

## DATA ANALYSIS - SCIENTIFIC COMPUTING

Practical Tutorial 2 - Subspace Iteration Methods

Freshman Year, Computer Science Department



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### Limitations of the Power Method

#### Question 01

#### Algorithm 1 Vector Power Method

```
Input: Matrix A \in \mathbb{R}^{n \times n}

Output: (\lambda_1; v_1) eigenpair associated to the largest (in module) eigenvalue. v \in \mathbb{R}^n given. \beta = v^T \cdot A \cdot v

repeat y = A \cdot v

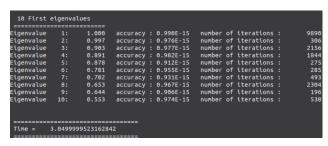
v = y/\|y\|

\beta_{old} = \beta

\beta = v^T \cdot A \cdot v

until |\beta - \beta_{old}|/|\beta_{old}| < \epsilon

\lambda_1 = \beta and v_1 = v
```



(a) Deflated Power Method



(b) LAPACK subroutine dsyev

Figure 1.1: Comparison between the running times of the subroutine deflated\_power\_method and the Lapack subroutine dysev when computing 10 eigenpairs.

One can see from the figures that, although the extracted eigenvalues are obviously the same, the Deflated Power Method is 30 times slower than the dysev LAPACK subroutine when trying to compute 10 eigenpairs.

#### Question 02

The main drawback of the Deflated Power Method is the fact that this method computes the whole spectral decomposition of the matrix A, which is a square  $n \times n$  matrix; a process which proves to be exceptionally time consuming. For the LAPACK subroutine dsyev, the matrix A is first reduced to tridiagonal form using

orthogonal similarity transformations, then the $QR$ algorithm is applied to the tridiagonal matrix to compute the eigenvalues which is significantly more optimized.

## Extending the Power Method to Compute Dominant Eigenspace Vectors

#### 2.1 A Basic Method to Compute a Dominant Eigenspace: subspace\_iter\_v0

#### Question 03

If one were to extend Algorithm 1 to iterate on the matrix V, then the latter will **not** converge towards a matrix with columns containing the m most dominant eigenvectors as one can see in the following example:

Let there be a matrix  $A = \begin{pmatrix} 7 & 9 & 9 \\ 9 & 7 & 9 \\ 9 & 9 & 7 \end{pmatrix}$ . The two most dominant eigenpairs of the matrix A are :  $\lambda_1 = 25$ ;  $v_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$  and  $\lambda_2 = -2$ ;  $v_2 = \begin{pmatrix} 0.4359 \\ -1.3831 \\ 0.9472 \end{pmatrix}$ . Trying to extract the two most dominant eigenvectors with the **edited\_power\_method.m** script will return

$$v_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$
 and  $\lambda_2 = -2$ ;  $v_2 = \begin{pmatrix} 0.4359 \\ -1.3831 \\ 0.9472 \end{pmatrix}$ 

the dominant eigenvalue  $\lambda_1 = 25$ , which normally corresponds to the eigenvector  $v_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ , and the vectors

$$V = \begin{pmatrix} -0.5738 & -0.0636 \\ -0.5738 & -0.0636 \\ -0.5738 & -0.0636 \end{pmatrix}.$$

One can thus notice that the matrix V converges towards a matrix with columns just representing the eigenvector  $v_1$  under a different form (which will be revealed shortly) instead of a matrix with columns containing the m=2 most dominant eigenvectors.

This "different form" is actually none other than beta/norm(beta) with beta = transpose(v) \* A \* v. If one computes its value after the while loop, they will find it to be equal to V.

To avoid this problem, v = y/norm(y) should be replaced with v = mgs(y) in the edited\_power\_method.m script (line 16). The matrix V will contain the eigenvectors associated to the m most dominant eigenvalues as a result. This, however, does not solve the drawback of the Power Method seen in Question 01.

(See Matlab Script edited\_power\_method.m)

#### Question 04

Although a computation of the whole spectral decomposition of the matrix H is performed in Algorithm 2, H is a square m×m matrix (with m being the number of eigenvalues extracted). Thus, this computation is far less significant, especially when compared to the one of the matrix A which is a square  $n \times n$  matrix (n> > m). The reason behind that is the fact that we only need a few number of eigenpairs in order to provide enough information about the data (as seen in TP1). Therefore, a data matrix containing thousands of columns could be analysed using only a few dozens of eigenpairs which leads us to choose a relatively small number m .

### Question 05

#### Algorithm 2 Subspace Iteration Version 0

Input: Symmetric Matrix  $A \in \mathbb{R}^{n \times n}$ , the number of required eigenpairs m, the tolerance  $\epsilon$  and the maximum number of iterations MaxIter.

Output: m dominant eigenvectors  $V_{out}$  and the corresponding eigenvalues  $\Lambda_{out}$ 

Generate a set of m orthonormal vectors  $V \in \mathbb{R}^{n \times m}$ ; k = 0

#### repeat

k = k + 1

 $Y = A \cdot V$ 

 $H = V^T \cdot A \cdot V$ 

Compute acc =  $||A \cdot V - V \cdot H||/||A||$ 

 $V \leftarrow$  orthonormalisation of the columns of Y

until  $(k > MaxIter \text{ or } acc \leq \epsilon)$ 

Compute the spectral decomposition  $X \cdot \Lambda_{out} \cdot X^T = H$ , where the eigenvalues of H (diag( $\Lambda_{out}$ )) are arranged in descending order of magnitude.

Compute the corresponding eigenspace  $V_{out} = V \cdot X$ 

(See Fortran Script iter\_v0.f90)

#### 2.2Improved Version Using Raleigh-Ritz Projection: subspace\_iter\_v1

#### Question 06

#### Algorithm 3 Rayleigh-Ritz Projection

Input: Matrix  $A \in \mathbb{R}^{n \times n}$  and an orthonormal set of Vectors V.

Output: The approximate eigenvectors  $V_{out}$  and the corresponding eigenvalues  $\Lambda_{out}$  Compute the Rayleigh quotient  $H=V^T\cdot A\cdot V$ 

Compute the spectral decomposition  $X \cdot \Lambda_{out} \cdot X^T = H$ , where the eigenvalues of H (diag( $\Lambda_{out}$ )) are arranged in descending order of magnitude.

Compute  $V_{out} = V \cdot X$ 

#### Algorithm 4 Subspace Iteration Version 1 with Rayleigh-Ritz Projection

Input: Symmetric Matrix  $A \in \mathbb{R}^{n \times n}$ , the number of required eigenpairs m, the tolerance  $\epsilon$ , the maximum number of iterations MaxIter and the target percentage of the trace of A, TracePercentage

Output:  $n_{ev}$  dominant eigenvectors  $V_{out}$  and the corresponding eigenvalues  $\Lambda_{out}$ 

Generate a set of m orthonormal vectors  $V \in \mathbb{R}^{n \times m}$ ; k = 0; PercentageReached = 0repeat

k = k + 1

Compute Y such that  $Y = A \cdot V$ 

 $V \leftarrow$  orthonormalisation of the columns of Y

Apply Rayleigh-Ritz projection on matrix A and orthonormal vectors V

Convergence Analysis: save the converged eigenpairs and update PercentageReached

until (PercentageReached > TracePercentage or  $n_{ev} > m$  or k > MaxIter)

All of the steps of Algorithm 4 are already identified and highlighted in French in the file

subspace\_iter\_v1.m

(See Matlab Script subspace\_iter\_v1.m)

## Towards an Efficient Solver: subspace\_iter\_v2 & subspace\_iter\_v3

Two ways of improving the efficiency of the solver are proposed. Our aim is to build an algorithm that combines both the block approach and the deflation method in order to speed-up the convergence of the solver.

## 3.1 Block approach (subspace\_iter\_v2)

Orthonormality is performed at each iteration and is quite costly. One simple way to accelerate the approach is to perform p products at each iteration (replace V = A.V (first step of the iteration) by  $V = A^p.V$ ). Note that this very simple acceleration method is applicable to all versions of the algorithm.

#### Question 07

The definition of matrix multiplication is that if C = AB for an  $n \times m$  matrix A and an  $m \times p$  matrix B, then C is an  $n \times p$  matrix with entries

$$c_{ij} = \sum_{k=1}^{m} a_{ik} b_{kj} \tag{3.1}$$

From this, a simple algorithm can be constructed which loops over the indices i from 1 through n and j from 1 through p, computing the above using a nested loop:

#### Algorithm 5 Iterative algorithm of matrix multiplication

```
1: Input: matrices A and B
2: Let C be a new matrix of the appropriate size
3: for i from 1 to n do
       for j from 1 to p do
4:
           sum = 0
 5:
           for k from 1 to m do
6:
               sum \leftarrow sum + A_{ik} * B_{ki}
 7:
8:
           end for
           C_{ij} \leftarrow sum
9:
10:
       end for
11: end for
12: \mathbf{return}\ C
```

This algorithm takes time  $\Theta(n \times m \times p)$ . A common simplification for the purpose of algorithms analysis is to assume that the inputs are all square matrices of size  $n \times n$ , in which case the running time is  $\Theta(n^3)$ , i.e., cubic. So if we assume that A is equal to B we will find that the calculation  $A^2$  has a complexity of  $\Theta(n^3)$ , then by recurrence we can show that the calculation  $A^p$  has a complexity of  $\Theta((p-1)n^3)$ . Now we suppose that we have a matrix  $V \in M_{n \times m}$ , the calculation of  $A^p$ . V has a complexity of  $\Theta(m \times n^2 + (p-1)n^3)$ .

One good way to reduce the cost is implementing a loop that calculates V = AV p times rather than calculating  $A^p$ , this will lead us to the same result  $V = A^pV$  in a less costy way due to the size of V, the complexity here should be  $\Theta(p \times m \times n^2)$ .

Another way out is Singular Value Decomposition SVD. Given an  $n \times n$  real matrix A of full rank, SVD splits it apart as  $A = U\Sigma U^T$  where  $\Sigma$  is a diagonal matrix, in time  $theta(n^3)$ . By the properties of SVD,  $A^m = U\Sigma^m U^T$ , so only the powers of the diagonal matrix need to be computed, and this can be done in  $\Theta(n \times log(m))$  time.

Performing the final multiplication  $U \times \Sigma^m \times U^T$  takes  $\Theta(n^{2.3727})$ , so we have altogether  $\Theta(n^3 + nlog(m))$  operations.

#### Question 08

iter\_v2.f90
(See Fortran file iter\_v2.f90)

### 3.2 Deflation Method (subspace\_iter\_v3)

Because the columns of V converge in order, we can freeze the converged columns of V. This freezing results in significant savings in the matrix-vector ( $V = A\Delta V$ ), the orthonormalisation and Rayleigh-Ritz Projection steps.

Specifically, suppose the first  $nbc^2$  columns of V have converged, and partition  $V = [V_c, V_{nc}]$  where  $V_c$  has nbc columns and  $V_{nc}$  has m - nbc columns 3. Then, we can form the matrix  $[V_c, A\Delta V_{nc}]$ , which is the same as if we multiply V by A. However, we still need to orthogonalise  $V_{nc}$  with respect to the frozen vectors  $V_c$  by first orthogonalising  $V_{nc}$  against  $V_c$  and then against itself.

Finally, the Rayleigh-Ritz Projection step can also be limited to the columns  $V_{nc}$  of V.

#### Question 09

The execution of the main program with the option disp = 2, displays the precision of a vector when it converges at the end of the computation to check if everything is OK. With the

subspace\_iter\_method\_v1, this precision is different for some of the vectors because of the Raleigh-Ritz projection which gives as output a vector containing the approximations of the eigenvalues which is used to calculate the norm of the residue, to deter-

mine if a vector converges or not, and thus to know if the eigenvalue makes it possible to reach the percentage.

#### Question 10

The subspace iter v2 method will be much faster than the subspace iter v1, because using  $V = A^p$  instead of  $V = A \times V$  allows us to accelerate the method globally, unlike the first one that uses an othonormalization and computation of proper couples all the iterations.

## Question 11

iter\_v3.f90
(See Fortran file iter\_v3.f90)

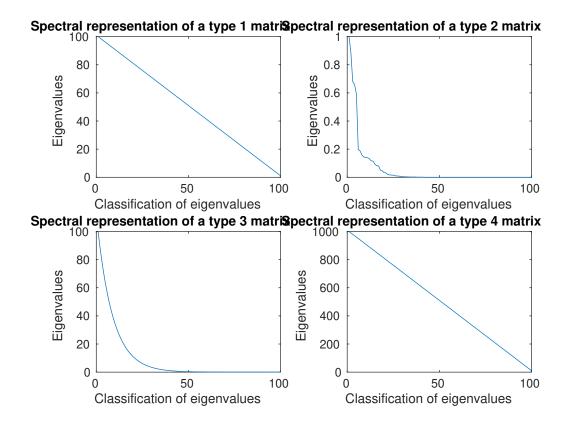
## Numerical experiments

#### Question 12

We can notice that when p increases, time decreases as a logical consequence of the decrease in the number of iterations in our algorithm. As such, the reduction in orthonormalization and eigenvector search allows us to save considerable time.

### Question 13

The following images show the eigenvalue distribution of these different types:



### Question 14

For the first and the fourth types , the DSYEV is faster with a matrix that has big dimensions than the rest of the methods followed by  $subspace_i ter_v 3$  method . For matrix with small dimensions, all of the methods have almost the same performance with a small advantage again for the DSYEV method and the  $power_v 11$  method. For the second and the third types , we can witness the same results except that  $subspace_i ter_v 2$  performs better in the second type.

## Fortran/Matlab Source Code Listings

## 5.1 Subspace Iteration Version 0

```
This file is provided as part of the "projet long" for the "Calcul Scientifique et Analyse
2
3
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38
39
40
41
42
```

```
subroutine subspace_iter_v0(n, m, a, maxit, eps, v, w, acc, it, ierr)
43
45
       integer,
                           intent(in)
                                                             :: n, m
46
47
                                                             :: a
48
49
                                                             :: maxit
50
51
52
                                                             :: eps
53
       double precision, dimension(m), intent(out)
                                                             :: w
54
55
56
57
58
59
                                                             :: acc
60
61
                           intent(out)
62
                           intent(out)
                                                             :: ierr
63
64
65
                                                             :: dlange
66
67
68
69
       integer, parameter
                                                             :: ione = 1
                                                             :: done = 1.d0, dzero = 0.d0, dmoins =
70
71
72
73
74
75
76
77
                                                             :: w_aux
78
79
       double precision, allocatable, dimension(:)
                                                             :: work
                                                             :: lwork
80
                                                             :: normF_A
81
82
83
84
85
       if (m.gt.n) then
86
87
          ierr = -1
88
89
90
       lwork = m*m + 5*m + n*n
91
92
       allocate(aux(n, m), y(n, m), h(m, m), x(m, m), w_{aux}(m), w_{aux}(m), w_{aux}(m)
93
94
         ierr = -2
95
96
       end if
97
98
       normF_A = dlange('f', n, n, a, n, work)
99
100
       k = 0
       acc = 100*eps
102
104
```

```
call gram_schmidt(v, n, m, y)
106
108
        do while((acc .ge. eps) .and. (k .lt. maxit))
109
          k = k + 1
111
112
          call dgemm('n', 'n', n, m, n, done, a, n, v, n, dzero, y, n)
113
114
115
          call dgemm('t', 'n', m, m, n, done, v, n, y, n, dzero, h, m)
116
117
118
119
          aux = y
120
          call dgemm('n', 'n', n, m, m, dmoins, v, n, h, m, done, aux, n)
121
122
123
          acc = dlange('f', n, m, aux, n, work) / normF_A
124
125
          write(*,'(" IT:",i5," -- Accuracy is: ",es10.2,a)',advance='no') k, acc, char(13)
126
127
          call gram_schmidt(y, n, m, v)
128
129
        end do
130
131
        if(acc .lt. eps) then
132
          ! compute the spectral decomposition of the Rayleigh quotient h call dsyev('v', 'u', m, h, m, w_aux, work, lwork, ierr)
133
134
135
136
137
            goto 999
138
139
140
141
142
143
            x(:, i) = h(:, m-i +1)
w(i) = w_aux(m-i +1)
144
145
146
147
148
149
          call dgemm('n', 'n', n, m, m, done, y, n, x, m, dzero, v, n)
150
151
152
          ierr = -3
154
   999 continue
156
        deallocate (aux, y, h, x, w_aux, work)
157
        write(*,*)
158
159
        it = k
160
161
162
     end subroutine subspace_iter_v0
163
```

## 5.2 Edited Power Method (Matlab)

```
function [ w, v0, it, flag ] = edited_power_method(A, m, eps, kmax)
2
3
5
6
       v = randn(n, m); v = mgs(v); %Randomized orthonormal n*m Matrix
7
8
9
       beta = norm(transpose(v)*A*v); %Eventual Eigenvalues
10
       cv = false; %Did it converge?
k = 0; %Number of iterations
11
12
13
14
           y = A * v;
15
16
           v = y/norm(y);
           beta_old = beta;
17
18
19
20
           beta = norm(transpose(v)*y);
21
           err1 = (abs(beta - beta_old) / abs(beta_old));
22
23
           cv = ((err1 <= eps) | (k >= kmax));
24
25
26
27
28
       w = beta;
29
30
31
32
34
```

## 5.3 Subspace Iteration Version 1 (Matlab)

```
version am lior e de la m thode de l'espace invariant (v1)
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5
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13
14
15
16
17
18
19
20
   function [ W, V, n_ev, it, flag ] = subspace_iter_v1( A, m, percentage, eps, maxit )
21
22
23
       normA = norm(A, 'fro');
24
25
26
       traceA = trace(A);
27
28
29
30
       vtrace = percentage*traceA;
31
       n = size(A,1);
32
       W = zeros(n,1);
33
34
35
36
37
38
       eigsum = 0.0;
39
40
       nb_c = 0;
41
42
43
       conv = 0;
44
45
       Vr = randn(n, m);
46
47
       Vr = mgs(Vr);
48
49
       while (~conv & k < maxit),
50
51
           k = k+1;
52
53
           Y = A * Vr;
54
55
           Vr = mgs(Y);
56
57
58
            [Wr, Vr] = rayleigh_ritz_projection(A, Vr);
59
60
61
           analyse_cvg_finie = 0;
```

```
% nombre de vecteurs ayant converg
63
64
65
66
            i = nb_c + 1;
67
            while (~analyse_cvg_finie),
68
69
70
71
                 if(i > m)
                     analyse_cvg_finie = 1;
72
73
74
75
76
                     aux = A*Vr(:,i) - Wr(i)*Vr(:,i);
77
                     res = sqrt(aux'*aux);
78
79
                     if(res >= eps*normA)
80
81
82
83
                          analyse_cvg_finie = 1;
84
85
86
87
                          nbc_k = nbc_k + 1;
88
89
                          W(i) = Wr(i);
90
91
92
                          eigsum = eigsum + W(i);
93
94
96
                          if(eigsum >= vtrace)
97
                               analyse_cvg_finie = 1;
98
99
100
                               i = i + 1;
101
102
106
107
            nb_c = nb_c + nbc_k;
108
109
110
            conv = (nb_c == m) | (eigsum >= vtrace);
112
113
114
        if (conv)
115
116
            n_ev = nb_c;
117
            V = Vr(:, 1:n_ev);
118
            W = W(1:n_{ev});
119
120
121
122
            W = zeros(1,1);
123
            n_ev = 0;
125
126
127
```

## 5.4 Subspace Iteration Version 2

```
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28
29
30
31
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41
42
43
44
45
46
47
     subroutine subspace_iter_v2(n, m, a, p, percentage, maxit, eps, v, w, n_ev, acc_ev, it_ev,
        ierr)
49
50
                           intent(in)
51
        integer,
                                                                  :: n, m
```

```
double precision, dimension(n, n), intent(in)
53
                                                              :: a
54
                         intent(in)
       integer,
55
56
57
                                                              :: percentage
58
59
                                                              :: maxit
60
                                                              :: eps
61
62
63
       double precision, dimension(n, m), intent(inout) :: v
64
65
       double precision, dimension(m), intent(out)
66
67
68
                                                              :: n_ev
69
                                             intent(out)
70
                                                              :: acc_ev
71
72
                                                              :: it_ev
73
                           intent(out)
74
                                                              :: ierr
75
76
77
                                                              :: dlange, ddot
78
79
80
                                                              :: ione = 1
                                                              :: done = 1.d0, dzero = 0.d0, dmoins =
81
        -1.d0
83
                                                              :: i, j
85
                                                              :: h, x
86
       double precision, allocatable, dimension(:)
87
                                                              :: aux_acc, w_aux, t
                                                              :: trace, p_trace, eig_sum, normF_A
88
89
                                                              :: conv
90
91
                                                              :: acc
92
                                                              :: beta
93
94
                                                              :: lwork
95
96
                                                              :: work
97
98
       double precision, dimension(n,n)
99
100
        ierr = 0
101
102
103
104
        if (m.gt.n) then
105
          ierr = -1
106
       end if
107
108
109
       lwork = m*m + 5*m + n*n
110
        allocate(y(n, m), h(m, m), x(m, m), w_aux(m), aux_acc(n), t(m), work(lwork), stat=ierr)
111
112
         ierr = -2
113
114
116
```

```
!! Calculate A^p
117
118
        do i = 1, p
119
120
            call dgemm('n', 'n', n, n, n, done, a, n, c, n, dzero, c, n)
        end do
121
122
123
        trace = 0.d0
124
125
          trace = trace + a(i,i)
126
127
        p_trace = percentage * trace
128
        eig_sum = 0.d0
129
130
        normF_A = dlange('f', n, n, a, n, work)
131
132
        it_ev = 0
133
        acc_{ev} = 0.D0
134
        n_ev = 0
135
        k = 0
136
137
138
        call gram_schmidt(v, n, m, y)
139
140
141
        do while((eig_sum .lt. p_trace) .and. (n_ev .lt. m) .and. (k .lt. maxit))
142
143
          k = k + 1
144
145
          !! A. Compute y = a*v call dgemm('n', 'n', n, m, n, done, c, n, v, n, dzero, y, n)
146
147
148
149
          call gram_schmidt(y, n, m, v)
150
152
154
          call dgemm('n','n', n, m, n, done, c, n, v, n, dzero, y, n)
155
156
          call dgemm('t', 'n', m, m, n, done, v, n, y, n, dzero, h, m)
157
          !! 2. Spectral decomposition
158
          call dsyev('v', 'u', m, h, m, w_aux, work, lwork, ierr)
159
          !problem in dsyev (ERROR) if ( ierr .ne.0 )then
160
161
162
            ierr = -4
163
            goto 999
164
          end if
165
166
167
168
169
            t(i) = w_{aux}(m-i+1)
170
171
          end do
172
173
174
175
176
          call dgemm('n', 'n', n, m, m, done, y, n, x, m, dzero, v, n)
177
178
179
          i = n_ev + 1
180
181
```

```
!\,! those corresponding to the smaller eigenvalue. !\,! for this reason, we test the convergence in the order
182
183
184
185
186
187
188
189
190
191
192
                aux_acc = v(:,i)
193
                beta = -t(i)
194
                call dgemv('n', n, n, done, a, n, v(1,i), ione, beta, aux_acc, ione)
195
                acc = sqrt(ddot(n, aux_acc, ione, aux_acc, ione))/normF_A
196
197
198
                if(acc.gt.eps) then
199
200
201
202
203
                  w(i) = t(i)
204
                  acc_ev(i) = acc
205
                  it_ev(i) = k
206
207
                  eig_sum = eig_sum + w(i)
                  i = i + 1
208
                  if( eig_sum .ge. p_trace) ok = .true.
209
210
             end if
211
212
213
214
           n_{ev} = n_{ev} + conv
215
216
        end do
217
218
219
         if (n_{ev} .eq. m) then
220
221
           ierr = 1
222
223
224
        if(k .eq. maxit) then
225
226
        end if
227
228
229
   999 continue
        deallocate(y, h, x, w_aux, aux_acc, t)
230
231
         write(*,*)
232
233
     end subroutine subspace_iter_v2
```