

# Math 578 HW#4

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**Problem 1.** The entirety of this code is contained in the included single file `hw4.py`. In the main executing loop (`if __name__ == "__main__":`), various sections have been commented out. Uncomment as desired and run.

- (a) Cholesky decomposition is performed by the function `hw4.cholesky`. The particular implementation handles sparse matrices as well, and most of the code is simply dedicated to choosing the right method based on the data object provided:

```
1  def cholesky(A):
2      """
3      computes the cholesky decomposition for symmetric, positive definite
4      matrices. returns a lower-triangular matrix L with positive diagonal
5      entries so that  $A=LL^T$ .
6      also returns an integer nzl that gives the number of
7      nonzero entries in the Cholesky factor L.
8
9      INPUT:
10
11      A - a positive definite matrix nxn
12          (may be np.array or scipy.sparse.spmatrix)
13
14      OUTPUT:
15
16      L - the cholesky factor L s.t.  $A = LL^T$ 
17      nzl - number of nonzero entries in L i.e. where  $|L_{ij}| > 0$ 
18
19      """
20
21      if sparse.issparse(A):
22          G = sparse.tril(A)
23          #a sparse matrix that still allows elementwise access
24          G = G.tocsc()
25      else:
26          G = np.tril(A)
27
28      n = A.shape[0]
29
30      for k in range(n):
31          G[k:,k] -= G[k:,:k] @ G[k,:k].T
32          G[k:,k] /= np.sqrt(G[k,k])
33
34      if sparse.issparse(G):
35          nzl = G.count_nonzero()
36      else:
37          nzl = np.count_nonzero(G)
38
39      return G, nzl
```

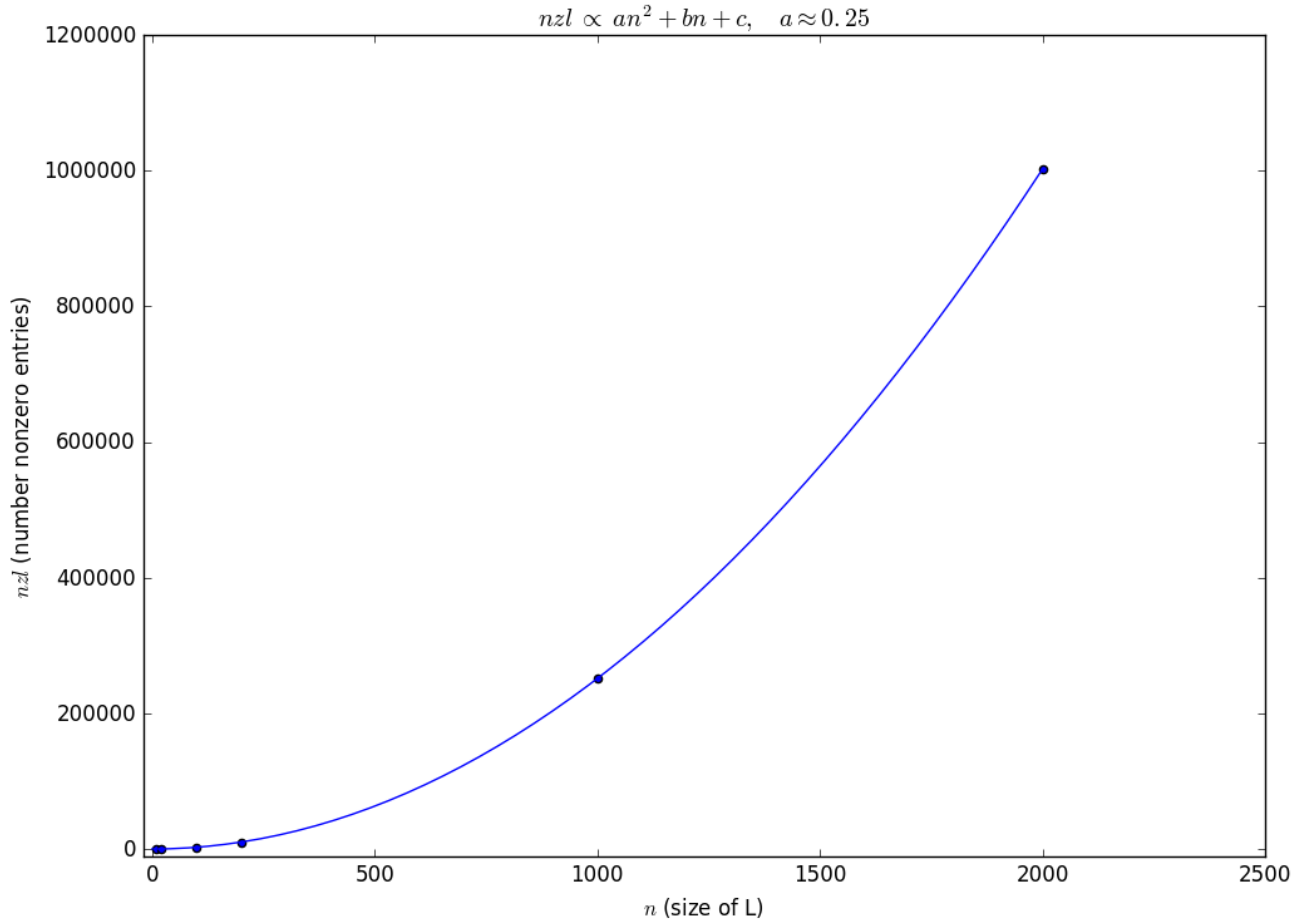


Figure 1: Relationship between size of system  $n$  and number of nonzero elements in Cholesky factor. The relationship was found to be quadratic with leading coefficient  $a \approx 0.25$ .

The following suggested sanity check was performed, which yielded the desired result:

```
In [1]: cholesky(np.array([[2,1,0],[1,2,1],[0,1,2]],dtype='f'))
Out[1]:
(array([[ 1.41421354,  0.          ,  0.          ],
        [ 0.70710677,  1.2247448 ,  0.          ],
        [ 0.          ,  0.81649655,  1.15470064]], dtype=float32), 5)
```

**(b)** Output of `spy(L)` for  $n = 2000$ :

**(c)** To calculate the size  $n$  of system possible to solve with 8GB of memory, we simply use our coefficients we found in part (b) and solve for  $n$ , given that a 8GB of space can store  $8\text{GB} \div 8$  bytes  $\rightarrow 1,000,000$  nonzero entries. Thus we calculate:

$$an^2 + bn + c = 10^9 \rightarrow \frac{1}{4}n^2 \approx 10^9 \rightarrow n \approx 63245$$

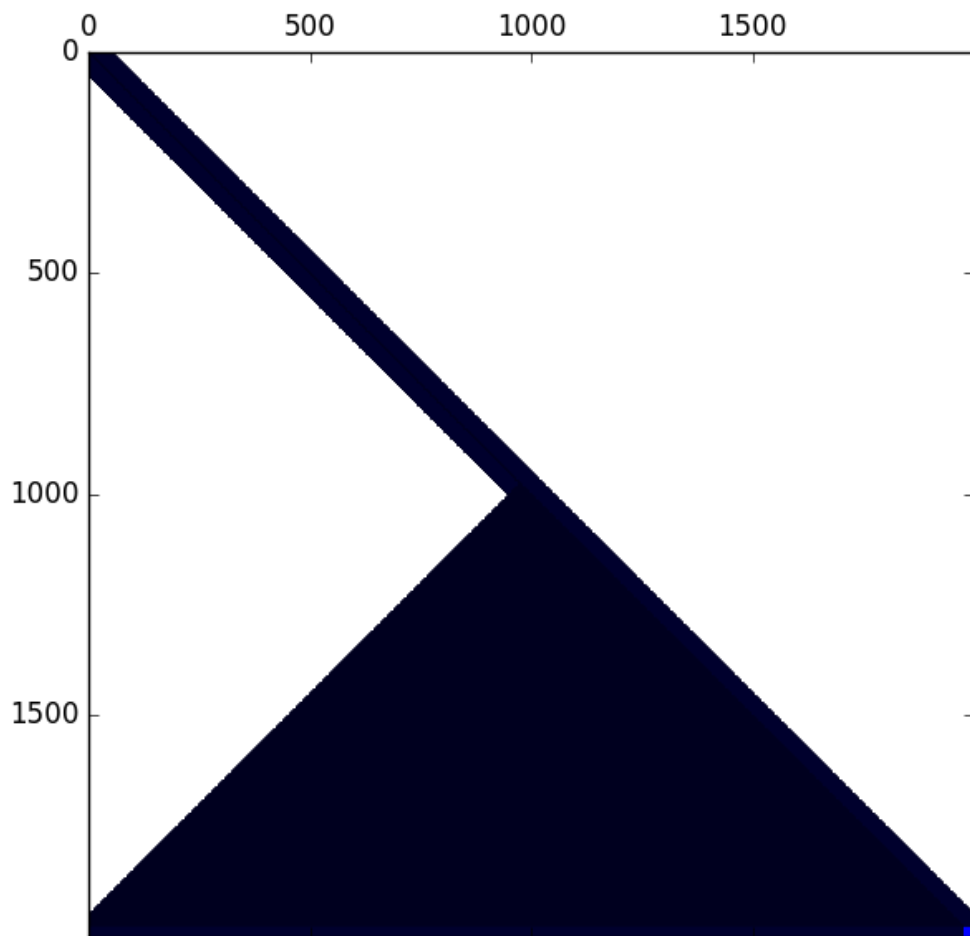


Figure 2: (for part (b)) A visualization of nonzero elements of the cholesky factor  $L$  of the matrix  $A$  when  $n = 1000$

**(d)** The multiply function is as follows:

```
1 def multiply(x, diagonal=None):
2     """
3     implicitly performs the matrix multiplication Ax
4     for the matrix given in (i)
5
6     # test multiply function
7
8     n = 60
9     x = np.expand_dims(np.random.randn(n), -1)
10    A = build_p1(n)
11
12    np.all(np.isclose(A@x, multiply(x))) -> True
13    """
14    if diagonal is None:
15
16        d = 3
17    else:
18        d = diagonal
19
20    y = np.empty_like(x)
21    n = x.size - 1
22    n2 = x.size // 2 - 1
23
24    # just overwrite the different entries later (ignore 0,n)
25    for i in range(1,n):
26        y[i] = d*x[i] - x[i+1] - x[i-1] - x[n-i]
27
28    y[0] = d*x[0] - x[1] - x[-1] # first entry
29    y[-1] = d*x[-1] - x[-2] - x[0] # nth (last) entry
30
31    # then overwrite the following:
32    y[n2] = d*x[n2] - x[n2+1] - x[n2-1]
33    y[n2+1] = d*x[n2+1] - x[n2+2] - x[n2]
34
35    return y
```

**(e)** Conjugate gradient was used to solve the system  $Ax = b$  as described. The following iteration numbers and relative errors were reported:

n	iterations	relative error
10	3	1.13492816813e-15
50	13	7.26595797191e-12
100	26	2.12606603652e-08
5000	1544	6.25257025384e-07
15000	4616	7.0254248905e-07
30000	9216	9.29915260829e-07

Clearly, CG does not fare well as the size of the system increases. The conjugate gradient method was implemented as follows:

```

1 def cg(b=None, n=None, mult=None, tol=1e-6):
2     """
3     non-preconditioned CG
4     initial estimate is b (defaults to normalized ones vector)
5     size of system n (can be inferred from b or vice versa)
6
7     using multiplication method mult
8     """
9
10    assert mult is not None
11
12    if b is None:
13        try:
14            # normalize vector of ones
15            b = np.ones((n,1)) / np.sqrt(n)
16        except NameError:
17            raise Exception('must specify system size or initial guess')
18    else:
19        n = b.size
20
21    # make sure initial guess is a column vector ala matlab
22    if b.ndim == 1:
23        b = np.expand_dims(b,-1)
24
25    # not sure if explicit copy is needed
26    x = np.zeros_like(b)
27    r = b.copy()
28    p = b.copy()
29
30    d = mult(p)
31
32    alpha = np.vdot(r,r) / np.vdot(p,d)
33
34    for iterations in count(1):
35
36        x += alpha*p
37        r_new = r - alpha*d
38
39        beta = np.vdot(r_new,r_new) / np.vdot(r,r)
40
41        p = r_new + beta*p
42
43        d = mult(p)
44
45        alpha = np.vdot(r_new, r_new) / np.vdot(p,d)
46
47        r = r_new
48
49        err = norm(mult(x) - b) / norm(b)
50
51        #print(iterations, err, sep='\t| ')
52        if err <= tol:
53            break
54
55    return x, iterations, err

```

- (f) The following iterations and errors were reported for CG when the diagonal elements of the system were perturbed slightly ( $3 \rightarrow 3.0001$ )

```
n iterations relative error
10 3 1.88574575416e-15
50 13 3.00488927641e-12
100 26 9.88035379143e-07
5000 1519 8.48965754023e-07
15000 1835 9.97779149178e-07
30000 1797 9.90061636977e-07
```

Comparing to the unperturbed system, CG converges faster here. The small perturbation has the effect of lowering the condition number of the matrix.

- (g) Another multiply function was created for the system  $A = I + BB^T$ , and used for conjugate gradient. Implementation as shown:

```
1 def multiply2(x):
2     """
3     multiply implicitly by A = I + BB.T
4     where B = np.tril(np.ones((n,3))) and n = x.size
5     i.e. B = array([[ 1,  0,  0],
6                     [ 1,  1,  0],
7                     [ 1,  1,  1],
8                     [ .  .  .],
9                     [ .  .  .],
10                    [ .  .  .],
11                    [ 1,  1,  1]])
12
13     this faster method is shown by first considering (B.T @ x) itself,
14     which yields the 3-vector:
15     [ S , S -x[0] , S - x[0] - x[1] ], where S = x.sum()
16     """
17
18     S = x.sum()
19
20     # do BB.T mult first
21     BBx = np.zeros_like(x)
22     BBx[0] = S
23     BBx[1] = 2*S - x[0]
24     BBx[2:] = 3*S - 2*x[0] - x[1]
25
26     # now add I part and return
27     return x + BBx
```

Size of system / Iterations / Relative error as shown:

```
10000 4 2.06562011245e-15
50000 4 1.82194210335e-14
100000 4 1.15615944448e-13
```

It's clear that A has at most 4 distinct eigenvalues. Clearly, the matrix  $BB^T$  has rank 3 and thus at most 3 distinct eigenvalues. Thus  $A = I + BB^T$  has these three plus 0 + 1, so 4.