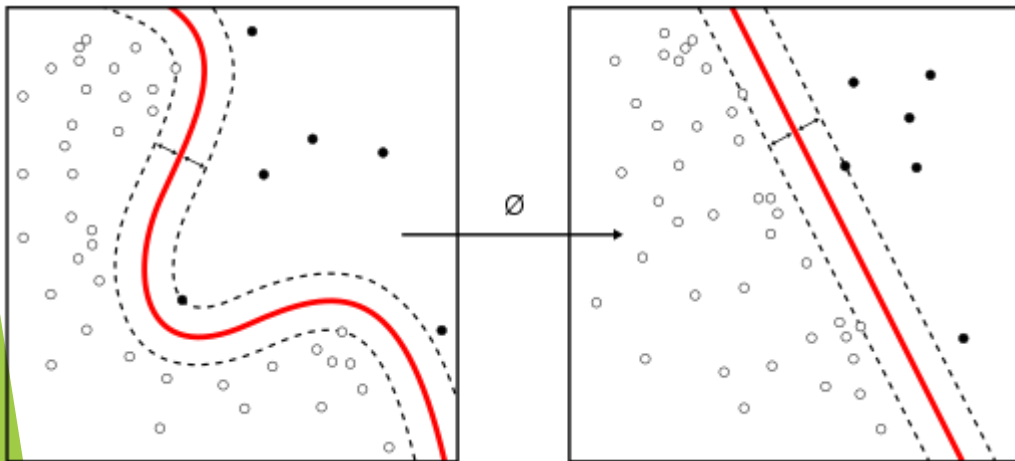
- ▶ Resized image
- ▶ Using PCA to form a basic set of images
- ▶ Using basic set to represent new images



Models

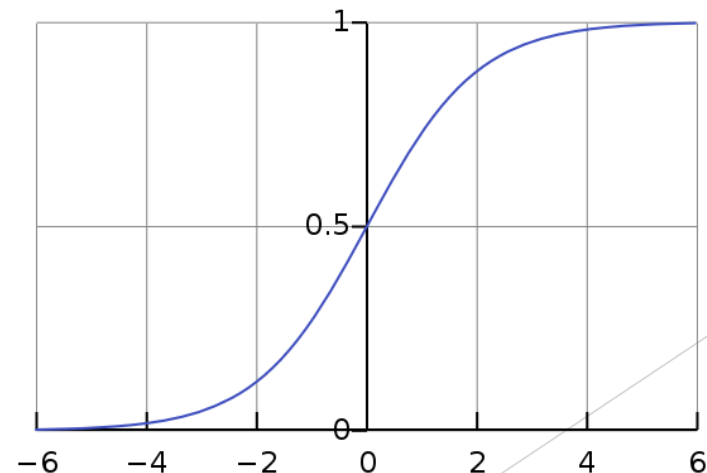
support vector machine(SVM)

- ▶ Supervised learning model used for classification and regression analysis
- ▶ SVM is applied to text categorization, image classification, and image segmentation



Logistic regression

- ▶ A classification method that generalizes logistic regression to multiclass problems
- ▶ Logistic regression models the probability of classes



Evaluation

Dataset

- ▶ Using part of data from Carbon Dioxide Information Analysis Center (CDIAC)
- ▶ Labeling 532 images, half for training and half for testing

	Gif	Png	Jpg	Bmp	Total
Number	18	64	449	1	532

	Line plot	Map	Map&chart	Map&colorplot	Map&histogram	figure
Number	51	236	105	87	49	4

Comparison of reduction methods

Comparison of naive reduction and PCA

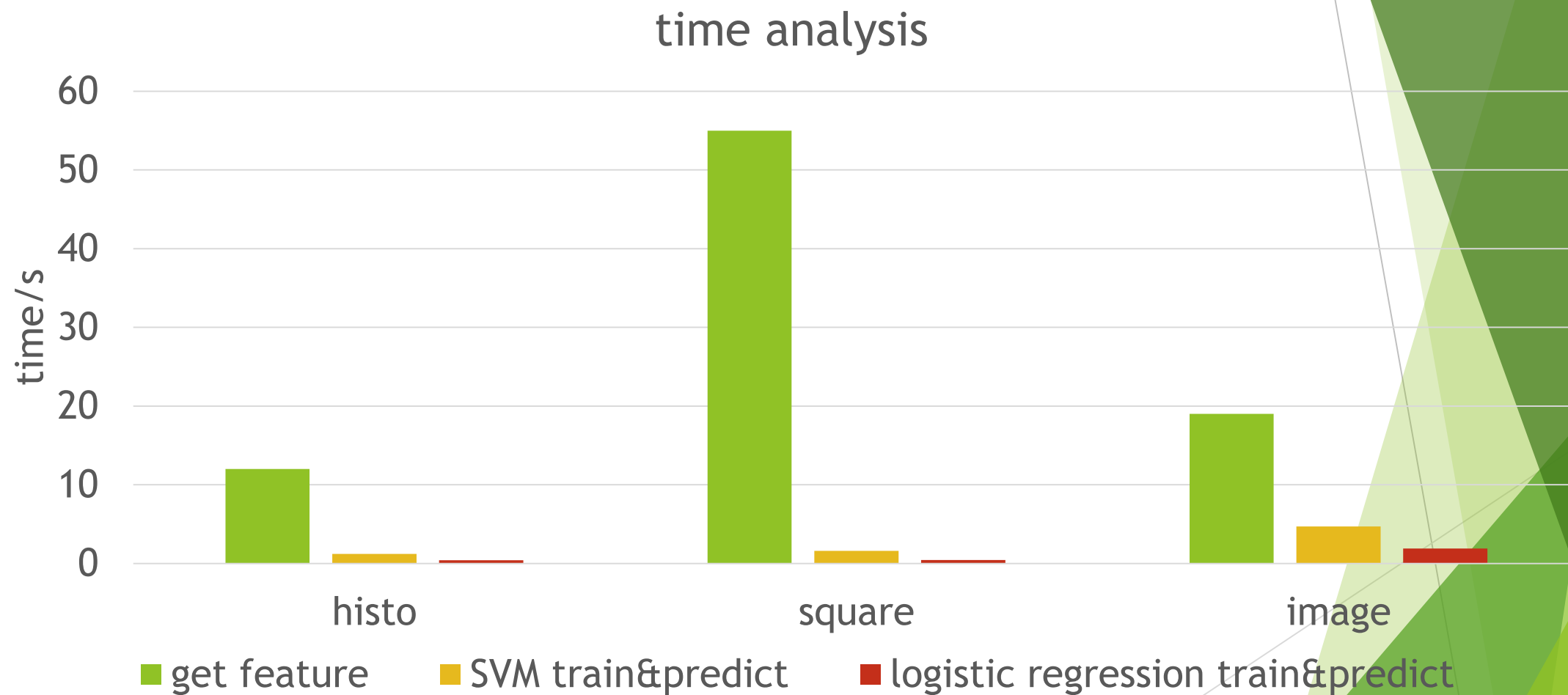


Comparison of models and features with PCA

comparison of models and features with PCA



Time analysis across models and features



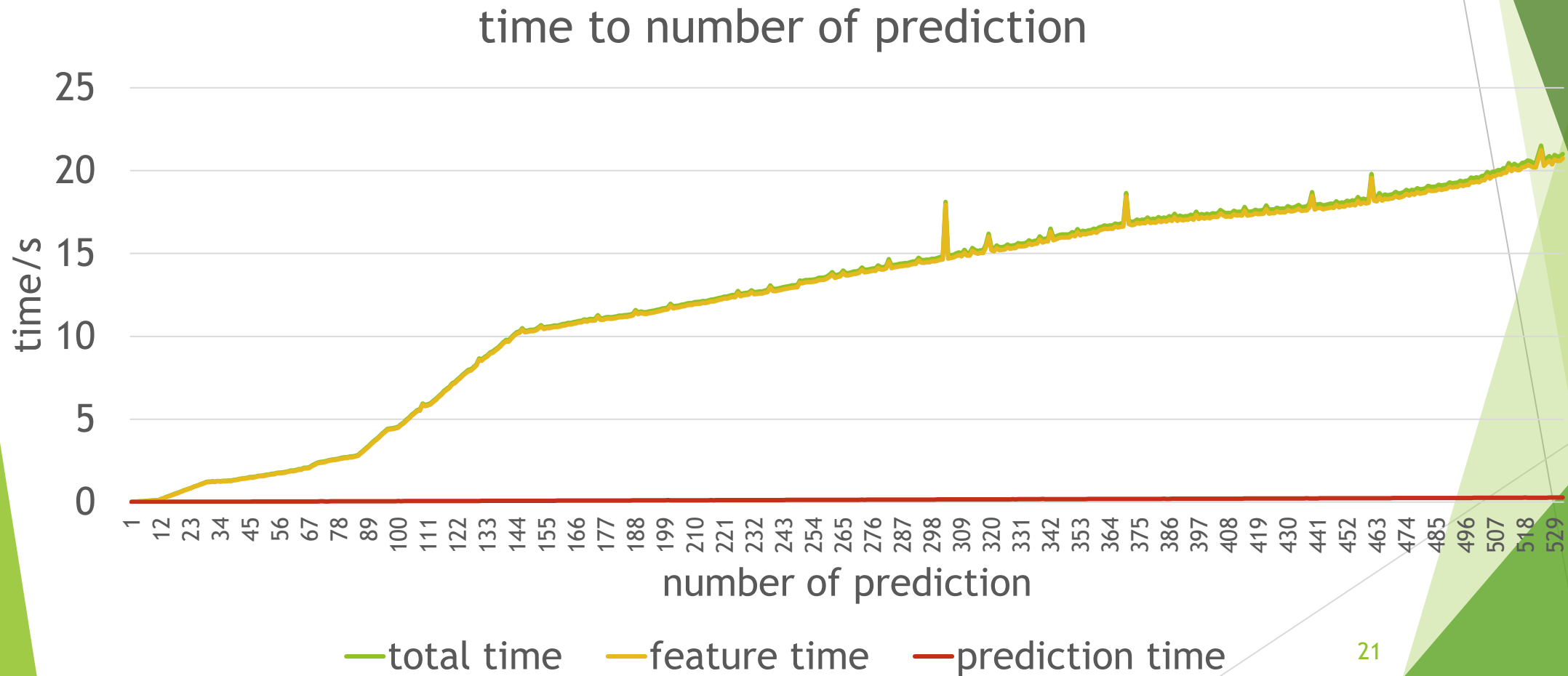
Detailed result analysis

-- logistic regression with image and PCA

	precision	recall	F-score	support
line plots	0.8947	1	0.9444	34
maps	0.9652	0.9823	0.9737	113
map&depth chart	1	1	1	44
map&colorplot	1	0.9565	0.9778	46
map&histogra m	1	1	1	25
figures	0	0	0	4

Detailed prediction time analysis

-- logistic regression with image and PCA



conclusion

- ▶ Applying PCA to get the feature can get better accuracy in image classification
- ▶ SVM and logistic regression model work well in image classification
- ▶ Future work
 - ▶ Test current model on larger dataset
 - ▶ Try convolutional layer with PCA
 - ▶ Try convolutional neural network and see performance
 - ▶ Extract more info from image

Citation

- ▶ Chapelle, O., et al. “Support vector machines for histogram-Based image classification.” *IEEE Transactions on Neural Networks*, vol. 10, no. 5, 1999, pp. 1055-1064., doi:10.1109/72.788646.
- ▶ P. Beckman, T. J. Skluzacek, K. Chard, and I. Foster, “Skluma: A statistical learning pipeline for taming unkempt data repositories,” in Proceedings of the 29th International Conference on Scientific and Statistical Database Management, SSDBM '17, (New York, NY, USA), pp. 41:1-41:4, ACM, 2017.
- ▶ U.S. Department of Energy, “Carbon dioxide information and analysis center,” 2018.
- ▶ Matthew A. Turk, Alex P. Pentland, “Face Recognition Using Eigenfaces.” MIT, IEEE 1991 <https://www.cs.ucsb.edu/~mturk/Papers/mturk-CVPR91.pdf>

Thanks!
Questions?

Eigenfaces

- ▶ Eigenfaces is the name given to a set of eigenvectors when they are used in the computer vision problem of human face recognition
- ▶ The eigenvectors are derived from the covariance matrix of the probability distribution over the high-dimensional vector space of face images
- ▶ The eigenfaces themselves form a basis set of all images used to construct the covariance matrix
- ▶ This produces dimension reduction by allowing the smaller set of basis images to represent the original training images
- ▶ Classification can be achieved by comparing how faces are represented by the basis set

Curse of dimensionality

- ▶ The curse of dimensionality refers to various phenomena that arise when analyzing and organizing data in high-dimensional spaces (often with hundreds or thousands of dimensions) that do not occur in low-dimensional settings such as the three-dimensional physical space of everyday experience
- ▶ In machine learning problems that involve learning a "state-of-nature" from a finite number of data samples in a high-dimensional feature space with each feature having a range of possible values, typically an enormous amount of training data is required to ensure that there are several samples with each combination of values
- ▶ A typical rule of thumb is that there should be at least 5 training examples for each dimension in the representation. With a fixed number of training samples, the predictive power of a classifier or regressor first increases as number of dimensions/features used is increased but then decreases, which is known as Hughes phenomenon or peaking phenomena