

University of California College of Engineering Department of Electrical Engineering and Computer Sciences

E. Alon, B. Ayazifar, C. Tomlin G. Ranade Thurs., Sep. 24, 2015 11:00-12:30pm

EECS 16B: FALL 2015-MIDTERM 1

Important notes: Please read every question carefully and completely – the setup may or may not be the same as what you have seen before. Also, be sure to show your work since that is the only way we can potentially give you partial credit.

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PROBLEM 1. Signal Analysis with DFT (13 points)

In this problem we will look at a few examples of signal analysis with DFT and how changes in the characteristics of the signals and/or the DFT window impact the resulting frequency-domain representation.

Throughout this problem, you must explain any answers you give in order to receive any credit - i.e., simply guessing an answer will result in zero points.

a) (3 pts) Shown below are two time domain signals (x[n], y[n]) and two magnitude plots of DFT coefficients (A[k], B[k]) – which DFT coefficients correspond with which time domain signal? (I.e., does A[k] correspond to x[n], or to y[n]?) Be sure to explain your answer.



y[n]



ž







b) (5 pts) For the x[n]/y[n] and A[k]/B[k] shown below, now which DFT coefficients correspond to which time domain signal? Hint: you should pay particular attention to the frequencies (k's) where the coefficients have zero value.



c) (5 pts) If $x[n] = e^{i(4\pi/M)n} + e^{i(6\pi/M)n}$ where M is some positive integer, what is the minimum number of points you must use in your DFT in order for X[k] to contain exactly two non-zero coefficients?

For general Ms the only my to guarantee no spectral leakage
(integer number of periods) is to make
$$W_0 = \frac{2\pi i}{M}$$
 (s.t. first
component corresponds to $k=2$ and second corresponds to $lc=3$).
So, need to use an $M-point DFT_0$

PROBLEM 2. Spectral Leakage and Windowing (18 pts)

As we saw in lecture and homework, if the signal we are taking the DFT of is periodic, but an exact integer period of the signal does not fit within the window we are using, we will end up with what is known as *spectral leakage*. In practice this situation is actually extremely common; e.g., consider a BMI system where the physical mechanisms that set the frequency of an oscillation in say an EEG signal have nothing to do with the sampling rate (and hence time window) of our electronics. In this problem we will examine a technique known as "windowing" that tries to mitigate spectral leakage by multiplying the original signal x[n] with a "window function" w[n]. Conceptually, the window function attempts to taper the signal near the boundaries of the DFT interval in order to make the signal "fit better".

Let's assume that our signal of interest is $x[n] = e^{i\pi n/2}$, and that we will be taking a DFT of length 6 over the interval n = 0, 1, ..., 5. The magnitudes of the DFT coefficients for this signal are |X[0]| = |X[3]| = 1.41, |X[1]| = |X[4]| = 3.86, and |X[2]| = |X[5]| = 1.04.

In this problem we'll examine the simplest type of window known as a "boxcar". Specifically, we will be multiplying x[n] by a window w[n] = 1 for $0 \le n < 4$ and zero otherwise.

a) (2 pts) Sketch the real part of the original signal x[n] and the real part of the new windowed signal $\hat{x}[n]$

$$\hat{x}[n] = x[n] \cdot w[n] = e^{i\pi n/2}$$
 for $0 \le n \le 3, 0$ otherwise

over the same interval we used to take the DFT as the original signal.

$$\begin{array}{c} \times [u] = 1 , \ \times [u] = e^{i\frac{\pi}{2}}, \ \times [v] = e^{i\frac{\pi}{2}}, \ \times [v] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = e^{i\frac{\pi}{2}}, \ \times [u] = 1 , \ \times [s] = 1$$

π .

b) (6 pts) If we use the same length-6 interval as we did for the original signal to compute the DFT coefficients $\hat{X}[k]$ of the new signal, for which two values of k will $\hat{X}[k]$ be equal to zero? You must show your work to receive any credit for this problem.

c) (5 pts) Assuming that $|\hat{X}[0]| = |\hat{X}[3]| = 0$, $|\hat{X}[1]| = |\hat{X}[4]| = 3.35$, $|\hat{X}[2]| = |\hat{X}[5]| = 0.9$, explain how applying the window w[n] captures the nature of the original input signal x[n] better than not windowing.

Oroginally had large values for X(0) and X(3], weither of which are even choosed in frequency to the actual signal. These have now both been zero and by the mindunings more accurately reflecting that the signal is actually a single tone. We still of course have 4 non-zero coefficients instead of just ones but it is an improvement over 6 non-zero coefficients (especially source the two We knocked out with windowing were relatively large). d) (5 pts) Defining the energy of a signal y[n] as $E_y = \sum_{n=0}^{5} |y[n]|^2$, compare the energy of the original signal x[n] against the energy of the windowed signal $\hat{x}[n]$. Based on this comparison, comment on how well windowing x[n] preserves the original signal.

Directly in time: $E_{x} = 6$ (low Parsonal: $E_{x} = \frac{2 \cdot 1.41^{2} + 2 \cdot 3.8(^{2} + 2 \cdot 1.04^{2})}{6} = 6$ (dust finget imaginary $E_{x}^{2} = 4$ $E_{x}^{2} = \frac{2 \cdot 3.35^{2} + 2 \cdot 0.9^{2}}{6} = 4$ purt of the signal) \hat{x} has approximately $\frac{2}{3}$ at the energy that x had - this makes sense since the length-4 vision is $\frac{2}{3}$ of the take DPY vision (6). So "met" of the signal energy is preserved, although ubvisibly A isont perfect.

PROBLEM 3. Three Letter Acronyms (23 points)

In this problem we will explore how using either DFT or SVD to analyze and perhaps even compress (by keeping track of only non-zero coefficients/components) a signal of interest can give us two different views of the same underlying characteristics of a signal. Throughout this problem, we will be considering the signal $x[n] = cos(\omega_0 n) + cos(2\omega_0 n)$, where $\omega_0 = (2\pi/10)$.

a) (1 pts) If every sample of the signal requires 4 bytes of memory and we keep 1000 total samples of the signal, how many bytes will it take to store the signal?

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4 bytes / sample . 1000 samples = 4000 bytes
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b) (8 pts) Compute the DFT coefficients X[k] corresponding to the signal x[n] for a DFT interval of n=0, 1, ..., 9. How many non-zero coefficients are there? If each coefficient and its corresponding frequency index (i.e., X[k] and k) require a total of 12 bytes of memory to store, how many bytes does it take to completely represent the signal?

Shuld be 4 numbers coefficients; easiest to find with inverse Euler:

$$x[n] = \frac{1}{2}e^{i\frac{2\pi}{10}N} + \frac{1}{2}e^{-i\frac{2\pi}{10}N} + \frac{1}{2}e^{i\frac{2\pi}{5}N} + \frac{1}{2}e^{-i\frac{2\pi}{5}N}$$

 $\int \int \int \int x[2] = 5 \int e^{2\pi} e^{i\frac{2\pi}{10}e^{i\frac{2\pi}{10}e^{-i\frac{2\pi}{5}N}} + \frac{1}{2}e^{-i\frac{2\pi}{5}N} + \frac{1}{2}e^{-i\frac{2\pi}{5}N} + \frac{1}{2}e^{-i\frac{2\pi}{5}N}$

Need 48 bytes titul

c) (5 pts) Now let's use a procedure similar to what we did with the neural data in the lab to construct a matrix based off of this signal that we can then analyze with SVD. Specifically, imagine that we construct a matrix A by taking 10-sample long intervals of the signal x[n] and using each one of those to populate the rows of the matrix – i.e.,:

 $A = \begin{bmatrix} x[0] & x[1] & \dots & x[9] \\ x[10] & x[11] & \dots & x[19] \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$

If we were to take the SVD of the matrix *A*, how many non-zero singular values will the matrix have in this case?

d) (3 pts) Given your answer to part c), if every singular value or entry in a singular vector requires 4 bytes of memory to store, how many total bytes does it take to completely represent the signal?

Need 1 singular value and 10 outries for the one right Singular vectors so a total of 44 bytes. e) (6 pts) If we were to construct a new matrix B using the same approach as we had taken to construct A in part b), but using intervals of length 5 (instead of length 10), how many non-zero singular values will the new matrix B have?



PROBLEM 4. Fortune Telling (10 pts + BONUS 5 pts)

Using your newfound knowledge of PCA and the SVD, you decide to play a little trick on a few (or even a few hundred) of your closest friends and gather some data that will allow you to make an educated prediction about whether or not they will successfully buy a house in the ultra-competitive Bay Area real estate market within the next 5 years. Knowing that each of these pieces of information in some way are likely to impact this, you collect the following data from each of your friends:

- Age (in years)
- How many years they have been with their current partner (0 if they are single)
- Age of their partner (0 if they are single)
- How many siblings they have
- Approximate salary (in \$/year)
- Approximate salary of their partner (in \$/year, 0 if single)
- Their height (in m)
- The height of their partner (in m, 0 if single)
- The number of times per week they go clubbing (0 if not single)
- Their overall satisfaction with life (rated on a scale from 0-10, with 10 being satisfied to the point of annoying everyone around them)

For the rest of this problem, let's assume that you successfully gathered this information from 100 of your friends.

a) (3 pts) Describe how you would construct a matrix *A* out of the data collected above that we might later be able to analyze in order to make a prediction about whether your friend will end up buying a house. You should arrange *A* such that the information from each friend is arranged in a row of the matrix. Be sure to indicate what the dimensions of the matrix would be.



b) (7 pts) Assuming that the *A* matrix has one very dominant singular value and that you find that the data is actually indicative by running a few test cases where you know whether your friend bought a house or not, for any one particular friend *i* whose data you have collected, describe how you would use the matrix *A* and their individual data vector a_i^T to predict whether or not they will buy a house in the next 5 years.

c) (BONUS: 5 pts) Using the same method as part b), suggest some other outcome (besides buying a house) that you might be able to make a prediction about, what data you might need, and under what conditions it is likely for the predicted outcome to be accurate. Note that most of the bonus credit will be assigned to addressing the final issue (i.e., under what conditions your prediction about the outcome is likely to be accurate).

The point of this problem was to show that SVD/PCA can be used to predict just about anything as long as you have the appropriate data. "Appropriate" in this case means that not only we there a (typically small) set of dominant principal components, but that when we project on to these components we can identify clusters of observations. If we then have a few known test curests tell as which clusters currespard to which outcomes we have a good churce that extual predictions (where we dust know the actions in advance) will be accurate as wells