## **Problem 3** In [45]: import numpy as np import time A = np.random.normal(0, 1, (5000, 5000))b = np.random.normal(0, 1, (5000, 1))In [46]: **def** sol1(A, b): s = time.time() x = np.linalg.solve(A, b) e = time.time() return e-s sol1(A, b) 0.5387320518493652 Out[46]: In [47]: **def** sol2(A, b): s = time.time() A inv = np.linalg.inv(A) $x = np.matmul(A_inv, b)$ e = time.time() return e-s In [48]: sol2(A, b) Out[48]: 1.589203119277954 using np.solve is roughly 2 times faster in terms of running time. Problem 4 In [49]: import numpy as np A = np.random.normal(0, 1, (100, 100))u, s, vh = np.linalg.svd(A, full\_matrices=True) $s_{dagger} = 1/s$ In [50]: np.allclose(np.transpose(vh).dot(np.diag(s\_dagger, k=0)).dot(np.transpose(u)), np.linalg.pinv(A)) Out[50]: True Problem 7 (a) In [51]: a = np.random.normal(0, 1, 500) b = np.random.normal(0, 1, 500)In [52]: **def** 12(v): return np.sqrt(np.sum(np.square(v))) In [53]: np.allclose(np.linalg.norm(a), 12(a)) Out[53]: True (b) In [54]: 1/500\*np.linalg.norm(a-b) Out[54]: 0.06047165654676527 Problem 10 In [55]: # (a) import numpy as np N = [10, 100, 1000]for n in N: print(n) A = np.random.normal(0, 1, (n,n))print(1/n \* A.dot(np.transpose(A))) $[[\ 1.40650755\ -0.32274061\ \ 0.52457356\ \ 0.36761455\ \ 0.07367104\ \ 0.2346426$ 0.12443221 -0.38801899 0.90601489 0.01211126] $[-0.32274061 \quad 0.54862164 \quad -0.17571886 \quad -0.20636088 \quad -0.17055541 \quad -0.15061271$ 0.25774497 - 0.1829213 - 0.49848589 - 0.24021468 $[ 0.52457356 -0.17571886 \ 1.05226245 \ 0.25528738 -0.08936804 -0.09218026 ]$ -0.1767688 0.16410137 0.32869132 0.31013734 $[ \ 0.36761455 \ -0.20636088 \ \ 0.25528738 \ \ 0.54853218 \ \ 0.07374337 \ \ 0.26453728$ -0.09220435 -0.00577407 0.36565624 0.20839377 $[ \ 0.07367104 \ -0.17055541 \ -0.08936804 \ \ 0.07374337 \ \ 0.3965839 \ \ \ 0.05428062$ 0.04308337 0.10949603 0.2780887 0.02752397] $[ \ 0.2346426 \ \ -0.15061271 \ \ -0.09218026 \ \ \ 0.26453728 \ \ \ 0.05428062 \ \ \ 0.69757313$ -0.04608612 0.12270763 -0.20864225 -0.14288277] $[ \ 0.12443221 \ \ 0.25774497 \ -0.1767688 \ \ -0.09220435 \ \ 0.04308337 \ -0.04608612$ 0.55255577 - 0.59540847 - 0.08720362 - 0.40453337 $[-0.38801899 -0.1829213 \quad 0.16410137 -0.00577407 \quad 0.10949603 \quad 0.12270763$ -0.59540847 1.23444086 0.29054501 0.4873365 ] $[ \ 0.90601489 \ -0.49848589 \ \ 0.32869132 \ \ 0.36565624 \ \ 0.2780887 \ \ -0.20864225$ -0.08720362 0.29054501 2.04630441 0.59302521 $[ \ 0.01211126 \ -0.24021468 \ \ 0.31013734 \ \ 0.20839377 \ \ 0.02752397 \ -0.14288277 ]$ -0.40453337 0.4873365 0.59302521 1.09335066]] $[[1.05868267 \quad 0.02992563 \quad -0.01602412 \quad ... \quad -0.12793841 \quad 0.05678259]$ 0.02039327] $[ 0.02992563 \ 1.37169139 \ 0.00861191 \ ... \ -0.12554726 \ 0.00263162 ]$ 0.09672779] $[-0.01602412 \quad 0.00861191 \quad 0.87299955 \quad \dots \quad 0.16661814 \quad -0.07445466$ 0.01336527] $[-0.12793841 - 0.12554726 \ 0.16661814 \dots \ 1.36203239 \ 0.02671174$ 0.01083847] $[ 0.05678259 \quad 0.00263162 \quad -0.07445466 \quad \dots \quad 0.02671174 \quad 1.03152965$ 0.06183014] [ 0.02039327 0.09672779 0.01336527 ... 0.01083847 0.06183014 1.14249676]] 1000 [[ 9.85688820e-01 5.56999893e-02 -3.73694946e-04 ... 5.24746065e-03 -7.76753981e-03 -4.79992316e-03] [ 5.56999893e-02 1.06670962e+00 -3.05592028e-02 ... 2.23388485e-02 8.94120282e-03 3.88993613e-02] [-3.73694946e-04 -3.05592028e-02 1.02078546e+00 ... 1.46442405e-02-8.93814954e-03 -1.82923061e-02] [ 5.24746065e-03 2.23388485e-02 1.46442405e-02 ... 8.99768391e-01 4.90532195e-02 -3.98556404e-03] [-7.76753981e-03 8.94120282e-03 -8.93814954e-03 ... 4.90532195e-02 1.05831676e+00 1.67648872e-02] $[-4.79992316e-03 \quad 3.88993613e-02 \quad -1.82923061e-02 \quad ... \quad -3.98556404e-03$ 1.67648872e-02 1.03133845e+00]] It gets close to identity matrix I as n goes to large In [56]: # (b) n=10 M = [10, 100, 1000]for m in M: print(m) samples = []for \_ in range(m): samples.append(np.random.normal(0, 1, (n,n))) print(1/m\*sum([A.dot(A) for A in samples])) 10 [[1.03638217 -0.93599024 0.67747892 1.92132169 -0.54683851 1.88093769]0.99370384 - 0.82473686 - 1.22684642 - 0.04248232 $-0.5992128 \quad -1.33844511 \quad 0.64288999 \quad 1.10491068$ $[-0.05529785 -2.02894777 \ 1.32230082 \ 0.35026318 \ 1.15957027 \ 1.79485933$ -1.04772295 0.6087262 0.66990206 0.24895119 $[-0.50961171 \quad 0.0687055 \quad -1.2363624 \quad 0.83843219 \quad -0.49446009 \quad -0.0588407$ -1.45141956 -1.01432874 -1.35947185 -0.58797739[-0.46184004 -0.40162953 -0.4143332 0.50325931 0.78080594 -0.233317820.63220501 - 0.223553 - 0.48455207 0.20616234 $[-0.0896985 \quad -0.76342759 \quad -0.42750407 \quad 0.65208608 \quad -0.09193262 \quad 0.29487608$ 0.34934174 0.5552761 -0.01189022 -1.24220082 $[ 0.66445897 \ 0.6876502 \ -0.54899823 \ 0.8855195 \ -1.22463109 \ -0.68277302 ]$ 1.08984342 1.05200418 -0.80294455 1.367485 ] $[ \ 1.31059491 \ \ 1.03102087 \ \ 1.74612498 \ -1.47379568 \ \ 0.03262548 \ -0.73607751$ 1.97273786 0.374869 -1.51204853 -0.37927116 $[ \ 0.50412952 \ -0.15447891 \ \ 0.41218498 \ \ 0.35746725 \ -0.91567378 \ \ 0.46156713$ -1.49298676 -0.94988796 1.50311231 -0.59347381 $[ \ 0.02495456 \ \ 2.67284614 \ -0.05716188 \ -1.28355411 \ -1.19424485 \ -0.43114366 ]$ -0.00453246 0.42502705 0.729496 2.78971646]] $[ [ \ 0.94355011 \ \ 0.12254689 \ -0.27187739 \ \ 0.50821612 \ \ 0.06944769 \ -0.07569204 ]$ 0.08840615 0.04098062 -0.03409669 -0.47849497] $[ \ 0.4236466 \quad \ \ 0.91935204 \quad \ \ 0.15143813 \quad \ \ 0.16048001 \ -0.17022485 \ -0.17851235$ 0.11278749 - 0.18012009 0.32548839 - 0.30372522 $[-0.05317777 -0.04267354 \ 0.48624434 -0.45158029 -0.19906039 \ 0.00587724$ -0.17746267 -0.39180712 0.03030927 0.00353438 $[-0.03126784 \quad 0.50067691 \quad -0.0371507 \quad 0.37950924 \quad 0.10808528 \quad -0.31320014$ 0.04977299 0.22138221 0.78799294 0.27245482 $[-0.64003223 \quad 0.19023125 \quad 0.48398286 \quad -0.16712261 \quad 0.67938387 \quad 0.13053045$ 0.4498163 - 0.25512271 - 0.17137297 0.53326061 $[ \ 0.28858228 \ \ 0.01360262 \ -0.62274922 \ \ 0.54290715 \ -0.39533914 \ \ 0.72815454$ -0.11188991 0.03000587 0.05684441 -0.81641523] $[ \ 0.20755797 \ \ 0.23211207 \ -0.80362356 \ \ 0.37351636 \ -0.13353719 \ \ 0.10487103$ $0.70447003 - 0.51409336 \quad 0.71065162 - 0.2106397$ [ 0.39612922 -0.01247442 0.29534166 0.17992007 -0.1637671 -0.14710787 ]0.3021556 0.80821603 0.28950116 0.32077824] $[ \ 0.67281376 \ -0.34201682 \ \ 0.18979566 \ \ 0.18695516 \ -0.05145348 \ \ 0.11059246 ]$ -0.64044257 0.31579285 0.30777852 -0.54689423] $[-0.06135255 \quad 0.26243655 \quad 0.3531865 \quad 0.02658097 \quad -0.13410605 \quad -0.28415521$ -0.0971166 0.32055799 0.11246977 0.74861504]][[ 1.08855653e+00 -1.09797941e-01 -2.67797316e-02 3.72145884e-02 -1.02090936e-02 -1.84810940e-01 6.78957153e-03 2.60957504e-03 2.30671808e-02 -1.31819893e-01] [-6.34809908e-02 9.60666089e-01 1.20525441e-01 -1.27914029e-02 -2.76151965e-02 -1.58002727e-02 -1.43417765e-01 -2.47076488e-02 4.62577293e-03 -9.81236711e-02] [-1.49563026e-01 -9.55173709e-02 1.02111625e+00 -3.22086344e-02 1.60179027e-01 1.02900986e-04 1.77939725e-01 -2.92069358e-02 -7.59883983e-02 7.32862735e-02] [-5.55983382e-02 -4.33420391e-02 6.26480705e-02 1.06004860e+00 -7.13405920e-02 1.04241342e-01 -6.03795331e-02 5.53072483e-02 -4.36525526e-02 -2.74341283e-02] [-4.57914538e-02 -1.32770070e-02 1.30533461e-01 6.91511520e-02 1.16641796e+00 -9.09930439e-02 -1.04654870e-01 -3.72762519e-02 3.21388673e-02 -4.84812532e-02] [-1.39133975e-01 -4.69189482e-02 -2.00560019e-03 -3.05730989e-02]-5.05633781e-02 1.13940406e+00 -5.07976263e-02 -3.73256434e-02 -7.18229555e-02 1.61973709e-01] [-1.13080374e-01 4.86059595e-02 -9.56500216e-02 5.63264253e-02 5.47404283e-02 1.83866903e-02 9.45856974e-01 7.27750702e-02 -4.51833429e-02 1.10102259e-02] [ 1.83595985e-01 -8.31421948e-02 9.94459807e-04 -8.33756526e-02 1.88445949e-02 -7.83048462e-02 -7.59372723e-02 9.04481603e-01 -7.67604652e-02 2.84401623e-03] [ 2.81509105e-02 -8.91575196e-02 6.37659096e-02 -1.86154389e-01 -2.35106587e-02 -9.42121729e-02 7.49150923e-02 2.58836464e-01 9.57396984e-01 8.45934068e-02]

-1.85018813e-02 1.03184616e+00]]

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