Supplementary Material for: Generating Correct Answers for Progressive Matrices Intelligence Tests

A Links for datasets

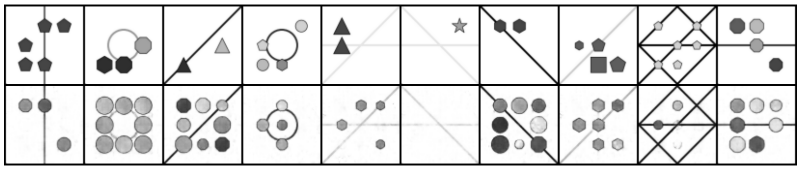
The Procedurally Generated Matrices (PGM) dataset can be found in `https://github.com/deepmind/abstract-reasoning-matrices` and the RAVEN-FAIR dataset can be found in `https://github.com/yanivbenny/RAVEN_FAIR`.

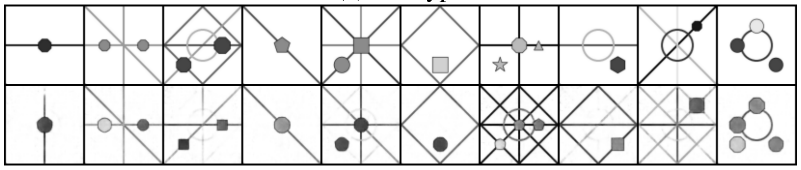
B Calculating FID

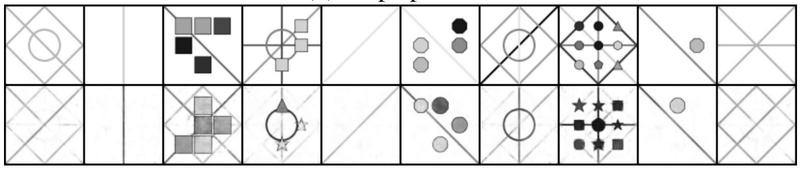
FID calculation was performed on the real target image and the generated image. For WReN we used the output of the CNN encoder of [32, 4,4] vector, flattened to a 512 size vector. For MRnet we used the outputs of the perception encoders – low, mid and high features sizes – [256, 1, 1], [128, 5, 5] and [64, 20, 20], and average pooled them to 256, 128 and 64 sized vectors. Than concatenated them to 448 size vector. And for LEN we used the output of the CNN encoder of [32, 4,4] vector, and average pooled to a 32 size vector.

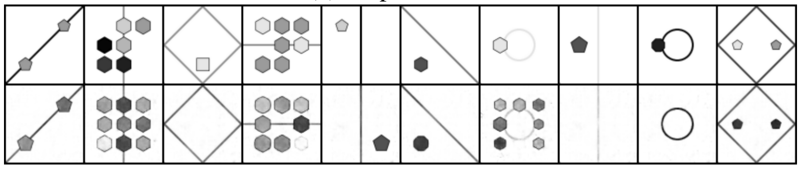
C Generated images

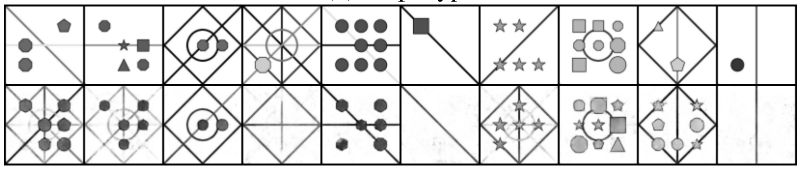
In Fig. 1 we present some examples of our method's generated images. For analyzing the generation results in PGM we must understand for each of the rules, what counts as a good generated image. For 'line type' (a) rules, the lines must stay at the same place, but all other attributes may change, here we get great results. For 'shape position' (b), the shape's position must always be the same, and all other attributes may change, including the shape's size, type, color, and the lines. Here we can see that almost all of the results are great. For 'shape number' (c), the shape's number must always be the same, and all other attributes may change, including the shape's size, type, color, position, and the lines. Here also, we get great results. For 'shape type' (d), the shape's type and number must always be the same, and all other attributes may change, including the shape's size, color, position, and the lines. Here we can see that the results are average. For 'shape color' (e), the shape's color and number must always be the same, and all other attributes may change, including the shape's size, type, position, and the lines. Here we can see that the results are also average. For 'shape size' (f), the shape's size and number must always be the same, and all other attributes may change, including the shape's type, position, color, and the lines. Results are average. For 'line color' (g), the line's color must always be the same, and all other attributes may change, including the shape's attributes and the line's type. Here results look good.

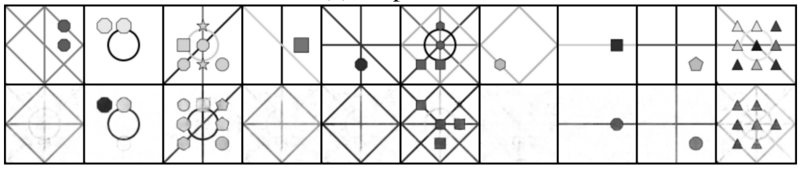

(a) line type


(b) shape position


(c) shape number


(d) shape type


(e) shape color


(f) shape size

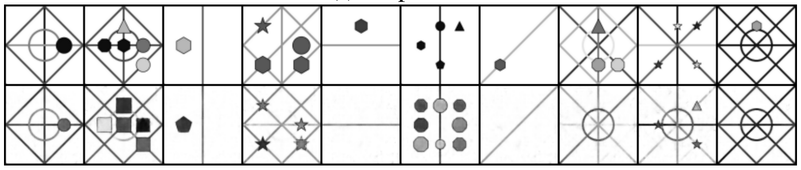

(g) line color

Figure 1: Generation results for selected rules in PGM, each with 10 problems. The top row is the ground truth answer. The bottom is the generated. (a) line type. (a) shape position. (c) shape number. (d) shape type.(e) shape color. (f) shape size. (g) line color.

D Architecture details

We detail each sub-module used in our method in Tab. 2-6. Since some modules re-use the same blocks, Tab. 1 details a set of general modules.

Table 1: ResBlocks, with variable number of channels c.

Module	layers	parameters	input	output
ResBlock(c)	Conv2D	CcK3S1P1	x	
	BatchNorm			
	ReLU			
	Conv2D	CcK3S1P1		
	BatchNorm			x'
	Residual		(x, x')	$x'' = x + x'$
	ReLU			
DResBlock(c)	Conv2D	CcK3S1P1	x	
	BatchNorm			
	ReLU			
	Conv2D	CcK3S1P1		
	BatchNorm			x'
	Conv2D	CcK1S2P0	x	
	BatchNorm			x_d
	Residual		(x_d, x')	$x'' = x_d + x'$
	ReLU			
ResBlock1x1(c)	Conv2D	CcK1S1P1	x	
	BatchNorm			
	ReLU			
	Conv2D	CcK1S1P1		
	BatchNorm			x'
	Residual		(x, x')	$x'' = x + x'$
	ReLU			

Table 2: E^C and RM modules

Module	layers	input	output
E_h^C	Conv2d(1, 32, kernel size=7, stride=2, padding=3, bias=False)	I_i	-
	BatchNorm2d(32)	-	-
	ReLU	-	-
	Conv2d(32, 64, kernel size=3, stride=2, padding=1, bias=False)	-	
	BatchNorm2d(64)	-	-
	ReLU	-	e_h^i
E_m^C	Conv2d(64, 64, kernel size=3, stride=2, padding=1, bias=False)	e_h^i	-
	BatchNorm2d(64)	-	-
	ReLU	-	-
	Conv2d(64, 128, kernel size=3, stride=2, padding=1, bias=False)	-	-
	BatchNorm2d(128)	-	-
	ReLU	-	e_m^i
E_l^C	nn.Conv2d(128, 128, kernel size=3, stride=2, padding=1, bias=False)	e_m^i	-
	BatchNorm2d(128)	-	-
	ReLU	-	-
	Conv2d(128, 256, kernel size=3, stride=2, padding=0, bias=False)	-	-
	BatchNorm2d(256)	-	-
	ReLU	-	e_l^i
RM_h	Reshape to (3 * 64, 20, 20)	-	-
	Conv2d(3*64, 64, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(64, 64)	-	-
	ResBlock(64, 64)	-	-
	Conv2d(64, 64, ker size=3, st=1, pad=1, bias=False)	-	-
	BatchNorm2d(64)	-	$r_h^1/r_h^2/c_h^1/c_h^2$
RM_m	Reshape to (3 * 128, 5, 5)	-	-
	Conv2d(3 * 128, 128, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(128, 128)	-	-
	ResBlock(128, 128)	-	-
	Conv2d(128, 128, ker size=3, st=1, pad=1, bias=False)	-	-
	BatchNorm2d(128)	-	$r_m^1/r_m^2/c_m^1/c_m^2$
RM_l	Reshape to (3 * 256, 1, 1)	-	-
	Conv2d(3*256, 256, ker size=1, st=1, pad=1, bias=False)	-	-
	ResBlock1x1(256, 256)	-	-
	ResBlock1x1(256, 256)	-	-
	Conv2d(256, 256, ker size=3, st=1, pad=1, bias=False)	-	-
	BatchNorm2d(256)	-	$r_l^1/r_l^2/c_l^1/c_l^2$

Table 3: P and C_O modules

Module	layers	input	output
P_h	Reshape to (3 * 64, 20, 20)	e_h^7, e_h^8, q_h /e_h^3, e_h^6, q_h	-
	Conv2d(3*64, 64, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(64, 64)	-	x_h
P_m	Reshape to (3 * 128, 5, 5)	e_m^7, e_m^8, q_m /e_m^3, e_m^6, q_m	-
	Conv2d(3*128, 128, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(128, 128)	-	x_m
P_l	Reshape to (3 * 256, 1, 1)	e_l^7, e_l^8, q_l /e_l^3, e_l^6, q_l	-
	Conv2d(3*256, 256, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(256, 256)	-	x_l
C_O^h	Reshape to (2 * 64, 20, 20)	cat(x_h, $e_h^{a_i}$)	-
	Conv2d(2*64, 64, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(64, 64)	-	-
	DResBlock(64,2 *64, stride=2)	-	-
	DResBlock(2 *64,128, stride=2)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_h
C_O^m	Reshape to (2 * 128, 5, 5)	cat(x_m, $e_m^{a_i}$)	-
	Conv2d(2*128, 128, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(128, 128)	-	-
	DResBlock(128,2*128, stride=2)	-	-
	DResBlock(2*128,128, stride=2)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_m
C_O^l	Reshape to (3 * 256, 1, 1)	cat(x_l, $e_l^{a_i}$)	-
	Conv2d(2*256, 256, ker size=3, st=1, pad=1, bias=False)	-	-
	ResBlock(256, 256)	-	-
	Conv2d(256, 128, ker size=1, st=1, bias=False)	-	-
	BatchNorm2d(128)	-	-
	ReLU	-	-
	ResBlock1x1(128, 128)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_l
final C_O	Linear(128*3, 256, bias=False)	cat(x'_h, x'_m, x'_l)	-
	BatchNorm1d(256)	-	-
	ReLU	-	-
	Linear(256, 128, bias=False)	-	-
	BatchNorm1d(128)	-	-
	ReLU	-	-
	Linear(128, 1, bias=True))	-	y_i

Table 4: C_M modules

Module	layers	input	output
C_M^h	DResBlock(64,2*64, stride=2)	x_h	-
	DResBlock(2*64,128, stride=2)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_h
C_M^m	DResBlock(128,2*128, stride=2)	x_m	-
	DResBlock(2*128,128, stride=2)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_m
C_M^l	ResBlock(256, 256)	x_l	-
	Conv2d(256, 128, ker size=1, st=1, bias=False)	-	-
	BatchNorm2d(128)	-	-
	ReLU	-	-
	ResBlock1x1(128, 128)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_l
C_M	Linear(128*3, 256, bias=False)	cat(x'_h, x'_m, x'_l)	-
	BatchNorm1d(256)	-	-
	ReLU	-	-
	Linear(256, 128, bias=False)	-	-
	BatchNorm1d(128)	-	-
	ReLU	-	-
	Linear(128, 12, bias=True))	-	ψ

Table 5: R modules

Module	layers	input	output
R_h	DResBlock(64,2*64, stride=2)	x_h	-
	DResBlock(2*64,128, stride=2)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_h
R_m	DResBlock(128,2*128, stride=2)	x_m	-
	DResBlock(2*128,128, stride=2)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_m
R_l	Conv2d(256, 128, ker size=1, st=1, bias=False)	x_l	-
	BatchNorm2d(128)	-	-
	ReLU	-	-
	ResBlock1x1(128, 128)	-	-
	AdaptiveAvgPool2d((1, 1))	-	x'_l
T	Linear(128*3, 128, bias=False)	x = cat(x'_h, x'_m, x'_l)	-
	ReLU	-	-
	Linear(128, 128, bias=False)	-	-
	ReLU	-	-
	Linear(128, 128, bias=False))	-	mu_g,$sigma_g$

Table 6: G, E and D

Module	layers	input	output
G	ConvTranspose2d(64, 64*8, ker size=5, st=1, pad=0, bias=False)	$h_g = \mu_g + \sigma_g \cdot z'$	-
	BatchNorm2d(64*8)	-	-
	ConvTranspose2d(64*8, 64*4, ker size=4, st=2, pad=1, bias=False)	-	-
	BatchNorm2d(64*4)	-	-
	ConvTranspose2d(64*4, 64*2, ker size=4, st=2, pad=1, bias=False)	-	-
	BatchNorm2d(64*2)	-	-
	ConvTranspose2d(64*2, 64*1, ker size=4, st=2, pad=1, bias=False)	-	-
	BatchNorm2d(64*1)	-	-
	ConvTranspose2d(64*1, 1, ker size=4, st=2, pad=1, bias=False)	-	I_g
E	Conv2d(1, 32, kernel size=3, stride=2)	I_{a_i}	-
	BatchNorm2d(32)	-	-
	ReLU	-	-
	Conv2d(32, 32, kernel size=3, stride=2)	-	-
	BatchNorm2d(32)	-	-
	ReLU	-	-
	Conv2d(32, 32, kernel size=3, stride=2	-	-
	BatchNorm2d(32)	-	-
	ReLU	-	-
	Conv2d(32, 32, kernel size=3, stride=2	-	-
	BatchNorm2d(32)	-	-
	ReLU	-	-
	Linear(32*4*4, 64*2)	-	$\mu_v^{a_i}$, $\sigma_v^{a_i}$
D	Conv2d(1, 64, ker size=4, st=2, pad=1, bias=False)	I_{a^*}/I_g	-
	leaky relu	-	-
	Conv2d(64,64*2, ker size=4, st=2, pad=1, bias=False)	-	-
	BatchNorm2d(64*2)	-	-
	leaky relu	-	-
	Conv2d(64*2,64*4, ker size=4, st=2, pad=1, bias=False)	-	-
	BatchNorm2d(64*4)	-	-
	leaky relu	-	-
	Conv2d(64*4,64*8, ker size=4, st=2, pad=1, bias=False)	-	-
	BatchNorm2d(64*8)	-	-
	leaky relu	-	-
	Conv2d(64*8, 1, ker size=4, st=1, pad=0, bias=False)	-	-
	leaky relu	-	-
	Conv2d(1, 1, ker size=2, st=1, pad=0, bias=False)	-	-
	sigmoid	-	D out