

Assignment on Googlenet

MTech in Applied AI Natural Language Processing

by

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1 Problem Statement

1. Write your own function in Python for computing the computation load, i.e., number of products and summations for each layer, dimensions of the output of a layer, and number of trainable parameters.

The function should accept the following arguments:

- (a) Type of layer
- (b) For a convolution layer: height of filter kernel, width of filter kernel, stride, padding, number of filter kernels.

For a dense layer: number of nodes.

(c) Dimension of the input

The function should return the following parameters:

- (a) Dimension of the output
- (b) Number of trainable parameters
- (c) Number of dot products
- (d) Total number of products and sums
- 2. **Using the function**, find out the dimensions of the output, number of trainable parameters, and total number of sums and products for each layer in the **GoogleNet architecture**.

1.1 Python code - Methods for computation load

```
class ComputationLoad:
      def layer_computation(layer_type, layer_params, input_dim):
           Compute architectural details for a neural network layer.
           Args:
10
               layer_type: str - 'conv' for convolutional, 'dense' for fully connected
               layer_params: dict - parameters for the layer
                   For conv: {'h': height, 'w': width, 'stride': stride,
13
                              'padding': padding, 'num_filters': number of filters}
14
                   For dense: {'nodes': number of nodes}
               input_dim: tuple - (channels, height, width) for conv,
16
                                   (nodes,) for dense
17
18
          Returns:
19
20
                   'output_dim': output dimensions,
21
22
                   'trainable_params': number of trainable parameters,
                   'dot_products': number of dot products,
23
                   'total_ops': total number of operations (products + sums)
24
25
           ....
26
           result = {}
27
28
           if layer_type == 'conv':
29
               # Unpack parameters
30
               C_in = input_dim[0]
               H_in = input_dim[1]
```

```
W_in = input_dim[2]
33
34
               F_h = layer_params['h']
               F_w = layer_params['w']
35
               stride = layer_params['stride']
36
               padding = layer_params['padding']
37
               num_filters = layer_params['num_filters']
38
39
              print(f"->Input Dimension : {input_dim}")
40
               print(f"->Filter Paramaters : {layer_params}")
41
42
               # Calculate output dimensions
43
              H_{out} = ((H_{in} - F_h + 2 * padding) // stride) + 1
44
               W_{out} = ((W_{in} - F_{w} + 2 * padding) // stride) + 1
45
               result['output_dim'] = (num_filters, H_out, W_out)
46
47
               # Number of trainable parameters
48
               # (weights + bias) for each filter
49
               result['trainable_params'] = num_filters * (C_in * F_h * F_w + 1)
50
51
              # Number of dot products (one per output pixel per filter)
52
              result['dot_products'] = num_filters * H_out * W_out
53
54
               \# Total operations: each dot product is F_h*F_w*C_i multiplications
55
               # and (F_h*F_w*C_in - 1) additions
56
               ops_per_dot = F_h * F_w * C_in * 2 - 1
57
               result['total_ops'] = result['dot_products'] * ops_per_dot
58
59
60
          elif layer_type == 'dense':
              # Unpack parameters
61
              nodes_in = input_dim[0]
62
              nodes_out = layer_params['nodes']
63
64
              print(f"->Input Dimension : {input_dim}")
65
66
               # Output dimension
67
              result['output_dim'] = (nodes_out,)
68
69
70
               # Number of trainable parameters (weights + bias)
              result['trainable_params'] = nodes_in * nodes_out + nodes_out
71
72
73
               # Number of dot products (one per output node)
              result['dot_products'] = nodes_out
74
75
              # Total operations: each dot product is nodes_in multiplications
76
77
              # and (nodes_in - 1) additions
               ops_per_dot = nodes_in * 2 - 1
78
79
               result['total_ops'] = result['dot_products'] * ops_per_dot
80
81
              raise ValueError(f"Unknown layer type: {layer_type}")
83
         return result
84
```

Listing 1: Code

```
# usage_example.py

from computation_load import ComputationLoad

def main():
    # Example 1: Convolutional Layer
    conv_params = {
        'h': 3,
        'w': 3,
        'stride': 1,
```

```
11
          'padding': 1,
12
          'num_filters': 64
      conv_input_dim = (3, 224, 224)
14
      conv_result = ComputationLoad.layer_computation('conv', conv_params, conv_input_dim)
15
      print(f" Convolutional Layer Result")
16
      print(f" Output dimension: {conv_result['output_dim']}")
17
      print(f"
                Trainable parameters: {conv_result['trainable_params']:,}")
18
      print(f" Total operations: {conv_result['total_ops']:,}")
19
20
      print("="*80)
21
      # Example 2: Dense (Fully Connected) Layer
22
      dense_params = {'nodes': 1000}
23
24
      dense_input_dim = (4096,)
      dense_result = ComputationLoad.layer_computation('dense', dense_params, dense_input_dim)
25
      print(f" Dense Layer Result:")
26
      print(f" Output dimension: {conv_result['output_dim']}")
27
      print(f"
                Trainable parameters: {conv_result['trainable_params']:,}")
28
      print(f" Total operations: {conv_result['total_ops']:,}")
29
30
31 if __name__ == "__main__":
main()
```

Listing 2: Sample usage of computation method

Output - Computation Load sample usage output 1.2

```
1 C:\Users\urssa\AppData\Local\Microsoft\WindowsApps\python3.11.exe C:\Sanjeev\VNIT_CLASSES\VNIT-AAI-SEM3\sul
2 ->Input Dimension: (3, 224, 224)
3 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 64}
   Convolutional Layer Result
   Output dimension: (64, 224, 224)
   Trainable parameters: 1,792
  Total operations: 170,196,992
8
9 -> Input Dimension : (4096,)
   Dense Layer Result:
10
   Output dimension: (64, 224, 224)
12
   Trainable parameters: 1,792
   Total operations: 170,196,992
13
15 Process finished with exit code 0
```

Listing 3: Output - Sample usage of computation method

```
1 from computation_load import ComputationLoad
def inception_module(input_dim, module_params):
       Compute architectural details for an Inception module.
4
5
6
       Args:
7
           input_dim: tuple - (channels, height, width)
           module_params: dict - parameters for each branch
9
                     'branches': [
                        {'type': 'conv', 'params': {...}}, # 1x1 branch
                         {'type': 'conv', 'params': {...}}, # 3x3 branch {'type': 'conv', 'params': {...}}, # 5x5 branch
12
                         {'type': 'pool', 'params': {...}}
                                                                  # pooling branch
14
                    ]
15
                }
16
17
18
       Returns:
           dict: same structure as layer_computation
19
```

85

```
21
       branch_results = []
22
       for branch in module_params['branches']:
23
            if branch['type'] == 'pool':
24
                # For pooling branch, we need to add a 1x1 conv after pooling
25
                # First do pooling (no trainable params)
26
                pool_params = branch['params']
27
                H_in = input_dim[1]
28
29
                W_in = input_dim[2]
                F_h = pool_params['h']
30
                F_w = pool_params['w']
31
32
                stride = pool_params['stride']
                padding = pool_params['padding']
33
34
                H_{out} = ((H_{in} - F_h + 2 * padding) // stride) + 1
35
36
                W_{out} = ((W_{in} - F_{w} + 2 * padding) // stride) + 1
                pool_output_dim = (input_dim[0], H_out, W_out)
37
38
                # Then do 1x1 conv
39
                conv_params = {
40
                     'h': 1, 'w': 1, 'stride': 1,
41
                     'padding': 0, 'num_filters': pool_params['num_filters']
42
43
44
                branch_result = ComputationLoad.layer_computation('conv', conv_params, pool_output_dim)
            else:
45
                branch_result = ComputationLoad.layer_computation(branch['type'], branch['params'], input_dim)
46
47
           branch_results.append(branch_result)
48
49
       # Concatenate all branches along the channel dimension
50
       total_filters = sum(br['output_dim'][0] for br in branch_results)
51
       output_dim = (total_filters,) + branch_results[0]['output_dim'][1:]
52
53
       # Sum all operations and parameters
54
       total_params = sum(br['trainable_params'] for br in branch_results)
55
       total_ops = sum(br['total_ops'] for br in branch_results)
56
57
           'output_dim': output_dim,
59
           'trainable_params': total_params,
60
61
            'dot_products': sum(br['dot_products'] for br in branch_results),
            'total_ops': total_ops
62
63
       }
64
65 def analyze_googlenet():
       current_dim = (3, 224, 224) # Input RGB image
66
67
       total_params = 0
       total_ops = 0
68
69
       def pool_output(dim, k, s, p):
70
           print(f"->Input Dimension : {dim}")
71
72
           print(f"->Filter Parameters : {{'h': {k}, 'w': {k}, 'stride': {s}, 'padding': {p}}}}")
73
           c, h, w = dim
74
           h_{out} = ((h - k + 2 * p) // s) + 1
75
           w_{out} = ((w - k + 2 * p) // s) + 1
76
77
           return (c, h_out, w_out)
78
       layers = [
79
            {'type': 'conv', 'params': {'h': 7, 'w': 7, 'stride': 2, 'padding': 3, 'num_filters': 64}}, # 1
80
           {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}}, # 2
{'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}}, # 3
{'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 192}}, # 4
                                                                                                                    # 2 - 1
81
82
83
            {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}},
84
```

```
# Inception modules
86
               {'type': 'inception', 'params': { # 6 - 3a
87
                      branches': [
88
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}};
 89
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 96}}
90
                          {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 128}]
91
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 16}}
92
                           {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 32}}
{'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 32}}
93
94
                     ]
95
               }}.
96
               {'type': 'inception', 'params': {  # 7 - 3b
97
                      'branches': [
98
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}]
99
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}]
100
                           {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 192}]
101
                          {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}} {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 96}} {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 64}}
103
104
                     ]
               }},
106
               {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}}, # 8 - MaxPool
107
108
               {'type': 'inception', 'params': { # 9 - 4a
109
                      'branches': [
                          {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 192}]
111
                          {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 96}} {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 208}} {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 16}}
114
                           {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 48}}
                           {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 64}}
116
                     ]
117
               }},
118
               {'type': 'inception', 'params': { # 10 - 4b
119
120
                      'branches': [
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 160}]
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 112}]
{'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 224}]
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 24}}
124
                           {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 64}}, {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 64}}
126
127
               }},
128
               {'type': 'inception', 'params': { # 11 - 4c
129
130
                     'branches': [
                          {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}} {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}} {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 256}}
133
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 24}}
134
                           {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 64}} {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 64}}
136
137
               }},
138
               {'type': 'inception', 'params': { # 12 - 4d
                     'branches': [
140
                          {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 112}]
{'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 144}]
{'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 288}]
141
142
143
                           {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}}
144
                           {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 64}}
145
                           {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 64}}
146
147
               }},
148
               {'type': 'inception', 'params': { # 13 - 4e
149
                     'branches': [
150
```

```
{'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 256}}
                      {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 160}} {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 320}} {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}} {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 128}}
153
154
                       {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 128}]
156
                  ]
157
             }},
158
             {'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}}, # 14 - MaxPool
159
160
             {'type': 'inception', 'params': { # 15 - 5a
161
                  'branches': [
                       {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 256}}
163
                       {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 160}}
164
                      {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 320}}
165
                       {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}}
                       {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 128}]
{'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 128}]
167
168
                 ]
169
             }},
             {'type': 'inception', 'params': { # 16 - 5b
171
                  'branches': [
                       {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 384}}
                       {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 192}]
174
                      {'type': 'conv', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 384}]
                      {'type': 'conv', 'params': {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 48}}
176
                       {'type': 'conv', 'params': {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 128}]
{'type': 'pool', 'params': {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 128}]
178
                  ]
179
             }}.
180
             {'type': 'pool', 'params': {'h': 7, 'w': 7, 'stride': 1, 'padding': 0}}, # 17 - AvgPool
181
             {'type': 'dense', 'params': {'nodes': 1000}} # 18 - Fully connected classifier
182
183
184
        print("GoogleNet Architecture Analysis (All 22 Layers):")
185
        print("=" * 70)
186
        print(f"Input dimension: {current_dim}")
187
        print("-" * 70)
188
189
        for i, layer in enumerate(layers):
190
191
             if layer['type'] == 'inception':
                  print(f"Layer {i + 1} (Inception module):")
192
                  result = inception_module(current_dim, layer['params'])
193
194
195
             elif layer['type'] == 'pool':
                  print(f"Layer {i + 1} (Pooling layer):")
196
                  result = {'output_dim': pool_output(current_dim, layer['params']['h'], layer['params']['stride
197
                              'trainable_params': 0, 'dot_products': 0, 'total_ops': 0}
198
199
                  print(f"Layer {i + 1} ({layer['type']}):")
                  result = ComputationLoad.layer_computation(layer['type'], layer['params'], current_dim)
201
202
             print(f" Output dimension: {result['output_dim']}")
203
             print(f" Trainable parameters: {result[', trainable_params']:,}")
204
             print(f" Total operations: {result['total_ops']:,}")
205
             print("-" * 50)
206
207
             total_params += result['trainable_params']
208
             total_ops += result['total_ops']
209
210
             current_dim = result['output_dim']
211
212
        print("=" * 70)
        print(f"Total trainable parameters: {total_params:,}")
213
        print(f"Total operations: {total_ops:,}")
214
215
```

```
216
217 # Run the analysis
218 analyze_googlenet()
```

Listing 4: Code - Googlenet layer by layer computation

1.3 Output - Googlenet layer by layer calculation output

```
1 C:\Users\urssa\AppData\Local\Microsoft\WindowsApps\python3.11.exe C:\Sanjeev\VNIT_CLASSES\VNIT-AAI-SEM3\sul
2 GoogleNet Architecture Analysis (All 22 Layers):
      -----
4 Input dimension: (3, 224, 224)
6 Layer 1 (conv):
7 -> Input Dimension : (3, 224, 224)
s ->Filter Paramaters : {'h': 7, 'w': 7, 'stride': 2, 'padding': 3, 'num_filters': 64}
    Output dimension: (64, 112, 112)
    Trainable parameters: 9,472
10
  Total operations: 235,225,088
12 --
13 Layer 2 (Pooling layer):
14 ->Input Dimension : (64, 112, 112)
15 -> Filter Parameters : {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}
   Output dimension: (64, 56, 56)
    Trainable parameters: 0
17
   Total operations: 0
19
20 Layer 3 (conv):
21 -> Input Dimension: (64, 56, 56)
22 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
    Output dimension: (64, 56, 56)
    Trainable parameters: 4,160
24
   Total operations: 25,489,408
25
26 -----
27 Layer 4 (conv):
28 ->Input Dimension : (64, 56, 56)
29 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 192}
   Output dimension: (192, 56, 56)
30
    Trainable parameters: 110,784
31
   Total operations: 693,030,912
32
33 -----
34 Layer 5 (Pooling layer):
35 -> Input Dimension : (192, 56, 56)
36 ->Filter Parameters : {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}
37
    Output dimension: (192, 28, 28)
38
    Trainable parameters: 0
39
   Total operations: 0
41 Layer 6 (Inception module):
42 ->Input Dimension : (192, 28, 28)
43 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
44 ->Input Dimension : (192, 28, 28)
45 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 96}
46 ->Input Dimension : (192, 28, 28)
47 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 128}
48 ->Input Dimension : (192, 28, 28)
->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 16}
->Input Dimension : (192, 28, 28)
51 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 32}
52 ->Input Dimension : (192, 28, 28)
53 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}
   Output dimension: (368, 28, 28)
54
55
   Trainable parameters: 415,088
   Total operations: 649,992,448
```

```
58 Layer 7 (Inception module):
59 ->Input Dimension: (368, 28, 28)
60 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
61 ->Input Dimension: (368, 28, 28)
62 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
63 ->Input Dimension: (368, 28, 28)
64 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 192}
65 ->Input Dimension : (368, 28, 28)
66 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}
67 ->Input Dimension : (368, 28, 28)
68 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 96}
69 ->Input Dimension: (368, 28, 28)
70 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
    Output dimension: (640, 28, 28)
    Trainable parameters: 1,649,280
72
73 Total operations: 2,584,565,760
74 -----
75 Layer 8 (Pooling layer):
76 ->Input Dimension : (640, 28, 28)
77 ->Filter Parameters : {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}
   Output dimension: (640, 14, 14)
    Trainable parameters: 0
79
   Total operations: 0
80
81 -----
82 Layer 9 (Inception module):
83 ->Input Dimension : (640, 14, 14)
84 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 192}
85 ->Input Dimension : (640, 14, 14)
86 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 96}
87 ->Input Dimension : (640, 14, 14)
88 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 208}
89 ->Input Dimension : (640, 14, 14)
90 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 16}
91 ->Input Dimension : (640, 14, 14)
92 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 48}
93 ->Input Dimension : (640, 14, 14)
94 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
    Output dimension: (624, 14, 14)
   Trainable parameters: 2,202,224
96
   Total operations: 862,904,896
97
98 -----
99 Layer 10 (Inception module):
->Input Dimension : (624, 14, 14)
101 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 160}
->Input Dimension : (624, 14, 14)
103 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 112}
104 ->Input Dimension: (624, 14, 14)
105 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 224}
->Input Dimension : (624, 14, 14)
107 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 24}
->Input Dimension : (624, 14, 14)
109 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 64}
->Input Dimension : (624, 14, 14)
-->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
112 Output dimension: (648, 14, 14)
113
   Trainable parameters: 2,481,672
   Total operations: 972,434,400
114
115 ---
116 Layer 11 (Inception module):
->Input Dimension : (648, 14, 14)
118 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
->Input Dimension: (648, 14, 14)
120 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
->Input Dimension : (648, 14, 14)
122 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 256}
```

```
123 ->Input Dimension: (648, 14, 14)
124 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 24}
->Input Dimension: (648, 14, 14)
126 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 64}
->Input Dimension : (648, 14, 14)
128 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
   Output dimension: (664, 14, 14)
    Trainable parameters: 2,753,368
130
131
    Total operations: 1,078,929,824
132
133 Layer 12 (Inception module):
->Input Dimension : (664, 14, 14)
->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 112}
->Input Dimension : (664, 14, 14)
->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 144}
138 ->Input Dimension: (664, 14, 14)
->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 288}
140 ->Input Dimension: (664, 14, 14)
141 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}
142 ->Input Dimension : (664, 14, 14)
143 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 64}
->Input Dimension : (664, 14, 14)
145 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 64}
   Output dimension: (704, 14, 14)
146
    Trainable parameters: 3,017,920
147
   Total operations: 1,182,610,688
149 -----
Layer 13 (Inception module):
151 -> Input Dimension: (704, 14, 14)
152 -> Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 256}
->Input Dimension: (704, 14, 14)
154 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 160}
155 -> Input Dimension: (704, 14, 14)
156 -> Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 320}
->Input Dimension: (704, 14, 14)
158 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}
159 ->Input Dimension: (704, 14, 14)
160 -> Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 128}
161 ->Input Dimension: (704, 14, 14)
162 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
    Output dimension: (1024, 14, 14)
163
    Trainable parameters: 4,686,848
164
    Total operations: 1,836,642,304
165
166 -----
167 Layer 14 (Pooling layer):
168 ->Input Dimension : (1024, 14, 14)
->Filter Parameters : {'h': 3, 'w': 3, 'stride': 2, 'padding': 1}
    Output dimension: (1024, 7, 7)
170
    Trainable parameters: 0
171
   Total operations: 0
173 ---
174 Layer 15 (Inception module):
175 ->Input Dimension: (1024, 7, 7)
->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 256}
->Input Dimension : (1024, 7, 7)
178 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 160}
179 -> Input Dimension: (1024, 7, 7)
180 ->Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 320}
181 ->Input Dimension: (1024, 7, 7)
182 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 32}
183 ->Input Dimension : (1024, 7, 7)
184 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 128}
185 ->Input Dimension : (1024, 7, 7)
186 -> Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
0utput dimension: (1024, 7, 7)
```

```
Trainable parameters: 6,816,768
   Total operations: 667,892,736
190 ---
191 Layer 16 (Inception module):
192 -> Input Dimension: (1024, 7, 7)
->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 384}
->Input Dimension : (1024, 7, 7)
                                 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 192}
195 ->Filter Paramaters : {'h': 1,
->Input Dimension : (1024, 7, 7)
197 -> Filter Paramaters : {'h': 3, 'w': 3, 'stride': 1, 'padding': 1, 'num_filters': 384}
198 ->Input Dimension: (1024, 7, 7)
->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 48}
->Input Dimension : (1024, 7, 7)
201 ->Filter Paramaters : {'h': 5, 'w': 5, 'stride': 1, 'padding': 2, 'num_filters': 128}
202 ->Input Dimension : (1024, 7, 7)
203 ->Filter Paramaters : {'h': 1, 'w': 1, 'stride': 1, 'padding': 0, 'num_filters': 128}
204 Output dimension: (1264, 7, 7)
205
    Trainable parameters: 7,587,056
    Total operations: 743,345,680
206
207 -----
208 Layer 17 (Pooling layer):
209 ->Input Dimension : (1264, 7, 7)
210 ->Filter Parameters : {'h': 7, 'w': 7, 'stride': 1, 'padding': 0}
   Output dimension: (1264, 1, 1)
211
   Trainable parameters: 0
212
   Total operations: 0
214
215 Layer 18 (dense):
216 ->Input Dimension : (1264, 1, 1)
   Output dimension: (1000,)
217
   Trainable parameters: 1,265,000
218
   Total operations: 2,527,000
219
   _____
221
222 Total trainable parameters: 32,999,640
223 Total operations: 11,535,591,144
224
225 Process finished with exit code 0
```

Listing 5: Output - Googlenet layer by layer computation

1.4 Archticture: Googlenet layer by layer

Layer No.	${f Type}$	Description
1	Conv	7×7 convolution, stride 2, 64 filters
2	Pool	MaxPool 3×3 , stride 2
3	Conv	1×1 convolution, 64 filters
4	Conv	3×3 convolution, 192 filters
5	Pool	MaxPool 3×3 , stride 2
6	Inception (3a)	Branches:
		-1×1 Conv (64 filters)
		$-1 \times 1 \rightarrow 3 \times 3 \text{ Conv } (96 \rightarrow 128)$
		$-1 \times 1 \rightarrow 5 \times 5 \text{ Conv } (16 \rightarrow 32)$
		$-3\times3 \text{ Pool} \rightarrow 1\times1 \text{ Conv } (32)$
7	Inception (3b)	Similar structure to 3a:
		– 128, 192, 96 filters, etc.
8	Pool	MaxPool 3×3 , stride 2
9	Inception (4a)	Input: 640 channels
		Includes: $192\rightarrow208$ (3×3), $96\rightarrow208$ (3×3), etc.

10	Inception (4b)	Moderate complexity
		Filters: 160, 112, 224, etc.
11	Inception (4c)	Filters: 128, 128, 256, etc.
12	Inception (4d)	Filters: 112, 144, 288, etc.
13	Inception (4e)	Largest block so far
		Output: 1024 channels
14	Pool	MaxPool 3×3 , stride 2
15	Inception (5a)	Filters: 256, 160, 320, 128 (5×5) , 128 $(pool)$
16	Inception (5b)	Filters: 384 , 192 , 384 , 128 (5×5), 128 (pool)
17	Pool	AvgPool 7×7 , stride 1
18	Dense	Fully connected, 1000 output nodes

1.4.1 Source Reference

Title: Going Deeper with Convolutions

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