

Integrating Machine Learning with GAMSPy

H. Burak Usul

Who I am?



- H. Burak Usul
- Software Engineer @ GAMS
- <https://github.com/hbusul/>
- <https://www.linkedin.com/in/hburaku/>
- busul@gams.com

Agenda

1. GAMSPy very brief intro
2. Our Goal
3. Pathways
4. Matrix API
5. Adverserial Image Generation Example
6. Conclusion

GAMSPy very brief intro

Free for Academics!



GAMSPy is now
officially available
for academics...

FOR FREE

Install GAMSPy today and get started:



Fully compatible with:



- Indexed-algebra style mathematical modeling in Python
- Eco-system of Python and power of GAMS execution system



Let's write down the following expression:

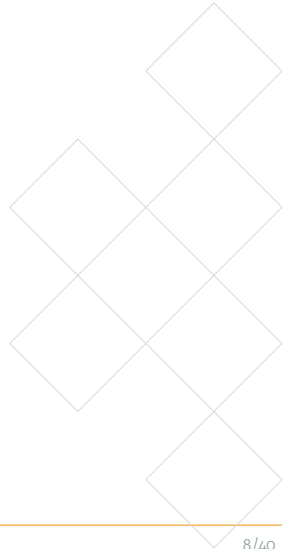
$$\sum_j a_{ij} \times x_{ij} \geq b_i \quad \forall i$$

```
1 import gamspy as gp
2
3 m = gp.Container()
4 i = gp.Set(m)
5 j = gp.Set(m)
6 a = gp.Parameter(m, domain=[i, j])
7 b = gp.Parameter(m, domain=[i])
8 x = gp.Variable(m, domain=[i, j])
9 e = gp.Equation(m, domain=[i])
10 e[i] = gp.Sum(j, a[i, j] * x[i, j]) >= b[i]
```

- Indexed-algebra style mathematical modeling in Python
- Eco-system of Python and power of GAMS execution system
- Enabling applications that were difficult to implement with GAMS



Our Goal



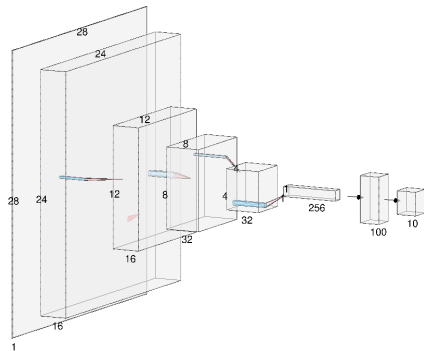
What do want to achieve?

Using GAMSPy:

- Embed
 - Trained neural networks in optimization problems
 - Classical machine learning methods in optimization problems
- Describe a neural network using GAMSPy
 - To infer from it
 - To train it
 - To sparsify it
 - ...

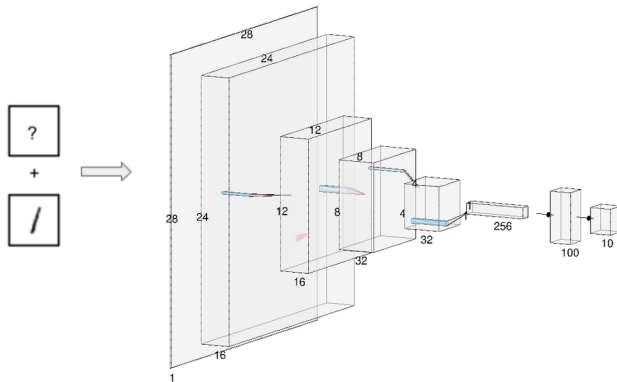
Optical Character Recognition

- Input is 28x28 pixel grayscale digits from MNIST dataset
- Output is the label of the digit

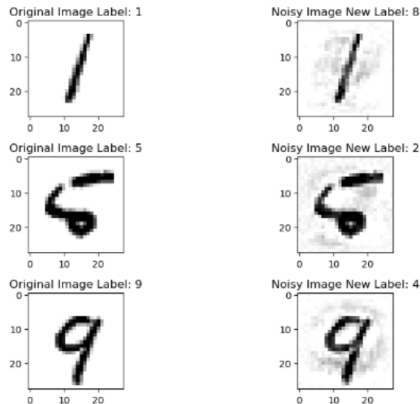


Adversarial Example Generation

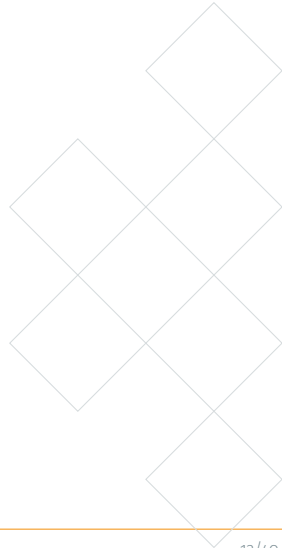
- Perturb the input image minimally so that guessed label changes



- Perturb the input image minimally so that guessed label changes

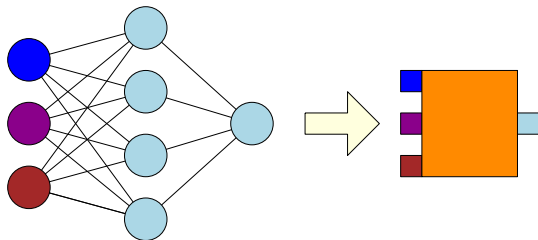


Pathways

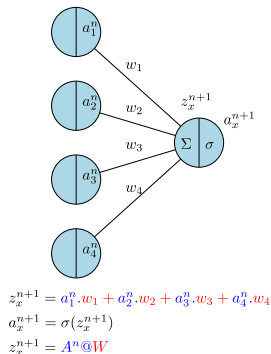


How we enable integration?

We implement complex blocks, abstracting away the complexity for users.



We provide fundamental building blocks that users can combine in their preferred ways



How we enable integration?

We implement complex blocks, abstracting away the complexity for users.

- Implement OMLT like functionality



<https://github.com/cog-imperial/OMLT>

We provide fundamental building blocks that users can combine in their preferred ways

- Implement matrix multiplication
- Implement activation functions
- Implement commonly used functions

How we enable integration?

We implement complex blocks, abstracting away the complexity for users.

- Implement OMLT interface like functionality with GAMSPy



Coming soon!

We provide fundamental building blocks that users can combine in their preferred ways

- Implement matrix multiplication
- Implement activation functions
- Implement commonly used functions

We started with this

Matrix API

```
1 import gamspy as gp
2 import numpy as np
3 from gamspy.math import dim
4
5 w1_data = np.random.rand(784, 20)
6 m = gp.Container()
7
8 w1 = gp.Parameter(m, name="w1", domain=dim([784, 20]),
9               records=w1_data)
10
11 a1 = gp.Variable(m, name="a1", domain=dim([64, 784]))
```

Introducing matrix multiplication

```
1  ...
2  w1 = gp.Parameter(m, name="w1", domain=dim([784, 20]),
3         records=w1_data)
4
5  a1 = gp.Variable(m, name="a1", domain=dim([64, 784]))
6
7  z2 = gp.Variable(m, name="z2", domain=dim([64, 20]))
8
9  calc_z2 = gp.Equation(m, name="calc_z2", domain=dim([64, 20]))
10
11 calc_z2[...] = z2 == a1 @ w1
```

Allows many use cases

```
1  ...
2  sq_data = np.eye(4) # identity matrix
3  sq = gp.Parameter(m, name="sq", domain=dim([4, 4]),
4  records=sq_data)
5
6  sq2 = gp.Parameter(m, name="sq2", domain=dim([4, 4]))
7
8  sq2[...] = sq @ sq @ sq @ sq @ sq
9
10 sq2.toDense()
11 # array([[1., 0., 0., 0.],
12 #        [0., 1., 0., 0.],
13 #        [0., 0., 1., 0.],
14 #        [0., 0., 0., 1.]])
```

```
1 ...  
2 ((a1 @ w1) @ (w1.t() @ a1)).domain  
3 # [<Set 'DenseDim64_1' (0x...)>, <Set 'DenseDim20_1' (0x...)>]
```

```
-----  
ValidationError                                Traceback (most recent call last)  
Cell In[16], line 24  
    19 a1 = gp.Variable(m , name = "a1" , domain=dim ([64 , 784]))  
    22 (a1 @ w1).gamsRepr()  
--> 24 ((a1 @ w1) @ (w1.t() @ a1))  
  
File ~/anaconda3/envs/ml/lib/python3.10/site-packages/gamspy/_algebra/operable.py:131, in Operable.__matmul__(self, other)  
    128 import gamspy._algebra.operation as operation  
    129 from gamspy.math.matrix import _validate_matrix_mult_dims  
--> 131 left_domain, right_domain, sum_domain = _validate_matrix_mult_dims(  
    132     self, other  
    133 )  
    134 return operation.Sum(  
    135     [sum_domain], self[left_domain] * other[right_domain]  
    136 )  
  
File ~/anaconda3/envs/ml/lib/python3.10/site-packages/gamspy/math/matrix.py:455, in _validate_matrix_mult_dims(left, right)  
    452 elif lr == (2, 2):  
    453     # Matrix multiplication  
    454     if not utils.set_base_eq(left.domain[1], right.domain[0]):  
--> 455         raise ValidationError(dim_no_match_err)  
    457     left_domain = left.domain[0]  
    458     right_domain = right.domain[1]  
  
ValidationError: Matrix multiplication dimensions do not match
```

```
1 ...
2 from gamspy.math import tanh, sigmoid
3 from gamspy.math import relu_with_binary_var
4 from gamspy.math import relu_with_complementarity_var
5 from gamspy.math import relu_with_sos1_var
6
7 a2 = gp.Variable(m, name="a2", domain=dim([64, 20])
8 calc_a2 = gp.Equation(m, name="calc_a2", domain=dim([64, 20])
9 calc_a2[...] = a2 == tanh(z2)
10
11 # ReLU is bit special
12 a3, constraints = relu_with_binary_var(z2) # OMLT
13 a4, constraints = relu_with_sos1_var(z2) # (Turner et al., 2024)
14 a5, constraints = relu_with_complementarity_var(z2) # OMLT
```

Turner, Mark, et al. "PySCIPOpt-ML: Embedding trained machine learning models into mixed-integer programs." arXiv preprint arXiv:2312.08074 (2023).
Ceccon, Francesco, et al. "OMLT: Optimization & machine learning toolkit." Journal of Machine Learning Research 23.349 (2022): 1-8.

```
1 ...
2 from gamspy.math import log_softmax
3 from gamspy.math import softmax
4
5 a2 = gp.Variable(m, name="a2", domain=dim([64, 20])
6 calc_a2 = gp.Equation(m, name="calc_a2", domain=dim([64, 20])
7 calc_a2[...] = a2 == tanh(z2)
8
9 a6, constraints = log_softmax(z2)
10 a7, constraints = softmax(z2)
```

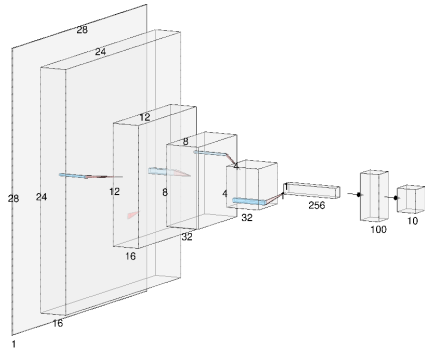
You can even use these if you want to train a neural network in GAMSPy!


```
1 import gamspy as gp
2 import numpy as np
3 from gamspy.math import vector_norm, dim
4
5 m = gp.Container()
6
7 vec = gp.Parameter(m, "vec", domain=dim([2]),
8                   records=np.array([3, 4]))
9 vlen = gp.Parameter(m, "vlen")
10 vlen[...] = gp.math.vector_norm(vec)
11 vlen.records
12 #      value
13 # 0      5.0
14
15 vlen.toDense()
16 #      value
17 # 0      5.0
```

Adversarial Image Generation Example

Step 1

- Train a simple Fully Convolutional Network using PyTorch
- Train it using MNIST dataset
- Get the weights into numpy arrays



Step 1

```
1 class SimpleModel(nn.Module):
2     def __init__(self):
3         ...
4
5     def forward(self, x):
6         x = self.conv1(x)
7         x = self.activation(x)
8         x = self.avg_pool(x)
9
10        x = self.conv2(x)
11        x = self.activation(x)
12        x = self.avg_pool(x)
13
14        x = self.conv3(x)
15        x = x.reshape(x.shape[0], -1)
16        x = self.l1(x)
17        x = self.activation(x)
18        logits = self.l2(x)
19
20        return logits
```

Step 2

Declare Parameters for weights:

```
1 conv1_weight = network.conv1.weight.detach().numpy()
2 conv1_bias   = network.conv1.bias.detach().numpy()
3
4 conv2_weight = network.conv2.weight.detach().numpy()
5 conv2_bias   = network.conv2.bias.detach().numpy()
6
7 conv3_weight = network.conv3.weight.detach().numpy()
8 conv3_bias   = network.conv3.bias.detach().numpy()
9
10 l1_weight = network.l1.weight.detach().numpy().T
11 b1_weight = network.l1.bias.detach().numpy()
12
13 l2_weight = network.l2.weight.detach().numpy().T
14 b2_weight = network.l2.bias.detach().numpy()
15
16 image_data = single_image.numpy()
17 image_target = single_target.numpy()
```

Declare GAMSPy Conv2d and AvgPool2d counterparts:

```
1 from gamspy.math import Conv2d, AvgPool2d #TODO include it to next  
                                     release  
2  
3 m = gp.Container()  
4 avg_pool = AvgPool2d(m, (2, 2), 2, 0) # near identical signature with  
                                     PyTorch  
5  
6 conv1 = Conv2d(m, 1, 16, 5, stride=1, bias=True) # near identical  
                                               signature with PyTorch  
7 conv1.load_weights(conv1_weight, conv1_bias)  
8  
9 conv2 = Conv2d(m, 16, 32, 5, stride=1, bias=True)  
10 conv2.load_weights(conv2_weight, conv2_bias)  
11  
12 conv3 = Conv2d(m, 32, 256, 4, stride=1, bias=True)  
13 conv3.load_weights(conv3_weight, conv3_bias)
```

Declare Other Parameters:

```
1 image = gp.Parameter(m, name="image", domain=dim(image_data.shape),
2                 records=image_data)
3
4 w1 = gp.Parameter(m, name="w1", domain=dim(l1_weight.shape),
5                 records=l1_weight)
6
7 b1 = gp.Parameter(m, name="b1", domain=dim(b1_weight.shape),
8                 records=b1_weight)
9
10 w2 = gp.Parameter(m, name="w2", domain=dim(l2_weight.shape),
11                 records=l2_weight)
12
13 b2 = gp.Parameter(m, name="b2", domain=dim(b2_weight.shape),
14                 records=b2_weight)
```

Declare Input to Network:

```
1 a1 = gp.Variable(m, name="x1", domain=dim([1, 1, 28, 28]))
2
3 add_noise_and_normalize = gp.Equation(m, "eq1", domain=dim([1, 1, 28,
4                                     28]))
5 add_noise_and_normalize[...] = \
6     a1 == (image + noise - mean[0]) / std[0]
7
8 #ensure bounds
9 a1.lo[...] = - mean[0] / std[0]
10 a1.up[...] = (1 - mean[0]) / std[0]
```


More forward propagation:

```
1 z2, _ = conv1(a1)
2 a2, _ = relu_with_binary_var(z2)
3 z3, _ = avg_pool(a2)
4
5
6 z3_2, _ = conv2(z3)
7 a3, _ = relu_with_binary_var(z3_2)
8 z4, _ = avg_pool(a3)
9 z5, _ = conv3(z4)
10
11 z5_2 = z5[:, :, "0", "0"] # (1 x 256 x 1 x 1) -> (1 x 256)
```

Define variable/equations for linear layers:

```
1 z6 = gp.Variable(m, name="z6", domain=dim([1, 100]))
2 set_z6 = gp.Equation(m, name="set_z6", domain=z6.domain)
3 set_z6[...] = z6[...] == z5_2 @ w1 + b1
4
5 a6, _ = relu_with_binary_var(z6)
6
7 z7 = gp.Variable(m, name="z7", domain=dim([1, 10]))
8 set_z7 = gp.Equation(m, name="set_z7", domain=z7.domain)
9 set_z7[...] = z7[...] == a6 @ w2 + b2
```

Define Problem Specific constraints:

```
1 # Set epsilon as you wish, higher it is, harder to solve
2 eps = 0.01
3
4 trick_nn = gp.Equation(m, name="false_label", ...)
5 trick_nn[...] = \
6     z7["0", "8"] >= z3["0", "6"] + eps
```

Define objective function

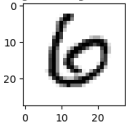
```
1 from gamspy.math import vector_norm
2 obj = gp.Variable(m, name="obj")
3
4 set_obj = gp.Equation(m, "set_obj")
5 set_obj[...] = obj == vector_norm(noise) ** 2
```

Optimize

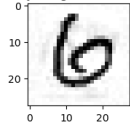
```
1 model = gp.Model(  
2     m,  
3     "min_noise",  
4     equations=m.getEquations(),  
5     objective=obj,  
6     sense="min",  
7     problem="MIQCP"  
8 )  
9  
10 # Pick the solver you want from ~20 MIQCP solvers  
11 # that we support  
12 model.solve(output=sys.stdout, solver="cplex")  
13 model.solve(output=sys.stdout, solver="gurobi")
```

Some examples

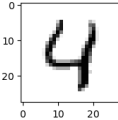
Original Image Label: 6



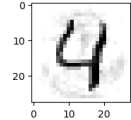
Noisy Image New Label: 8



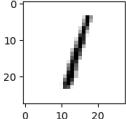
Original Image Label: 4



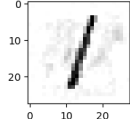
Noisy Image New Label: 2



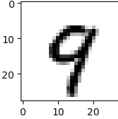
Original Image Label: 1



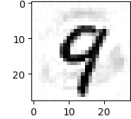
Noisy Image New Label: 5



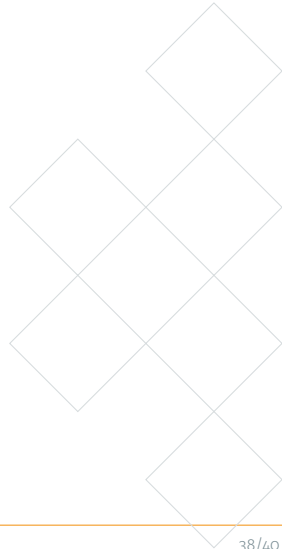
Original Image Label: 9



Noisy Image New Label: 7



Conclusion



- 3-4 months implementing backend for OMLT
- Implement more Computer Vision Formulations
 - MaxPool2d
 - ...
- Implement Recurrent Formulations
 - RNNs
 - LSTMs
 - GRUs
 - Transformers
 - ...
- Investigate Reduced-Space Formulations



GAMSPy is now
officially available
for academics...

FOR FREE

Install GAMSPy today and get started:



Fully compatible with:



Upcoming talks:

- GAMSPy - Where Convenience of Python Meets GAMS' Performance
Today 11:30am - 1:00pm @ Theresianum 2605
- The Lifecycle of OR Solutions: From Rapid Prototypes to Market Deployment
Today 2:00pm - 3:30pm @ Theresianum 2605