

Inference and Representation

Lecture 5

Joan Bruna
Courant Institute, NYU



Lecture 4 Reminder

- Approximate Sampling is the only viable strategy on large, complicated graphical models.
- We saw two techniques:
 - Monte-Carlo methods.
 - Gibbs Sampling (also covered in PS4).

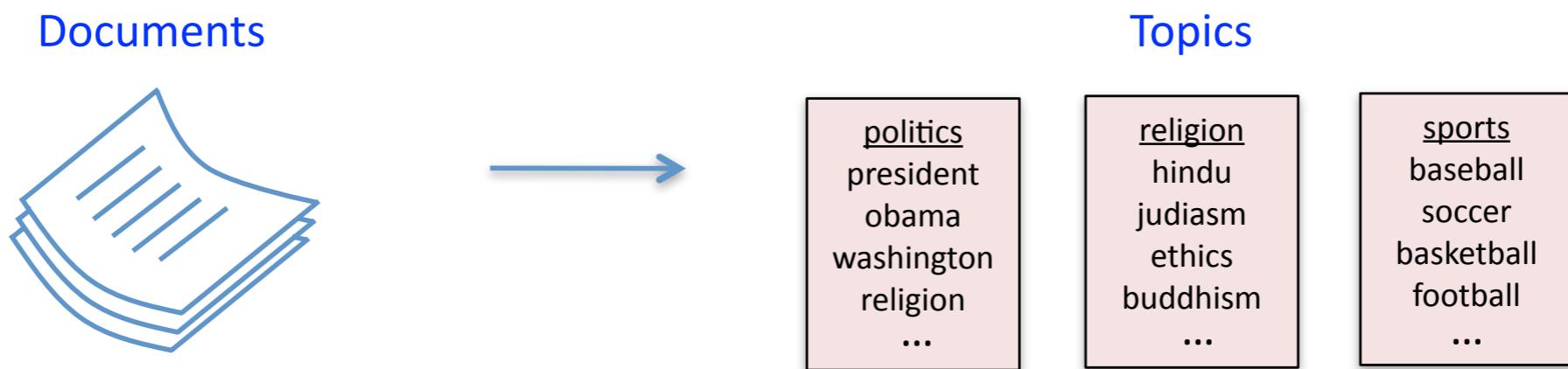
Reminder: Gibbs Sampler

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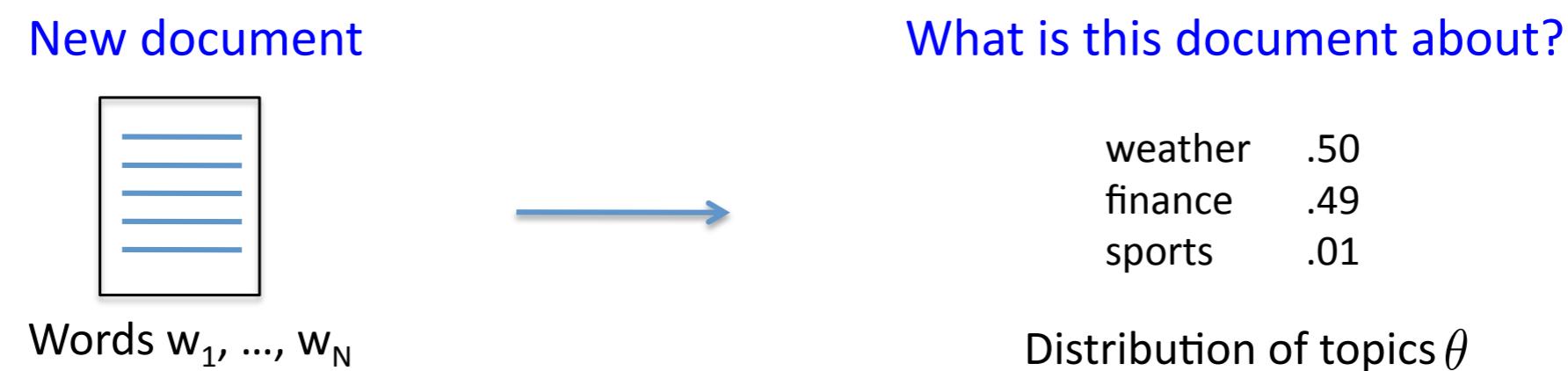
- The GS algorithm:
 1. Suppose the graphical model contains variables x_1, \dots, x_n
 2. Initialize starting values for x_1, \dots, x_n
 3. Do until convergence:
 1. Pick an ordering of the n variables (can be fixed or random)
 2. For each variable x_i in order:
 1. Sample $x \sim P(x_i | x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$, i.e. the conditional distribution of x_i given the current values of all other variables
 2. Update $x_i \leftarrow x$
 - When we update x_i , we immediately use its new value for sampling other variables x_j

Reminder: Topic Modeling

- **Topic models** are powerful tools for exploring large data sets and for making inferences about the content of documents



- Many applications in information retrieval, document summarization, and classification



- LDA is one of the simplest and most widely used topic models

Reminder: Latent Dirichlet Allocation

- 1 Sample the document's **topic distribution** θ (aka topic vector)

$$\theta \sim \text{Dirichlet}(\alpha_{1:T})$$

where the $\{\alpha_t\}_{t=1}^T$ are fixed hyperparameters. Thus θ is a distribution over T topics with mean $\theta_t = \alpha_t / \sum_{t'} \alpha_{t'}$

- 2 For $i = 1$ to N , sample the **topic** z_i of the i 'th word

$$z_i | \theta \sim \theta$$

- 3 ... and then sample the actual **word** w_i from the z_i 'th topic

$$w_i | z_i \sim \beta_{z_i}$$

where $\{\beta_t\}_{t=1}^T$ are the *topics* (a fixed collection of distributions on words)

Reminder: LDA

Topics

gene	0.04
dna	0.02
genetic	0.01
...	

life	0.02
evolve	0.01
organism	0.01
...	

brain	0.04
neuron	0.02
nerve	0.01
...	

data	0.02
number	0.02
computer	0.01
...	

Documents

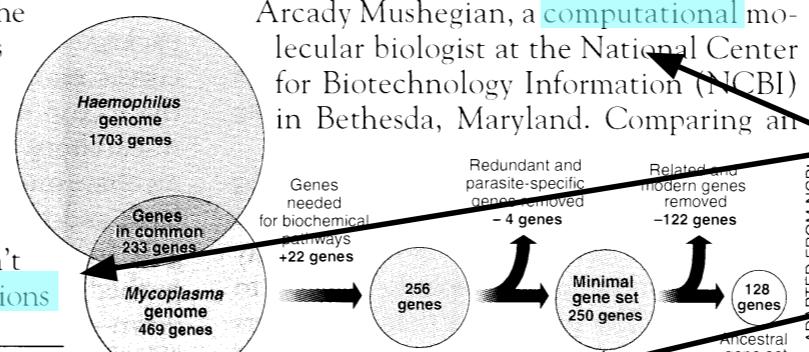
Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

"are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

Topic proportions and assignments

z_{1d}

θ_d

z_{Nd}

(Blei, *Introduction to Probabilistic Topic Models*, 2011)

Lecture 5 Objectives

- Modeling Survey Data
- Factor Analysis
 - Principal Component Analysis
 - Independent Component Analysis
- Gaussian Mixture Models
- The Expectation-Maximization (EM) algorithm

Survey Data

- How are these statements inferred?



Politics Sports Science & Health Economics Culture

MAY 3, 2016 AT 2:45 PM

The Mythology Of Trump's 'Working Class' Support

His voters are better off economically compared with most Americans.

By Matt Silver

Filed under [2016 Election](#)



Politics Sports Science & Health Economics Culture

MAR 14, 2016 AT 6:02 AM

What Trump Supporters Were Doing Before Trump

By Dan Hopkins

Filed under [2016 Election](#)



JUNE 2, 2016



★ [Election 2016](#) ▾

More 'warmth' for Trump among GOP voters concerned by immigrants, diversity

BY BRADLEY JONES AND JOCELYN KILEY | 10 COMMENTS

Survey Data

- We typically see these sort of data

How the GOP candidates' supporters differed on issues

POSITION	YEAR	STANCE OF SUPPORTERS		
		TRUMP	CRUZ	RUBIO
Raise taxes on rich	2007	0.25	0.24	0.27
Pro-gay marriage	2007	0.31	0.20	0.28
Conservative ideology	2007	0.64	0.76	0.67
Pro-choice	2007	0.63	0.39	0.42
Stay in Iraq	2007	0.62	0.81	0.87
Hawk (vs. dove)	2008	0.68	0.57	0.52
No special help for blacks	2012	0.88	0.82	0.80
Obama rating	2012	0.21	0.17	0.20
Anti-Obamacare	2012	0.76	0.82	0.80
Very critical of system	2012	0.70	0.64	0.62
Pro-government spending	2012	0.20	0.15	0.15
Create pathway to citizenship	2012	0.21	0.29	0.37
Anti-Hispanic prejudice	2012	0.53	0.50	0.49
Anti-black prejudice	2012	0.58	0.54	0.55
Pro-NAFTA	2012	0.40	0.50	0.52

Stance on a position ranges from 0-1, with 0 being totally against and 1 being totally in agreement with

SOURCE: HOPKINS/MUTZ

Share of Republican electorate with household income below \$50,000

STATE	2012	2016
Alabama	37%	41%
Florida	34	35
Georgia	24	26
Illinois	28	23
Maryland	19	19
Massachusetts	24	20
Michigan	35	37
Mississippi	36	37
New Hampshire	26	27
Ohio	32	30
Oklahoma	41	30
South Carolina	36	27
Tennessee	35	33
Vermont	37	30
Virginia	25	19
Wisconsin	32	20
Average	31	29

SOURCE: EDISON RESEARCH EXIT POLLS

Within GOP, views of immigration, Islam, diversity strongly associated with ratings of Trump

% of Republican and Republican-leaning registered voters who rate Trump on a feeling thermometer from 0 (coldest rating) to 100 (warmest rating) ...

■ Very cold ■ Somewhat cold ■ Neutral ■ Somewhat warm ■ Very warm

All Rep/Rep-leaning voters	23	11	12	17	36
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Among those who say ...

Growing number of newcomers from other countries ...

Threatens U.S. values (77%)	16	11	11	18	42
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Strengthens U.S. society (21%)

42	13	13	15	14
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The Islamic religion is ...

More likely than others to encourage violence (77%)

19	12	11	18	38
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No more likely to encourage violence (20%)

37	8	16	11	25
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According to census, in 30 years U.S. pop. will be majority black, Latino & Asian. This is ...

Bad for the country (39%)

15	11	10	18	47
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Good/Neither good nor bad for the country (61%)

28	12	13	18	28
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Feeling thermometer ratings: Very cold (zero to 24), somewhat cold (25-49), neutral (50), somewhat warm (51-75), very warm (76-100).

Source: Survey conducted April 5-May 2, 2016

PEW RESEARCH CENTER

Survey Data: other prime example

- Medical surveys
 - Children's Depression Inventory [3]
 - 27 items scored 0,1,2 assessing aspects of depressive symptoms for children and adolescents
 - 1 total scale
 - sum of the 27 items after reverse coding 13 of them
 - higher scores indicate higher depressive symptom levels
 - 5 subscales measuring different aspects of depressive symptoms
 - negative mood, interpretation problems, ineffectiveness, anhedonia, and negative self-esteem
 - the total scale equals the sum of the subscales
 - total scale used in practice rather than subscales
- Financial Markets
- EEG recordings

(credit: G. Knafl, ohsu)

Factor Analysis for Survey Data

- **Goal:** extract interpretable, summary information out of a series of correlated survey responses.
- Factor Analysis refers to a series of statistical techniques to achieve that.
- That is, given answers x_1, \dots, x_L to L questions, infer latent variables (=factors) that explain the underlying phenomena under study.

Principal Component Analysis

- We start with the simplest setting: suppose that

$$X_l = \sum_{j=1}^J \alpha_{j,l} Y_j , \quad l = 1 \dots L .$$

with $Y_1 \dots J$ iid and $X_1 \dots L$ jointly Gaussian.

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- Observation 2:

If $\mathbf{Y} = (Y_1, \dots, Y_J)$ is jointly Gaussian,
 Y_i, Y_j independent $\Leftrightarrow Y_i, Y_j$ decorrelated.

Principal Component Analysis

- We define $\mu_X = \mathbb{E}(X)$, $\Sigma_X = \mathbb{E}\{(X - \mu_X)(X - \mu_X)^T\}$.
- **Reminder:** Let $\mathbf{Y} = A\mathbf{X} + b$. Then
 - $\mu_Y = A\mu_X + b$.
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 - $\mu_Y = A\mu_X + b$.
 - $\Sigma_Y = A\Sigma_X A^T$.
- In our previous model, if $A_{l,j} = \alpha_{l,j}$, we have $\mathbf{X} = A\mathbf{Y}$.
- Hence $\Sigma_Y = A\Sigma_X A^T$.
- Q: How to find A such that $A\Sigma_X A^T$ defines an uncorrelated random vector?

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Reminder: [Real Spectral Theorem]: If $A \in \mathbb{R}^{n \times n}$ is symmetric and positive semidefinite ($A \succ 0$), then A diagonalizes in a real orthonormal basis with non-negative eigenvalues.

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Therefore, Σ_X admits a real eigenbasis:

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Thus $U^T \Sigma_X U = \Lambda$.

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Moreover, we can write $\Lambda = S \cdot S$, with $s_{i,i} = \sqrt{\lambda_i}$.
If $\min_i \lambda_i > 0$, it results that $\tilde{U} = US^{-1}$ satisfies $\tilde{U}^T \Sigma_X \tilde{U} = 1$.

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- We have just shown that $\mathbf{Y} = \tilde{U}(\mathbf{X} - \mu_{\mathbf{X}})$ provides variables that are uncorrelated and jointly Gaussian, thus independent.

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- Remarks
 - The decomposition is not unique: Any orthogonal transformation of \mathbf{Y} also satisfies the same property.
 - PCA provides linear compression: if $J < \text{rank}(\Sigma_{\mathbf{X}})$, what is the best linear approximation of \mathbf{X} with J independent components?

$$\min_{A \in \mathbb{R}^{L \times J}} \mathbb{E}(\|X - AX\|^2) .$$

$A = \{ \text{eigenvectors of } \Sigma_{\mathbf{X}} \text{ corresponding to } J \text{ largest eigenvalues.}\}$
(again, A is determined up to an orthogonal transformation)

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- In practice, we will observe x_1, \dots, x_N iid samples of X
- Empirical Covariance:

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- $\hat{\Sigma}_N$ is symmetric, positive definite. (why?)
- Estimated Principal Components:

$$\hat{\Sigma}_N = \hat{U} \hat{\Lambda} \hat{U}^T .$$

Estimating the Principal Components

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$$\|\hat{\Sigma}_N - \Sigma\| \lesssim O(\log \log N)^2 \left(\frac{N}{L}\right)^{1/2-2/q}.$$
- It results that for a desired approximation $\|\hat{\Sigma}_N - \Sigma\| \leq \epsilon$ we need $O((\log \log L)^\alpha L) \approx O(L)$ samples.
- **Very Important Consequence: PCA does not suffer from the curse of dimensionality!**

Estimating Principal Components

- Q: What is the computational complexity of computing PCA?
 - Naïve estimation of covariance: $O(NL^2)$
 - Diagonalizing covariance: $O(L^3)$
 - So, in big data applications we are doomed.

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- Reminder: Given a data matrix, the principal components are directly given by

The **Singular Value Decomposition** (SVD) of $B \in \mathbb{R}^{n \times p}$ is defined as $B = U\Lambda V^T$, with

$$U \in \mathbb{R}^{n \times n}, V \in \mathbb{R}^{p \times p}, \Lambda = \text{diag}(\lambda_1, \dots, \lambda_{\min(n,p)}),$$

$$UU^T = \mathbf{1}, V^TV = \mathbf{1}.$$

Computing the first p principal components costs $O(pNL)$.

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- Alternatives?

Interlude: Randomized PCA

- Suppose we suspect that the data matrix $\mathbf{X} \in \mathbb{R}^{N \times L}$ has rank $p \ll \min(N, L)$.
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- Q: Can we leverage that prior into a faster algorithm?
- **Idea:** Break the estimation into two steps:
 1. Compute an approximate basis for the range of \mathbf{X} :
$$\mathbf{X} \approx \mathbf{Q}\mathbf{Q}^T\mathbf{X}, \text{ with } \mathbf{Q} \in \mathbb{R}^{N \times n}, n \ll N, \mathbf{Q}^T\mathbf{Q} = \mathbf{I}.$$
 2. Form $\mathbf{B} = \mathbf{Q}^T\mathbf{X} \in \mathbb{R}^{n \times L}$ and compute its SVD: $\mathbf{B} = \tilde{\mathbf{U}}\Lambda\mathbf{V}^T$.
 3. Set $\mathbf{U} = \mathbf{Q}\tilde{\mathbf{U}}$.
- How to solve stage 1?

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 3. Set $\mathbf{U} = \mathbf{Q}\tilde{\mathbf{U}}$.
- How to solve stage 1? Randomize!!

Interlude: Randomized PCA

- If we target a rank- k approximation, we simply draw a random matrix $\Omega \in \mathbb{R}^{L \times (k+p)}$, form the matrix $Y = X\Omega \in \mathbb{R}^{N \times (k+p)}$, and perform a SVD of Y : $Y = V\Lambda Q^T$.

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- Strong guarantees from concentration of measure:

Theorem: [Halko, Martinsson, Tropp] Given data matrix $X \in \mathbb{R}^{N \times L}$ and $\Omega \in \mathbb{R}^{L \times (k+p)}$ drawn from iid standard Gaussian, the resulting Q satisfies

$$\|X - QQ^T X\| \leq \left(1 + C\sqrt{(k+p) \min(N, L)}\right) \lambda_{k+1},$$

whp, where λ_{k+1} is the $k+1$ -th singular value of X .

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whp, where λ_{k+1} is the $k+1$ -th singular value of X .

- Resulting computational gains:

from $O(NLk)$ to $O(NL \log(k))$ for k ppal components.

Factor Analysis

- We have seen that PCA can be interpreted as a linear latent model:

$$X_i = \sum_j \alpha_{i,j} Y_j + \mu_i , \quad (i = 1, \dots, L) ,$$

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- Lack of unicity: given an $L \times L$ orthogonal matrix R , we also have

$$X = \mu + AR^T RY = \mu + \tilde{A}\tilde{Y} ,$$

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- Also, an underlying assumption is that data has *low-rank*, i.e. covariance directly reveals dependencies in data.

Factor Analysis

- An alternative to PCA is *Factor Analysis*. Suppose a generative model of the form

$$X_i = \sum_{j \leq J} \alpha_{i,j} Y_j + \mu_i + \epsilon_i , \quad (i = 1, \dots, L) ,$$

with $J < L$ and ϵ_i uncorrelated, zero-mean.

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- Interpretation:
 - Latent variables Y_j are common factors of variability.
 - Latent variables ϵ_i explain the remaining individual variability, uncorrelated from the rest.
- Example:
 - Factor analysis on the topics of your final project.

Factor Analysis

- Gaussian joint likelihood model:

$$X \sim \mathcal{N}(\mu, AA^T + \text{diag}(\beta))$$

- with $\beta_i = \text{Var}(\epsilon_i)$.
- Parameter Estimation? The covariance is a sufficient statistic:

$$\Sigma_X = AA^T + \text{diag}(\beta) .$$

↑
low rank

- SVD is still useful, but does not automatically yield the solution.
- We will soon see an alternative estimation algorithm.

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- We have seen that in the Gaussian case, this does not alleviate the problem. (why?)
- But, as it turns out, it is the exception. The model becomes uniquely identifiable if

Y_i and Y_j independent and non-Gaussian.

Independent Component Analysis

- Without loss of generality, we can assume \mathbf{X} has trivial covariance: $\Sigma_{\mathbf{X}} = \mathbf{1}$.
- Since $\Sigma_{\mathbf{Y}} = \mathbf{1}$ as well, it results that $\mathbf{1} = A\Sigma_{\mathbf{Y}}A^T = AA^T$

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- so we are reduced to finding an orthogonal transformation such that $\mathbf{Y} = A^T \mathbf{X}$ becomes independent and non-Gaussian.
- It is a form of “inverse” Central Limit Theorem method.
- Q: How to measure/estimate statistical independence?

Entropy

- For a continuous random variable X with density $p(x)$, the *differential entropy* is

$$H(X) = - \int p(x) \log p(x) dx = -\mathbb{E}(\log p(X)) .$$

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- it extends the notion of uncertainty/information carried by X .
- Entropy measures independence through the *mutual information*: Given X_1, \dots, X_n , the mutual information is

$$I(Y) = \sum_{i \leq n} H(Y_i) - H(Y) \geq 0 .$$

Entropy

- For a continuous random variable X with density $p(x)$, the *differential entropy* is

$$H(X) = - \int p(x) \log p(x) dx = -\mathbb{E}(\log p(X)) .$$

- it extends the notion of uncertainty/information carried by X .
- Entropy measures independence through the *mutual information*: Given X_1, \dots, X_n , the mutual information is
$$I(Y) = \sum_{i \leq n} H(Y_i) - H(Y) \geq 0 .$$
- **Fact:** $I(Y) = 0$ iff Y_i and Y_j are mutually independent.
- **Fact:** If A is unitary and $Y = A^T X$, then $H(Y) = H(X)$.

Independent Component Analysis

- So ICA attempts to solve the following problem:

$$\arg \min_{A^T A = 1} \sum_{i \leq L} H(\langle A_i, X \rangle) - H(X) = \arg \min_{A^T A = 1} \sum_{i \leq L} H(\langle A_i, X \rangle)$$

- Ex from ESLL:

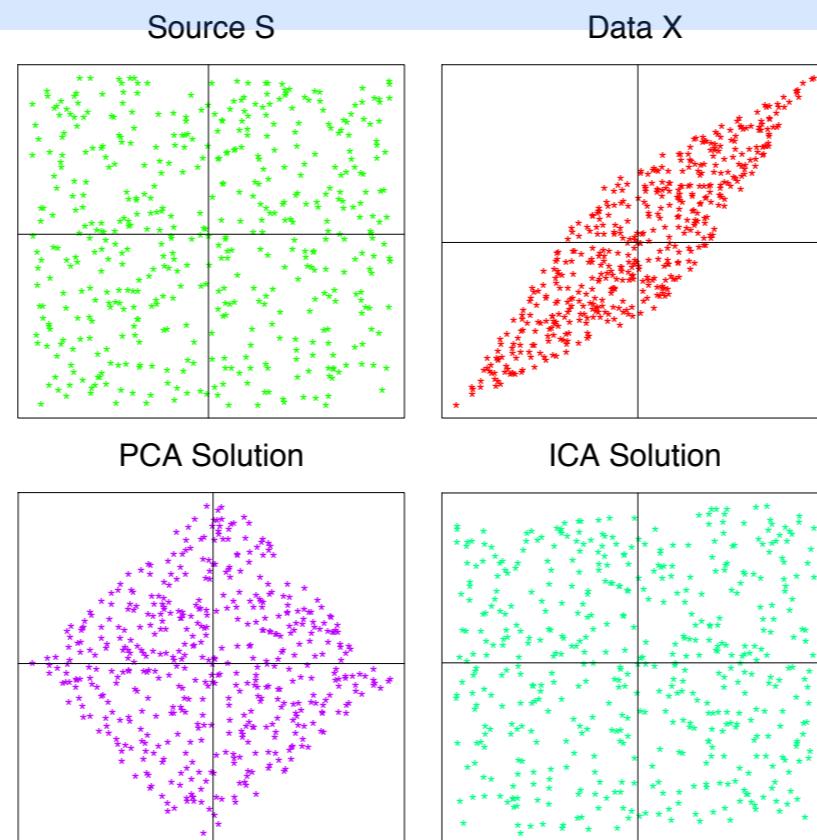


FIGURE 14.38. Mixtures of independent uniform random variables. The upper left panel shows 500 realizations from the two independent uniform sources, the upper right panel their mixed versions. The lower two panels show the PCA and ICA solutions, respectively.

- Challenge: computing entropy requires estimating the density: exposed to curse of dimensionality!