Test 2: preparation sheet

Computer Vision (CS364/AM792)

The points below are what I consider to be the important theoretical aspects covered since the previous test, and the things that could be expected of you in the test on **Saturday 16 November at 14:00 in A203**.

Depth from two views

- the previous test covered theory up to the end of slide 7 of Lecture 17, but this test also won't cover image rectification so you may skip Lecture 17 entirely
- remind yourself of the overall process on slides 2 and 3 of Lecture 18, and how elements in this chapter come together (the test won't cover specific details of any of those components)
- know what the projective ambiguity is, when attempting to recover P and P' from F
- be aware of normalized image coordinates and how we reduce the camera matrix pair to canonical form
- know what the essential matrix is, and its relation to the fundamental matrix (slide 8 of Lecture 18)
- know about the four possible solutions to P' extractable from E, and be able to explain how triangulation can be used to pick the correct one (the details behind slide 5 of Lecture 19)
- understand how to reconstruct 3D points from two images and calibration matrices (slide 6 of Lecture 19)

Basic intro to machine learning

- our focus is on supervised learning: fitting a model to training data consisting of input-output pairs
- have a good understanding of the two (often conflicting) requirements on this model: describe the training data, and generalize to new data
- you may skip the details on slide 6 of Lecture 20
- have an idea of how a deep feed-forward neural network is built from simple linear perceptrons and activation functions (we return to it in the last chapter)
- glance over slide 9 of Lecture 20, but no need to memorize any of the detail
- be aware of the problems of over- and underfitting, and how to implement early stopping
- know what is meant by training data, validation data and test data, and the purpose of each in the framework of supervised learning

Image classification

- explain how an image classification model can be built with supervised learning
- understand the process of feature engineering, where raw image data is converted to a lower-dimensional (and ideally more class discriminative) feature vector, before classification is performed
- know about tiny image features, the motivation for using them, and how they are computed
- be aware of the limitations of using histograms as feature vectors (as illustrated on slide 7 of Lecture 21)
- know how GIST descriptors are computed, but skip the technical details of what Gabor filters are
- be aware of how k-means clustering works, and take note of its limitations (slide 6 of Lecture 22)
- know how a visual dictionary can be learned from a set of images, and how an image can then be converted to a bag-of-words representation
- know and understand the SVD-based method of dimensionality reduction, and how we can use it to learn a lower-dimensional representation for a class of images (like faces) in an unsupervised manner

- have an idea of how we can use these lower-dimensional representations in a simple image recognition system (summarized on slide 8 of Lecture 23)
- know the details of kNN classification, but skip the probabilistic view on slide 4 of Lecture 24
- have a clear understanding of the binary classification problem and linear classifier (slide 3 of Lecture 25)
- have an understanding of the notion of maximum margin solutions for linearly separable data (in many dimensions, not only 2D)
- understand what all the components in the two optimization problems on slide 7 of Lecture 25 mean, and what each problem means as a whole (but you need not memorize these two problems)
- understand the presence and effect of the regularization parameter C in the optimization problem on slide 10 of Lecture 25
- know how multiple 2-class SVM classifiers can be combined to perform multi-class classification
- the test won't cover the kernel trick (for separating classes that are not linearly separable)

Deep learning

- have an idea of how deep learning revolutionized the feature-engineering approach to image classification
- know the mathematical details behind the basic perceptron, a layer of perceptrons, and a composition of layers (slides 5,6,7 of Lecture 26)
- glance over the universal approximation theorem
- understand why we need a nonlinear activation function and why the sign function is not that good of an option, and know about the sigmoid, hyperbolic and ReLU activation functions
- have an idea of what learning in a neural network entails: picking optimal values for all the weights across all the layers that result in a minimum classification error on the training samples
- understand the concept of convolution, as a special restricted case of the general neural network layer, the concepts of weight sharing and stationarity, what convolutions typically pick up, and how a hierarchy of convolutions can lead to good feature extraction for the task of image classification
- know the operations, learnable parameters and hyperparameters involved in: convolutional layers, pooling layers, activation layers, fully connected layers, and the final softmax output layer; also be able to argue the purpose of each of these types of layers
- know about one-hot encoding: how it works and where it's used
- be aware of the log loss as defined on slide 6 of Lecture 28, and how gradient descent with a pre-specified learning rate can be used to minimize this loss
- know what backpropagation is and where in the learning process it is used (it will not be expected of you to perform calculations like those on slide 5 of Lecture 29)
- be aware of the stochastic form of gradient descent, as well as batching, and understand the statements and calculations on slide 4 of Lecture 30
- be aware of potential problems with a too large or too small learning rate, but you may skip the heuristic strategies on slide 5 of Lecture 30
- have a broad understanding of transfer learning, as summarized on slide 7 of Lecture 30 and implemented in Assignment 6
- the test will not cover Lecture 31

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