

Final exam info

- In-class exam
 - Closed books/notes, closed electronics, 2 sided A4 hand-written (not printed) cheat sheet allowed (upload somewhere by some date)
 - Videos on (contact instructor if there is issue by TOMORROW)
 - Academic integrity violations will have severe consequences
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- Multiple choice and Short answer
 - Via Canvas
 - Only 1 attempt allowed
 - ~20 questions – 75 mins (3-4 mins/question)
 - ~40% are hard (think open book), ~60% are easy
 - Grading will be curved
 - Ask questions via private Zoom chat

Topics (all, more emphasis since midterm)

$$\min_w p(w) \rightarrow L(w, z)$$
$$\text{st. } \underline{g(w)} \geq 0 \quad \downarrow \quad \max_{\alpha} d(\alpha)$$

duality, KKT conditions

- Basics - Probability, Matrix/vector calculus, Optimization (convexity etc)
- Basic ML concepts – training vs test data, overfitting, generalization, ML tasks, loss metrics, optimal classifier/regressor, decision boundaries, **model selection (hold out, cross-validation, model complexity)**, theory (Haussler, Hoeffding, VC dimension)
- Unsupervised
 - Distribution/Density estimation – MLE, MAP, Histogram, Kernel density estimation
 - Dimensionality reduction – PCA** $v \leftarrow \text{evec}(X X^T)$ $D \times n \quad n \times D$ *data centered*
 - Clustering – K-means, Gaussian mixture models (GMM), EM algorithm, Hierarchical** *mixture models*
- Supervised
 - Classification – Naïve Bayes, Logistic Regression, Neural Networks, k-Nearest Neighbors, **SVM, Kernel trick, Decision Trees, Boosting** $H(x) = \text{sign}(\sum_i \alpha_i h_i(x))$ *margin* *local* *kernelized ridge regression*
 - Regression – Linear Regression, Ridge, Lasso, Neural Networks, Kernel regression

Comparison chart (classification)

Algorithm	Generative/ Discriminative	Assumptions	Decision boundary	Loss function	Training
Naïve Bayes					
Logistic Regression					
Neural Networks					
k-Nearest Neighbors					
SVM	D	-	-		linear prog.
Decision Tree	D		-		int gain $\leftarrow$ ID3, C4.5 dynamic prog. $\leftarrow$ CART (MDL, Inf(n))
Boosting	?				coordinate descent α_t, h_t on exp loss

Comparison (regression)

Algorithm	Generative/ Discriminative	Assumptions	Decision boundary	Loss function	Training
Linear Regression					
Neural Networks					
Local Kernel regression					
Kernel Ridge Regression					

Unsupervised learning

PCA

Clustering $\left\{ \begin{array}{l} \text{Partition (K-means, GMM+EM)} \\ \text{Hierarchical} \end{array} \right.$

Distribution est.

Practice problems

9.



$$\| \cdot \|_2$$

$$\| \cdot \|_\infty$$

$$\| \cdot \|_1$$

$$K \left(\frac{\|x - x_i\|}{h} \right)$$



10.

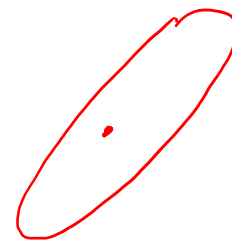
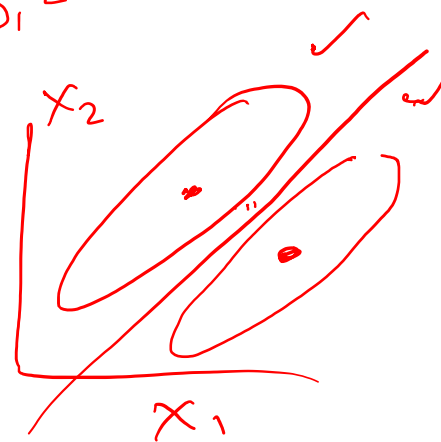
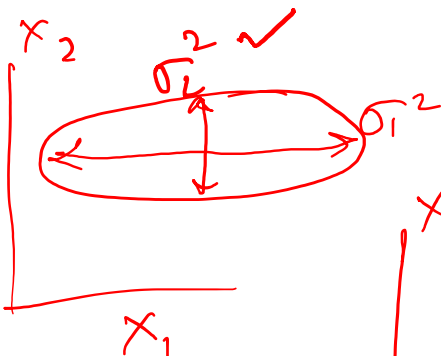
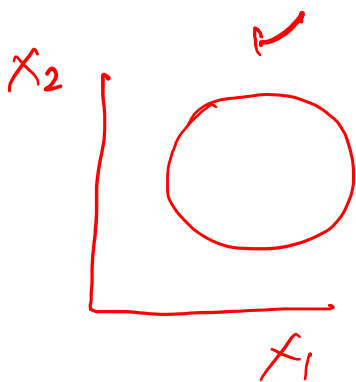
$$p(x|Y=y) \propto \mathcal{N}(\mu_y, \Sigma_y)$$

$$\Sigma_y = \begin{bmatrix} \ddots & \ddots \\ \ddots & \ddots \end{bmatrix} \mathcal{O}(d^2)$$

$$x = [x_1 \dots x_d]^T$$

$$p(x|Y=y) = \prod_{j=1}^d p(x_j|Y=y)$$

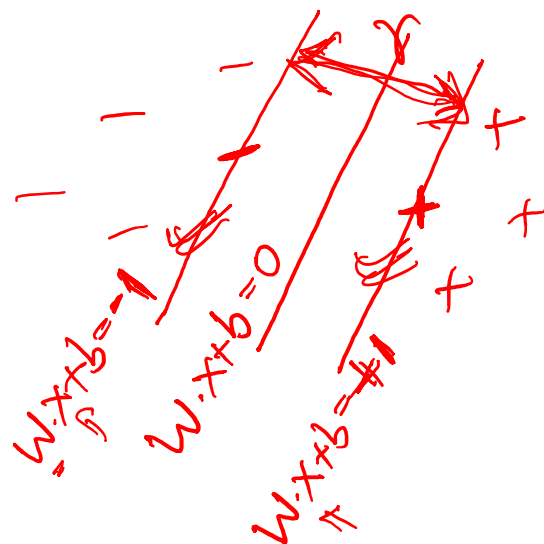
$$\Rightarrow \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_d^2 \end{bmatrix} \mathcal{O}(d)$$



$2d$
 d

$$\Phi_1(x) = \begin{bmatrix} x \\ x^2 \end{bmatrix}$$

margin

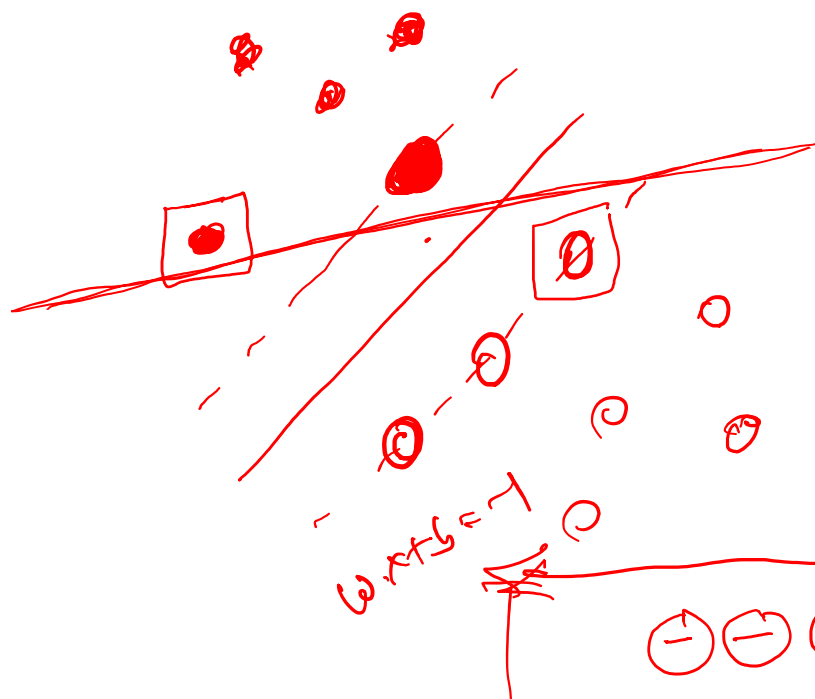


$$\gamma \propto \frac{1}{\|w\|^2}$$

$$\min \|w\|^2$$

$$\Phi_2(x) = \begin{bmatrix} 2x \\ 2x^2 \end{bmatrix} \quad \checkmark$$

17.



18.

$$\|w\|^2 + C \sum_j \xi_j \rightarrow \infty$$

$$(w \cdot x_j + b) y_j \geq 1 - \xi_j$$

$$\|w\|^2 + 0 \cdot \sum_j \xi_j$$

$$(w \cdot x_j + b) y_j \geq 1 - \xi_j$$

$$\xi_j \geq 0$$

12.

