# **Real time survey**



eduVote is an Audience Response System for the Academic Environment:

The use of ARS, also known as a TED-System or voting system, is considered very beneficial in large lecture halls and various other teaching arenas: Our Partners:

 $\cdot$  Students are engaged through active participation in the material, thus increasing their attention span.

eduVote - ARS

 $S^2$ SimpleSoft

 As the students must give precise answers, they gain an awareness of where they may have knowledge gaps.

 In addition, the instructor is able to gain a quick overview of the audience's current knowledge on the subject being discussed.

In comparison with other voting systems that require proprietary hardware (e.g. a hand-held clicker), eduVote is very cost-efficient since it provides Apps that run on a student's laptop or smartphone. Thus minimizing the time and effort required to organize and distribute equipment and eradicating any purchase or maintenance costs.

In comparison to a web-based system, we take privacy extremely seriously. The eduVote server does not receive data regarding the instructor's question or the student's voting results. The question and answers are stored locally on the instructor's local machine. We are aware and respect that instructors value this control over their questions and results.

Anything else? eduVote incurs no usage-based costs! eduVote can be integrated into PowerPoint for Windows! And, since 2011, eduVote has been successfully used at a number of universities across Germany, Austria and Switzerland.

eduVote Testimonials: evaluation and feedback on eduVote can be viewed here.

T&C's LEGAL NOTICE CONTACT

#### http://www.eduvote.de/en/

#### Exercises:

- maximal number of points: 110
- Typically, 1 exercise sheet per week: 10 points
- Sometimes larger sheets for two subsequent weeks:
   20 points

Grading policy:

- 50% of all points: eligible for the final exam (date to be determined)
- 75% of all points: improves the exam grade by 0.3/0.4
   e.g. 2.0->1.7, 1.7->1.3, 1.0->1.0

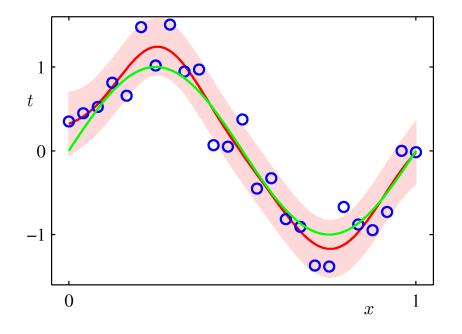
# Today's topics

- Curve fitting (and overfitting)
- Regularization
- Probability and expectation
- Normal distribution
- Likelihood
- Mixture of Gaussians
- Non-parametric methods

Slides modified from: PATTERN RECOGNITION AND MACHINE LEARNING CHRISTOPHER M. BISHOP

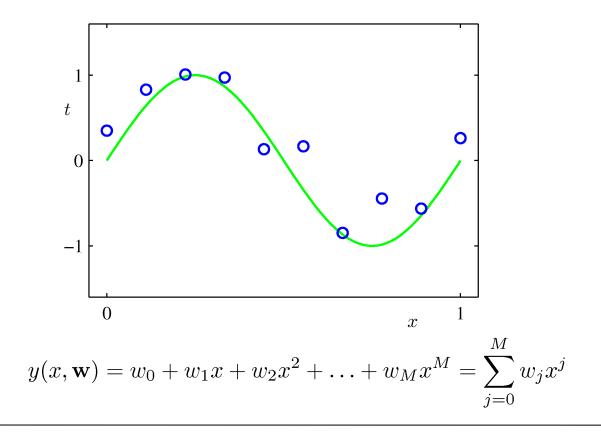
and: Computer vision: models, learning and inference. ©2011 Simon J.D. Prince

#### Pattern recognition: an example

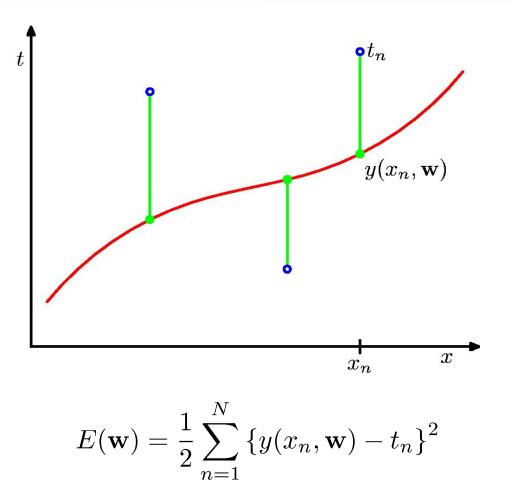


## Linear Basis Function Models (1)

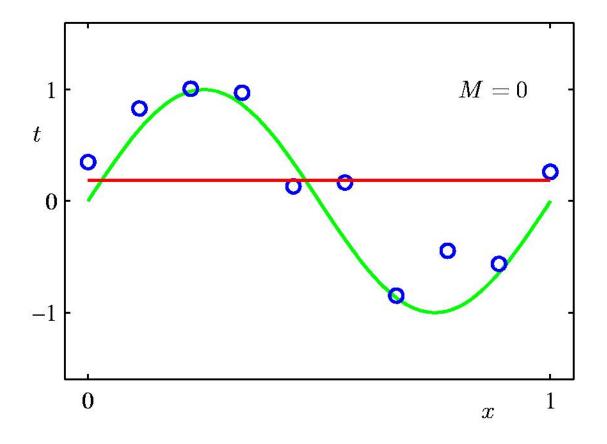
#### **Example: Polynomial Curve Fitting**



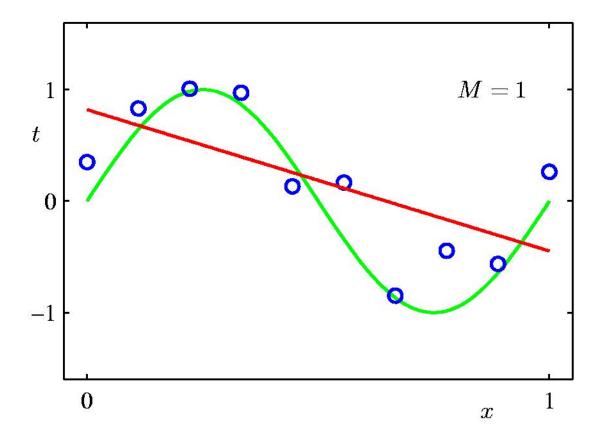
### Sum-of-Squares Error Function



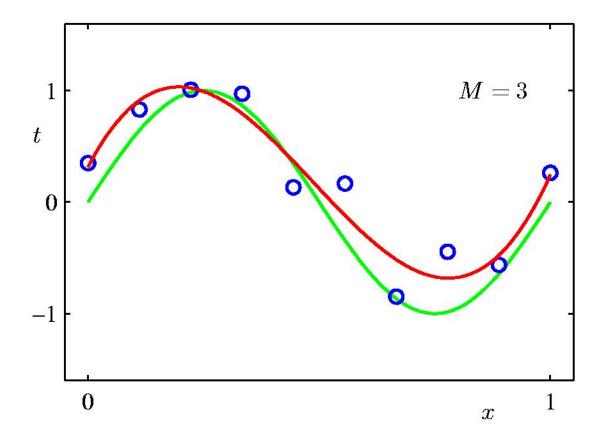
# 0<sup>th</sup> Order Polynomial



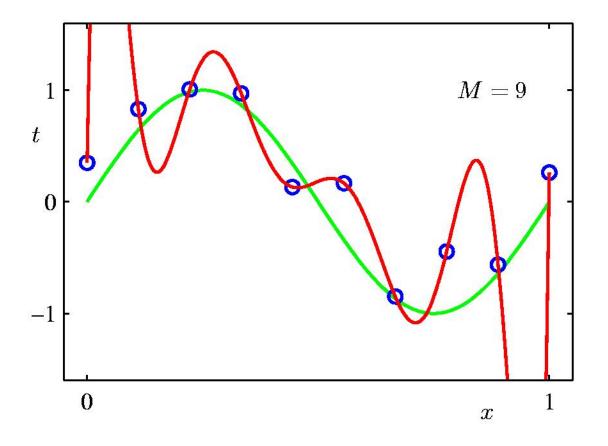
# 1<sup>st</sup> Order Polynomial



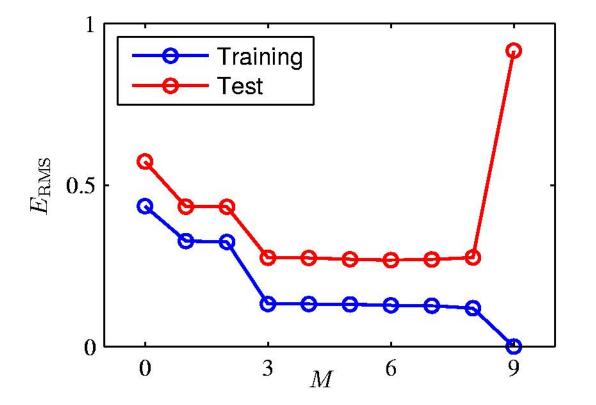
# 3<sup>rd</sup> Order Polynomial



# 9<sup>th</sup> Order Polynomial



# **Over-fitting**



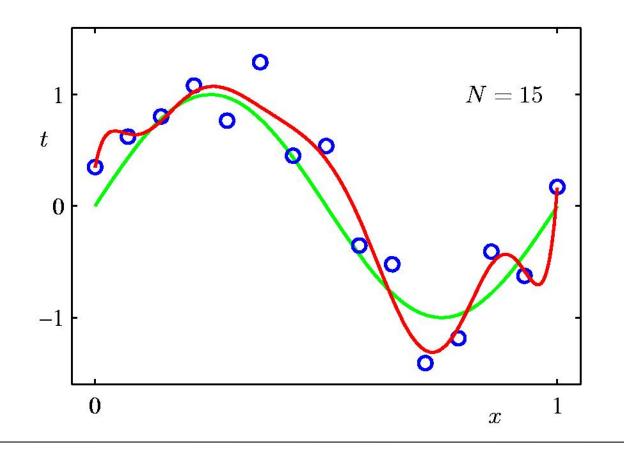
Root-Mean-Square (RMS) Error:  $E_{\rm RMS} = \sqrt{2E(\mathbf{w}^{\star})/N}$ 

# **Polynomial Coefficients**

	M=0	M = 1	M=3	M = 9
$w_0^\star$	0.19	0.82	0.31	0.35
$w_1^\star$		-1.27	7.99	232.37
$w_2^\star$			-25.43	-5321.83
$w_3^\star$			17.37	48568.31
$w_4^\star$				-231639.30
$w_5^{\star}$				640042.26
$w_6^\star$				-1061800.52
$w_7^{\star}$				1042400.18
$w_8^{\star}$				-557682.99
$w_9^{\star}$				125201.43

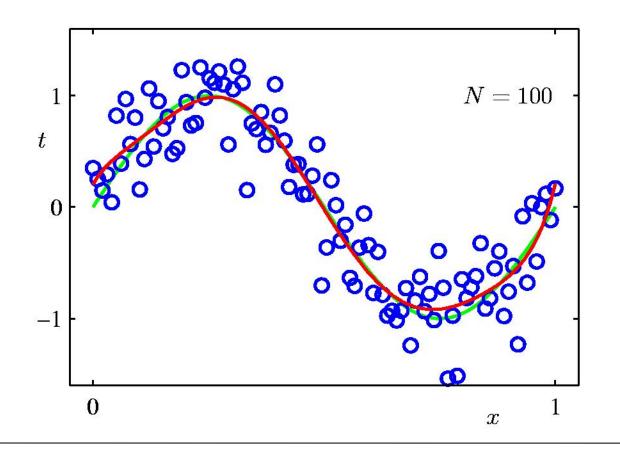
#### Data Set Size: N = 15

9<sup>th</sup> Order Polynomial



#### Data Set Size: N = 100

9<sup>th</sup> Order Polynomial

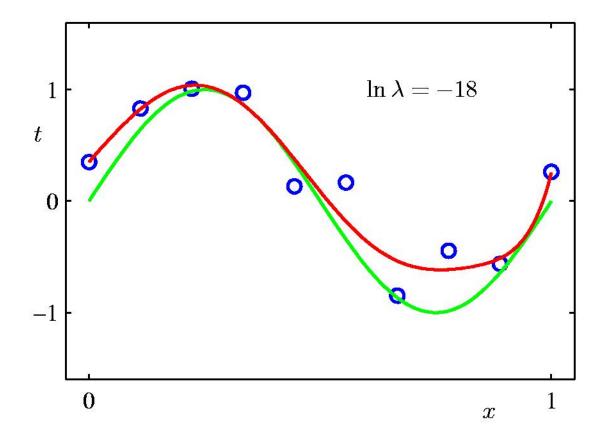


# Regularization

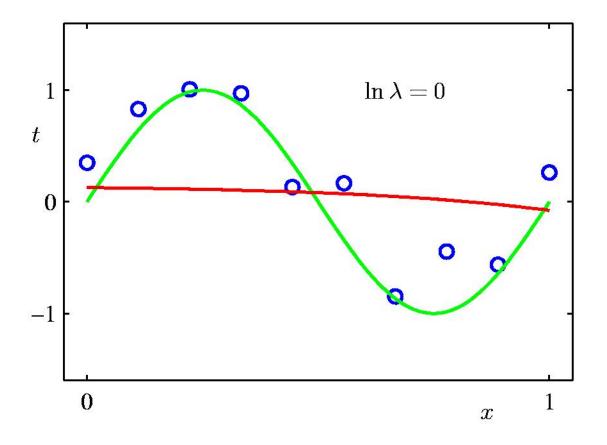
Penalize large coefficient values

$$\widetilde{E}(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^{N} \{y(x_n, \mathbf{w}) - t_n\}^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2$$

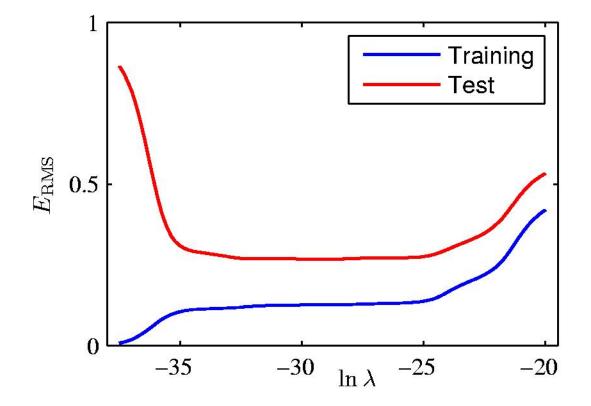
#### **Regularization:** $\ln \lambda = -18$



#### **Regularization:** $\ln \lambda = 0$

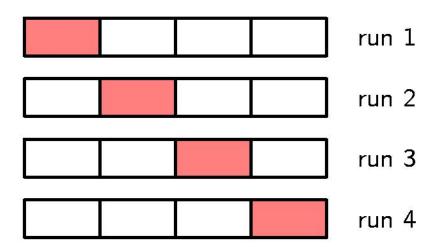


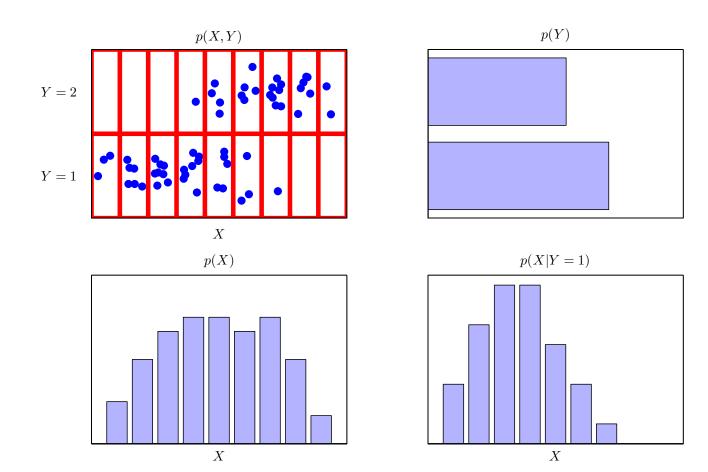
#### **Regularization:** $E_{\rm RMS}$ **vs.** $\ln \lambda$



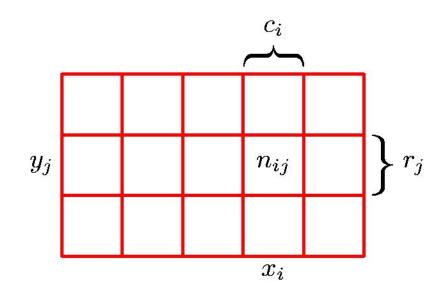
## **Model Selection**

#### **Cross-Validation**





# **Probability Theory**



**Marginal Probability** 

$$p(X = x_i) = \frac{c_i}{N}.$$

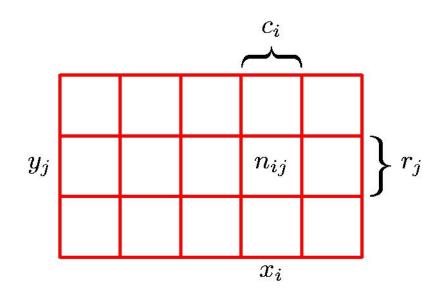
Joint Probability

$$p(X = x_i, Y = y_j) = \frac{n_{ij}}{N}$$

**Conditional Probability** 

$$p(Y = y_j | X = x_i) = \frac{n_{ij}}{c_i}$$

# **Probability Theory**

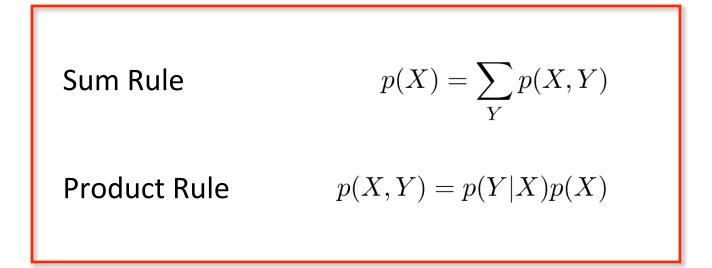


Sum Rule  $p(X = x_i) = \frac{c_i}{N} = \frac{1}{N} \sum_{j=1}^{L} n_{ij}$   $= \sum_{j=1}^{L} p(X = x_i, Y = y_j)$ 

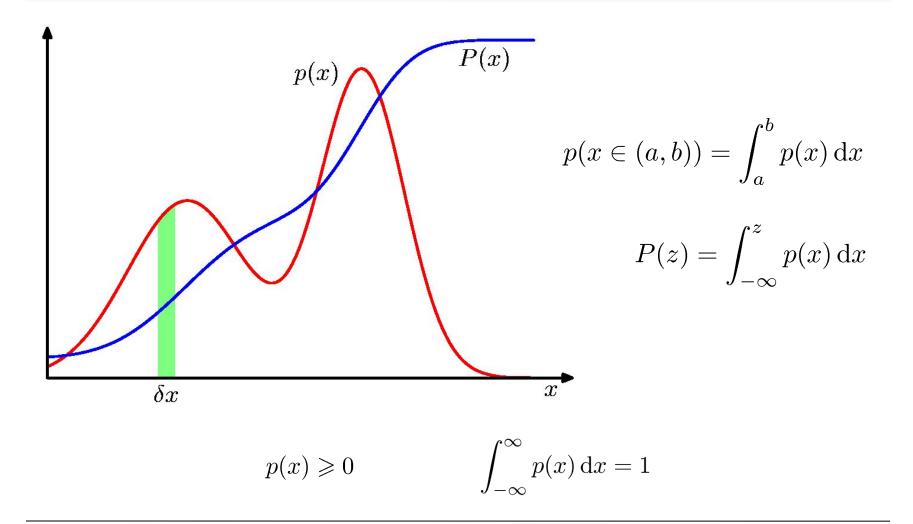
**Product Rule** 

$$p(X = x_i, Y = y_j) = \frac{n_{ij}}{N} = \frac{n_{ij}}{c_i} \cdot \frac{c_i}{N}$$
$$= p(Y = y_j | X = x_i) p(X = x_i)$$

# The Rules of Probability



## **Probability Densities**



### Bayes' Theorem

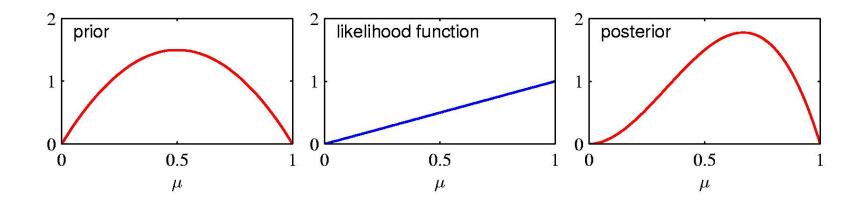
$$p(Y|X) = \frac{p(X|Y)p(Y)}{p(X)}$$

$$p(X) = \sum_{Y} p(X|Y)p(Y)$$

#### posterior $\propto$ likelihood $\times$ prior

Use 
$$p(X,Y) = p(Y|X)p(X)$$

### Prior · Likelihood = Posterior



## Expectations

$$\mathbb{E}[f] = \sum_{x} p(x) f(x)$$

$$\mathbb{E}[f] = \int p(x)f(x) \,\mathrm{d}x$$

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$$\mathbb{E}[f] = \sum_{x} p(x)f(x)$$

$$\mathbb{E}[f] = \int p(x)f(x) \,\mathrm{d}x$$

$$\mathbb{E}_{x}[f|y] = \sum_{x} p(x|y)f(x)$$

Conditional Expectation (discrete)

$$\mathbb{E}[f] \simeq \frac{1}{N} \sum_{n=1}^{N} f(x_n)$$

Approximate Expectation (discrete and continuous)

### Variances and Covariances

$$\operatorname{var}[f] = \mathbb{E}\left[\left(f(x) - \mathbb{E}[f(x)]\right)^2\right] = \mathbb{E}[f(x)^2] - \mathbb{E}[f(x)]^2$$

$$\operatorname{cov}[x, y] = \mathbb{E}_{x, y} \left[ \{ x - \mathbb{E}[x] \} \{ y - \mathbb{E}[y] \} \right]$$
$$= \mathbb{E}_{x, y} [xy] - \mathbb{E}[x] \mathbb{E}[y]$$

$$\begin{aligned} \operatorname{cov}[\mathbf{x}, \mathbf{y}] &= & \mathbb{E}_{\mathbf{x}, \mathbf{y}} \left[ \{ \mathbf{x} - \mathbb{E}[\mathbf{x}] \} \{ \mathbf{y}^{\mathrm{T}} - \mathbb{E}[\mathbf{y}^{\mathrm{T}}] \} \right] \\ &= & \mathbb{E}_{\mathbf{x}, \mathbf{y}}[\mathbf{x}\mathbf{y}^{\mathrm{T}}] - \mathbb{E}[\mathbf{x}] \mathbb{E}[\mathbf{y}^{\mathrm{T}}] \end{aligned}$$

## The Gaussian Distribution

$$\mathcal{N}\left(x|\mu,\sigma^{2}\right) = \frac{1}{(2\pi\sigma^{2})^{1/2}} \exp\left\{-\frac{1}{2\sigma^{2}}(x-\mu)^{2}\right\}$$

$$\mathcal{N}(x|\mu,\sigma^{2}) \qquad \qquad \mathcal{N}(x|\mu,\sigma^{2}) > 0$$

$$\int_{-\infty}^{\infty} \mathcal{N}\left(x|\mu,\sigma^{2}\right) \, \mathrm{d}x = 1$$

#### **Gaussian Mean and Variance**

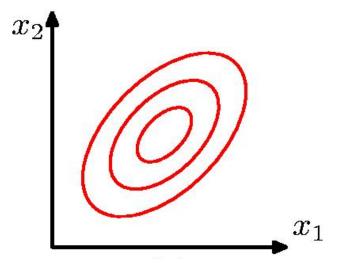
$$\mathbb{E}[x] = \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) \, x \, \mathrm{d}x = \mu$$

$$\mathbb{E}[x^2] = \int_{-\infty}^{\infty} \mathcal{N}(x|\mu,\sigma^2) x^2 \,\mathrm{d}x = \mu^2 + \sigma^2$$

 $\operatorname{var}[x] = \mathbb{E}[x^2] - \mathbb{E}[x]^2 = \sigma^2$ 

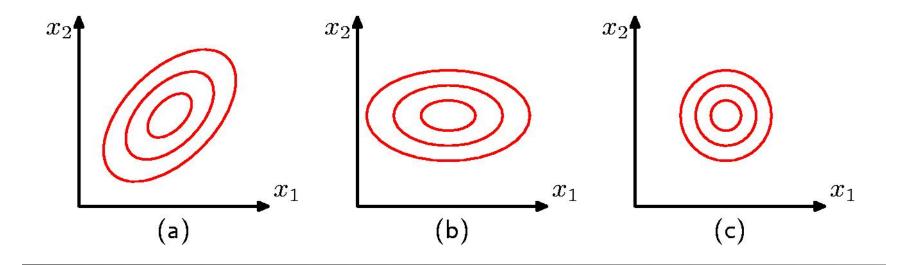
### The Multivariate Gaussian

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2}} \frac{1}{|\boldsymbol{\Sigma}|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right\}$$



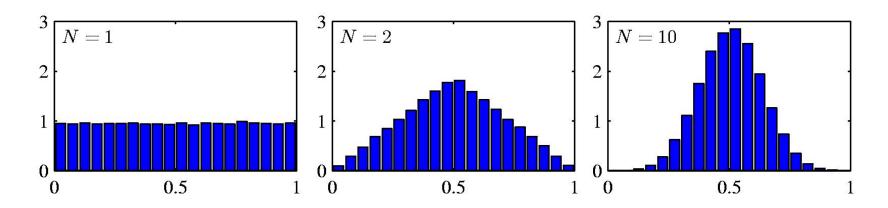
#### Moments of the Multivariate Gaussian (2)

$$\mathbb{E}[\mathbf{x}\mathbf{x}^{\mathrm{T}}] = \boldsymbol{\mu}\boldsymbol{\mu}^{\mathrm{T}} + \boldsymbol{\Sigma}$$
$$\operatorname{cov}[\mathbf{x}] = \mathbb{E}\left[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x} - \mathbb{E}[\mathbf{x}])^{\mathrm{T}}\right] = \boldsymbol{\Sigma}$$



The distribution of the sum of N i.i.d. random variables becomes increasingly Gaussian as N grows.

Example: N uniform [0,1] random variables.



## Partitioned Conditionals and Marginals

