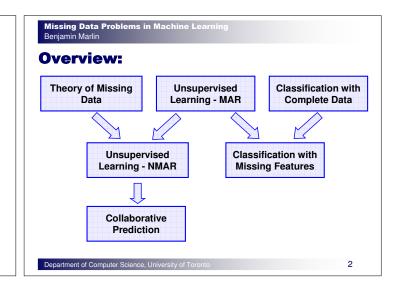
# Missing Data Problems in Machine Learning

#### **Senate Thesis Defense**

Ben Marlin Machine Learning Group Department of Computer Science University of Toronto April 8, 2008

Department of Computer Science, University of Toronto



Missing Data Problems in Machine Learning Benjamin Marlin

# **Introduction: Notation for Missing Data**

$\mathbf{x}_n$	0.1 0.9 0.2 0.7 0.3	Data Vector
$r_n$	1 0 0 1 1	Response Vector
$\mathbf{o}_n$	1 4 5	Observed Dimensions
$\mathbf{m}_n$	2 3	Missing Dimensions
$\mathbf{x}_n^{\mathbf{o}_n}, \mathbf{x}_n^o$	0.1 0.7 0.3	Observed Data
$\mathbf{x}_n^{\mathbf{m}_n}, \mathbf{x}_n^m$	0.9 0.2	Missing Data

Department of Computer Science, University of Toronto

Missing Data Problems in Machine Learning Benjamin Marlin

## **Theory of Missing Data:** Factorizations

#### **Data/Selection Model Factorization:**

$$P(\mathbf{X}, \mathbf{R}, \mathbf{Z} | \theta, \mu) = P(\mathbf{R} | \mathbf{X}, \mathbf{Z}, \mu) P(\mathbf{X}, \mathbf{Z} | \theta)$$

• The probability of selection depends on the true values of the data variables and latent variables.

#### Classification of Missing Data:

MCAR:  $P(\mathbf{R}|\mathbf{X}, \mathbf{Z}, \mu) = P(\mathbf{R}|\mu)$ 

MAR:  $P(\mathbf{R}|\mathbf{X},\mathbf{Z},\mu) \times P(\mathbf{R}|X^o,\mu)$ 

**NMAR:**  $P(\mathbf{R}|\mathbf{X}, \mathbf{Z}, \mu)$  No simplification in general.

Department of Computer Science, University of Toronto

4

Missing Data Problems in Machine Learning Benjamin Marlin

# **Theory of Missing Data: Inference**

#### MCAR/MAR Posterior:

$$P(\theta|\mathbf{x}^{o}, \mathbf{r}) \propto \int \int \int P(\mathbf{X}, \mathbf{Z}|\theta) P(\mathbf{R}|\mathbf{X}, \mu) P(\theta|\omega) P(\mu|\eta) d\mu dZ d\mathbf{x}^{m}$$
$$\propto P(\mathbf{X}^{o} = \mathbf{x}^{o}|\theta) P(\theta|\omega)$$

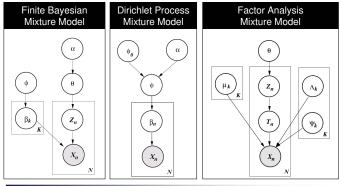
#### **NMAR Posterior:**

$$P(\theta|\mathbf{x}^o,\mathbf{r}) \propto \int \int \int P(\mathbf{X},\mathbf{Z}|\theta) P(\mathbf{R}|\mathbf{X},\mathbf{Z},\mu) P(\theta|\omega) P(\mu|\eta) d\mu dZ d\mathbf{x}^m$$

Department of Computer Science, University of Toronto

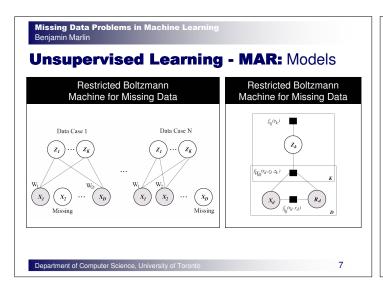
Missing Data Problems in Machine Learning Benjamin Marlin

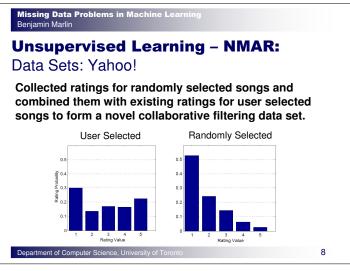
# **Unsupervised Learning - MAR:** Models



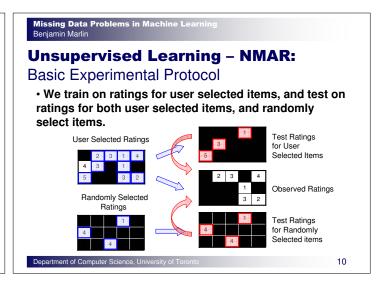
Department of Computer Science, University of Toronto

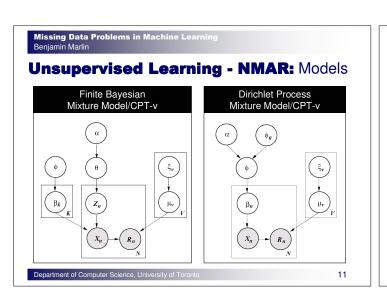
6

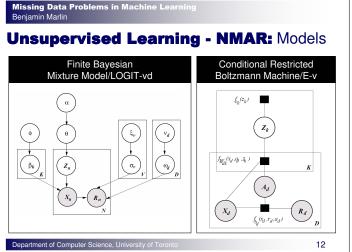




Missing Data Problems in Machine Learning Benjamin Marlin **Unsupervised Learning - NMAR:** Data Sets: Jester Jester gauge set of 10 jokes used as complete e860 data. Synthetic missing data was added. 15,000 users randomly selected • Missing data model:  $\mu_v(s) = s(v-3)+0.5$ s=0.125 0.5 P(T Rating Value Rating Value Rating Value Rating Value Rating Value Department of Computer Science, University of Tol 9







# **Unsupervised Learning - NMAR:**

Comparison of Results on Yahoo! Data

	Complexity	Rand MAE	Complexity	User MAE
EM MM	1	$0.7725 \pm 0.0024$	5	$0.5779 \pm 0.0066$
EM MM/CPT-v	20	$0.5431 \pm 0.0012$	10	$0.6661 \pm 0.0025$
EM MM/Logit	5	$0.5038 \pm 0.0030$	5	$0.7029 \pm 0.0186$
EM MM/CPT-v+	5	$0.4456 \pm 0.0033$	20	$0.7088 \pm 0.0087$
MCMC DP	N/A	$0.7624 \pm 0.0063$	N/A	$0.5767 \pm 0.0077$
MCMC DP/CPT-v	N/A	$0.5549 \pm 0.0026$	N/A	$0.6670 \pm 0.0071$
MCMC DP/CPT-v+	N/A	$0.4428 \pm 0.0027$	N/A	$0.7537 \pm 0.0026$
CD RBM	20	$0.7179 \pm 0.0025$	10	$0.5513 \pm 0.0077$
CD cRBM/E-v	1	$0.4553 \pm 0.0031$	20	$0.5506 \pm 0.0085$

Department of Computer Science, University of Toronto

14

Missing Data Problems in Machine Learning

# **Unsupervised Learning - NMAR:**

**NEW:** Ranking Results

$$NDCG(n) = \frac{\sum_{i=1}^{T} \frac{2^{x_{ni}^t} - 1}{\log(1 + \hat{\pi}(i, n))}}{\sum_{i=1}^{T} \frac{2^{x_{ni}^t} - 1}{\log(1 + \pi(i, n))}}$$

- $\hat{x}_{ni}^t$  : mean of posterior predictive distribution for test item i.
- $\widehat{\pi}(i,n)$  : rank of test item i according to  $\widehat{x}_{ni}^t$  .
- $\pi(i,n)$  : rank of test item i according to  $x_{ni}^t$  .

Department of Computer Science, University of Toronto

. \_

Missing Data Problems in Machine Learning Benjamin Marlin

#### **Unsupervised Learning – NMAR:**

**NEW:** Comparison of Yahoo! Ranking Results

#### Strong Generalization:

	Complexity	Rand NDCG
EM MM	1	$0.8162 \pm 0.0022$
EM MM/CPT-v	20	$0.8352 \pm 0.0023$
EM MM/Logit	5	$0.8398 \pm 0.0012$
EM MM/CPT-v+	20	$0.8377 \pm 0.0012$
MCMC DP	N/A	$0.8167 \pm 0.0025$
MCMC DP/CPT-v	N/A	$0.8248 \pm 0.0020$
MCMC DP/CPT-v+	N/A	$0.8319 \pm 0.0011$
CD cRBM	20	$0.8207 \pm 0.0011$
CD cRBM/E-v	10	$0.8244 \pm 0.0017$

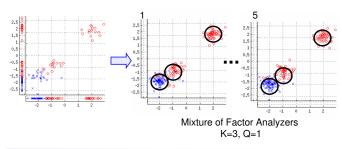
Department of Computer Science, University of Toronto

16

Missing Data Problems in Machine Learning Benjamin Marlin

### Classification: Imputation

**Multiple Imputation:** Replace missing feature values with samples of  $\mathbf{x}^m$  given  $\mathbf{x}^o$  drawn from several imputation models.



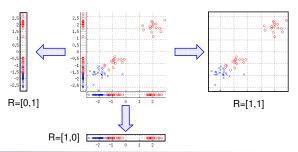
Department of Computer Science, University of Toronto

17

Missing Data Problems in Machine Learning Benjamin Marlin

#### Classification: Reduced Models

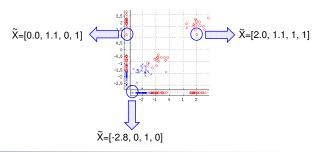
**Reduced Models:** Each observed data subspace defined by a pattern of missing data gives a separate classification problem.



**Missing Data Problems in Machine Learning** Benjamin Marlin

# Classification: Response Augmentation

**Response Augmentation:** Set missing features to zero and augment feature representation with response indicators.



Department of Computer Science, University of Toronto

19

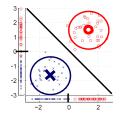
#### Classification: Generative Models

#### Generative Model (LDA-FA):

$$P(Y_n = c) = \theta_c$$

$$P(\mathbf{X}_n = \mathbf{x}_n | Y_n = c) = \mathcal{N}(\mathbf{x}_n | \mu_c, \Sigma)$$

$$\Sigma = \Lambda \Lambda^T + \Psi$$

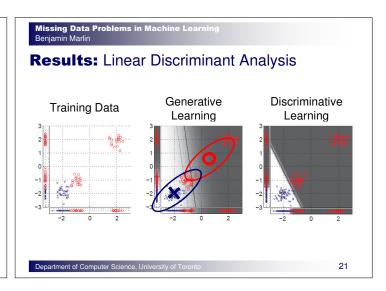


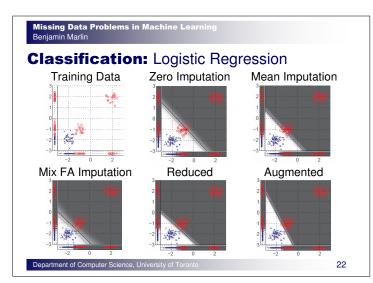
#### **Predictive Distribution with Missing Data:**

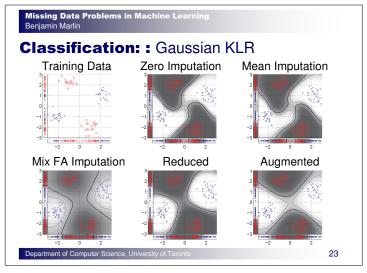
$$P(Y=c|\mathbf{X}_{n}^{o}=\mathbf{x}_{n}^{o}) = \frac{\theta_{c}\mathcal{N}(\mathbf{x}_{n}^{o}|\mu_{c}^{o},\Sigma^{oo})}{\sum_{c}\theta_{c}\mathcal{N}(\mathbf{x}_{n}^{o}|\mu_{c}^{o},\Sigma^{oo})}$$

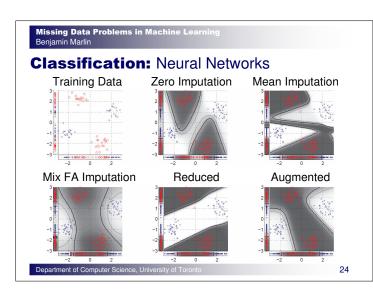
Department of Computer Science, University of Toronto

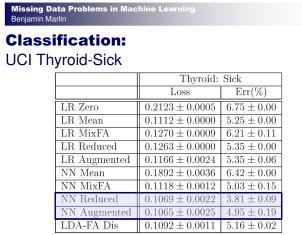
20





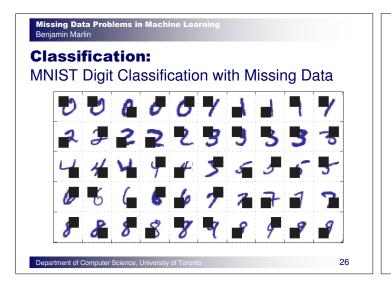






25

Department of Computer Science, Univer



#### **Classification:**

# MNIST Digit Classification with Missing Data

•		_	
	MNIST Digits		
	Loss	Err(%)	
LR Zero	$0.6350 \pm 0.0110$	$19.75 \pm 0.41$	
LR Mean	$0.6150 \pm 0.0112$	$19.15 \pm 0.34$	
LR Reduced	$0.7182 \pm 0.0135$	$22.62 \pm 0.45$	
LR Augmented	$0.6160 \pm 0.0112$	$19.35 \pm 0.36$	
LDA-FA Dis	$0.6355 \pm 0.0051$	$19.95 \pm 0.25$	
NN Mean	$0.6235 \pm 0.0541$	$18.34 \pm 0.42$	
NN Reduced	$0.6944 \pm 0.0088$	$21.51 \pm 0.27$	
NN Augmented	$0.5925 \pm 0.0161$	$17.76 \pm 0.18$	
gKLR Mean	$0.4147 \pm 0.0075$	$13.02 \pm 0.24$	
gKLR Reduced	$0.5694 \pm 0.0079$	$18.32 \pm 0.49$	
gKLR Augmented	$0.3896 \pm 0.0101$	$12.34 \pm 0.46$	

Department of Computer Science, University of Toronto

27

Missing Data Problems in Machine Learning Benjamin Marlin

# The End

Department of Computer Science, University of Toronto

28