Course Outline ECE271A – Statistical Learning I Department of Electrical and Computer Engineering University of California, San Diego Nuno Vasconcelos

Your responsibilities in this class fall into three main categories:

- 1. Take-home quizzes
- 2. Midterm
- 3. Final

The midterm is held on a Pass/Fail basis. Scores above a threshold will earn 100% midterm credit, scores below the threshold will earn 0% credit. The threshold will be announced before the exam.

The course grade will be a combination of

- 1. Take-home quizzes 30%
- 2. Exams 70% (midterm 20%, final 50%, but if you fail the midterm, the grade of the final exam will be used as your total Exams grade).

The following formula will be used to compute the course grade

Course Grade = max(.3 quizzes + .5 final + .2 midterm, .3 quizzes + .7 final)

The HW assignments are composed of two types of problems.

- **pen-and-paper:** Each assignment includes a number of "pen and paper" problems that are not graded. The solutions are handed out with the assignment and they are mostly for you to practice the concepts that we discuss in class. These are the types of problems that appear in the midterm and final.
- take-home quizzes: there will be roughly one take-home quiz per HW set. These are computer problems, where you get to implement and test some of the ideas we discuss in class. These problems are graded and must be solved individually, without consultation of other students or resources like sites on the Internet. They are part of your evaluation for the class. You can talk to the TAs or instructor for clarification questions. Quizzes are typically due one week after they are assigned, see the course site for details.

The official language for solving the computer problems is Matlab. I assume that students have access to it since it is free for UCSD students. You can use other languages, like Python, but at your own risk. Depending on the libraries you use, there could be differences between certain functions (e.g. matrix inversion, especially when matrices are nearly singular) between Matlab and other languages. This may create discrepancies with the solutions. Given the large size of the class, it is impossible for the TAs to take this into account. The solutions are produced with Matlab and these issues should not rise if you use Matlab.

Note, that there are always issues that depend on your particular implementation, say how you handle image borders. There are many ways to do this, zero-padding, copying pixels, etc., and there is "no right way" to do it. However, these variations do not affect the results significantly. Hence, the grading already accounts and accepts these type of variations.

Instructor Nuno Vasconcelos, EBU1 5602, 4-5550, e-mail: nuno@ece.ucsd.edu Office hours: see course site

TA See course site.

Exam dates:

- Mid-term In class, lecture 11 (assuming 1.5h lectures)
- Final finals week

Text: We will follow closely

• Richard O. Duda, Peter E. Hart and David G. Stork *Pattern Classification*. New York, NY: John Wiley&Sons, 2001.

Supplementary hand-outs will be distributed when appropriate. There are various other books of interest. These are not required but can be used for alternative explanations of the material.

- 1. C. Bishop, Pattern Recognition and Machine Learning. Springer, 2006.
- 2. T. Hastie, R. Tibshirani, J. H. Friedman, The Elements of Statistical Learning. Springer Verlag, 2001.
- Luc Devroye, Laszlo Gyorfi, Gabor Lugosi, A Probabilistic Theory of Pattern Recognition. Springer Verlag, 1998.
- 4. Andrew Gelman, Donald B. Rubin, Hal S. Stern, *Bayesian Data Analysis, Second Edition*, CRC Press; 2nd edition, 2003.
- 5. Tom Mitchell, Machine Learning, McGraw-Hill, 1997.
- 6. Christopher Bishop, Neural Networks for Pattern Recognition. Oxford University Press, 1996.
- 7. Vladimir Vapnik, The Nature of Statistical Learning Theory. Springer Verlag, 1999.

There is a web page for the course,

http://www.svcl.ucsd.edu/courses/ece271A/ece271A.htm

(also accessible from http://www.svcl.ucsd.edu/~nuno)

LECTURE SUBJECT

Number of classes

Introduction	1
Bayesian decision theory	2
The Gaussian classifier	1
Maximum likelihood estimation	1
Bias and variance	2
Bayesian parameter estimation	2
Conjugate and non-informative priors	1
Dimensionality and dimensionality reduction	2
The nearest neighbor classifier	1
Kernel-based density estimation	1
Mixture models and EM	3
Applications	1