ML-Based Constellation Shaping for Arbitrary Channels

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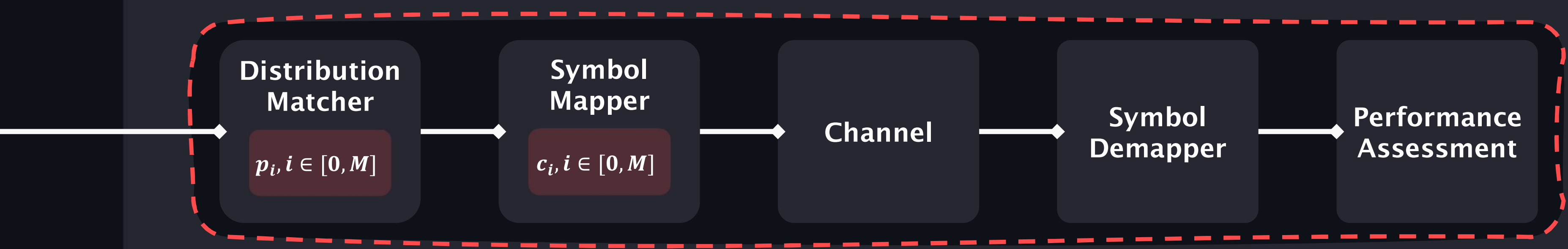
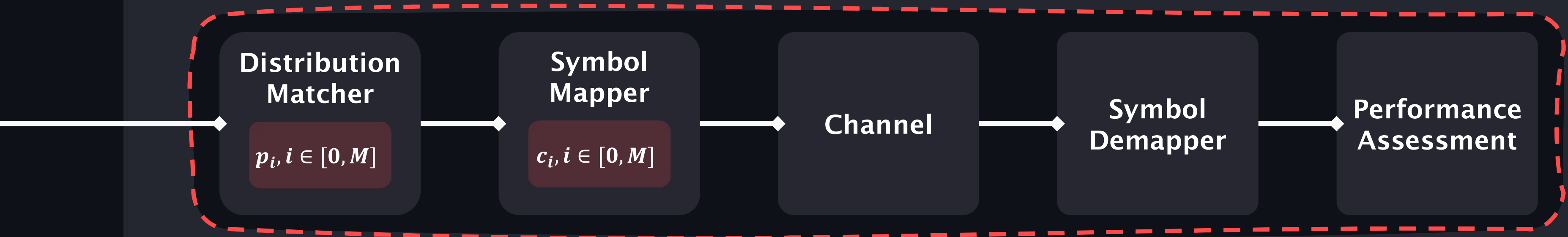
Motivation

- For AWGN channels, the optimal constellation geometry and probability distribution function is well-known
- When we enter uncharted territories, often system contraints make it non-trivial to find optimal solutions for throughput maximization

Your typical simulation environment



Your typical simulation environment

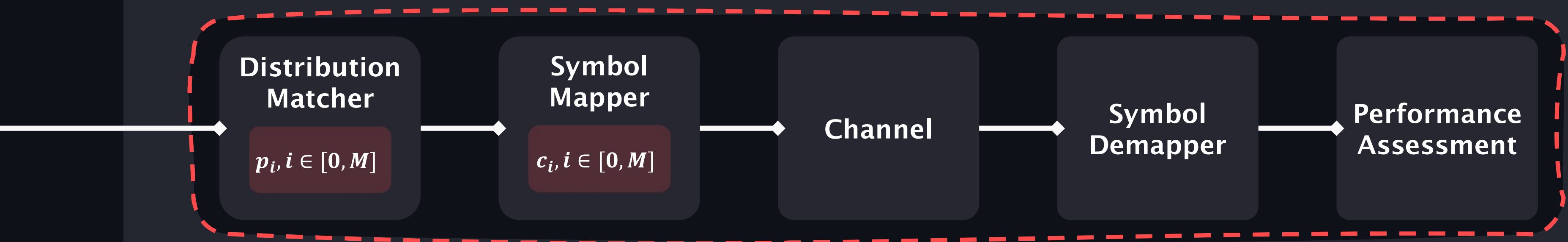


10000

[0.2 0.4 0.4 0.2]

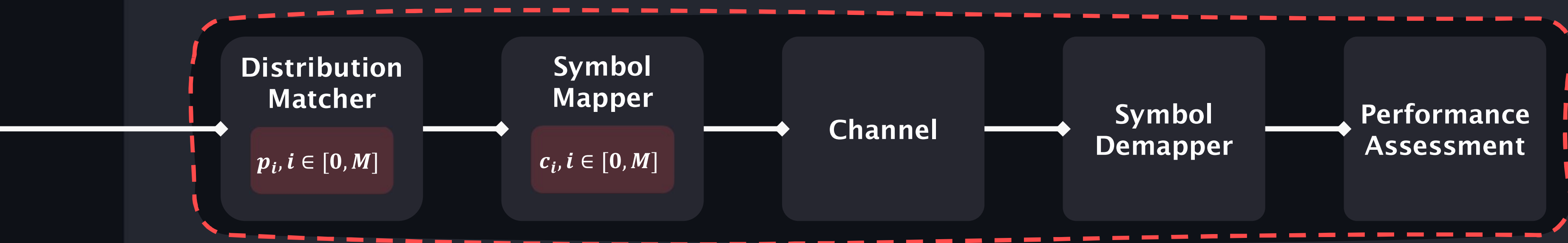
```
# Sampling from probs
>> sampled_syms_idx = sample_dist(batch_size, probs)
```

Your typical simulation environment



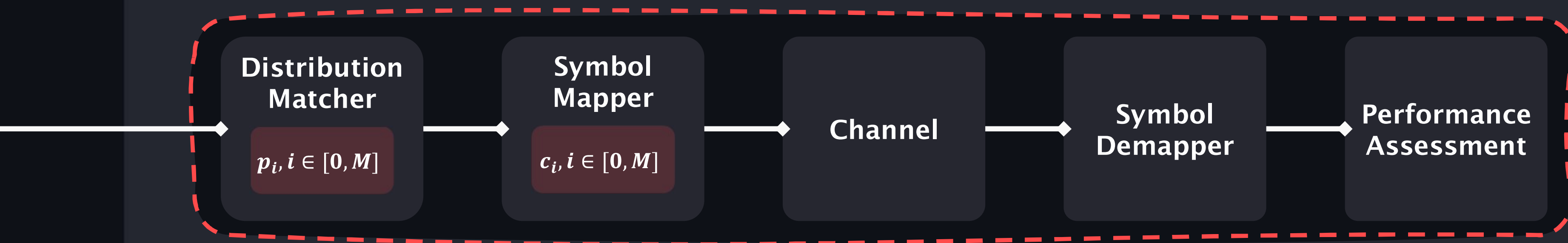

```
# Normalizing Constellation with average power constraint (APC)
>> const_points_n = norm_const(const_points, probs)
# Turning the indexes into one-hot vectors
>> one_hot_syms = one_hot(sampled_syms_idx, M)
# Mapping
>> syms = matmul(one_hot_syms, const_points_n)
```

Your typical simulation environment



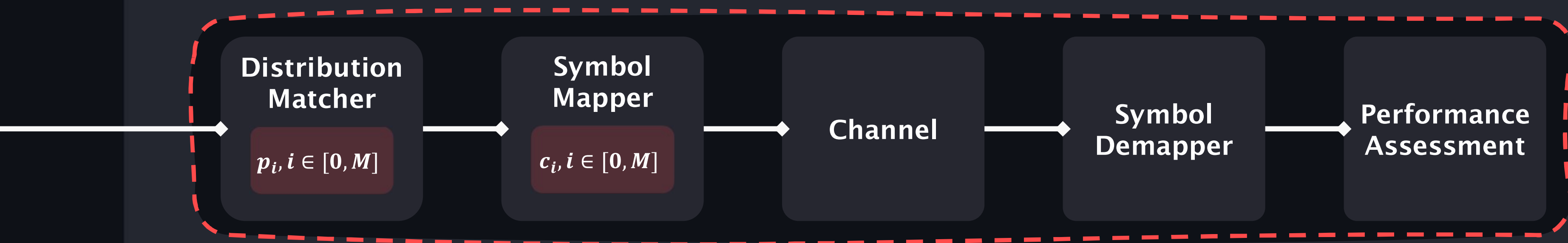

```
# AWGN channel
>> syms_noisy = syms +
      + random.normal(shape=syms.shape,stddev=np.sqrt(var_noise))
```

Your typical simulation environment



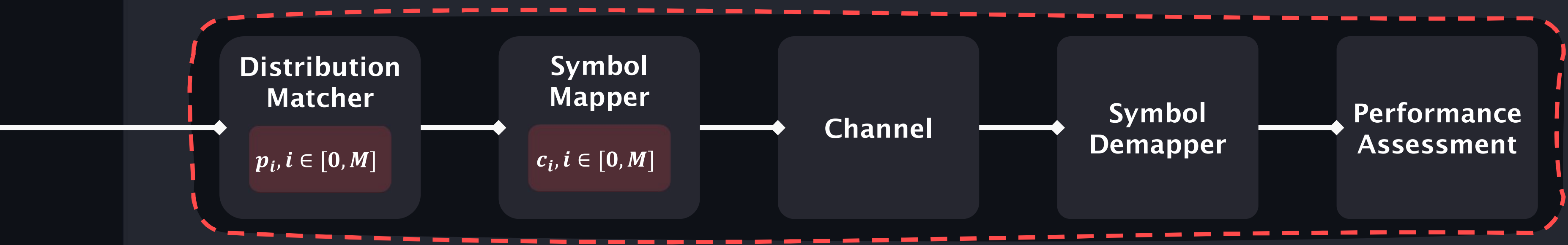

```
# Demapper
>> rx_syms = demapper(syms_noisy, probs)
```

Your typical simulation environment




```
# Compute performance metrics
>> H, MI, GMI, MSE, CE = metrics_fcn(probs,
                                     const_points_n,
                                     sampled_syms_idx,
                                     syms_noisy,
                                     rx_syms)
```

Your typical simulation environment



..and that about sums up the

typical Monte Carlo situation!

Adding the *learning* part

1st – Done! (pretty much)

Tensorflow library makes it easy!

Adding the *learning* part

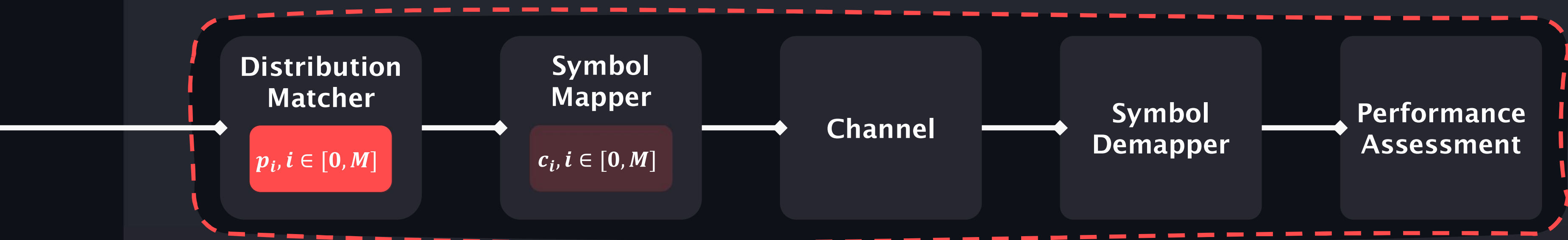
All we have to do is replace the used library:

```
>> import numpy as np
>>
>> a = np.ones((2, 100))
>> b = np.dot(a,a.T)
>> c = np.sum(b)
>> print("c = " + str(c))
[Out] c = 400.0
```

```
>> import tensorflow as tf
>>
>> a = tf.ones((2, 100))
>> b = tf.matmul(a,tf.transpose(a))
>> c = tf.reduce_sum(b)
>> print("c = " + str(c))
[Out] c = tf.Tensor(400.0, shape=(),
dtype=float32)
```

Adding the *learning* part

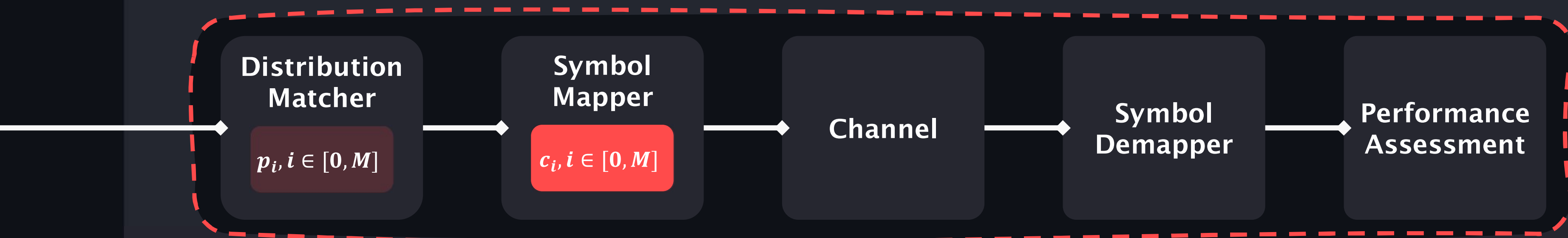
And for the variables we aim to learn/optimize:




```
# Symbol Probabilities
>> log_probs = tf.Variable(tf.ones((M,))/M, trainable = True)
>>
>> probs = tf.nn.softmax(log_probs)
```

Adding the *learning* part

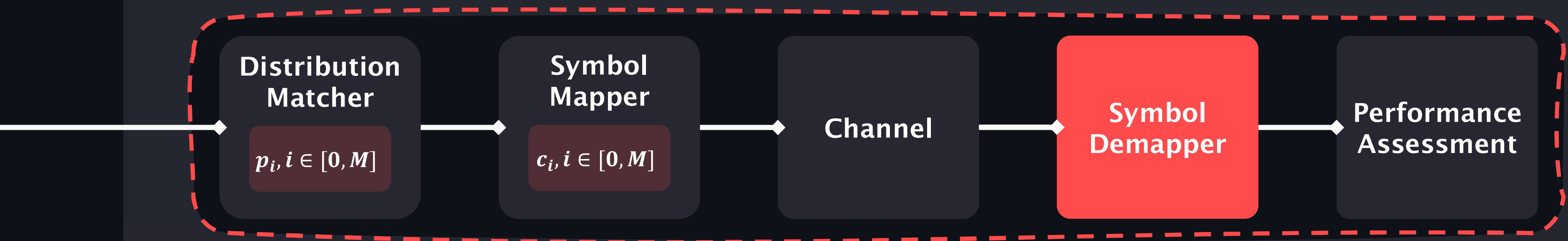
And for the variables we aim to learn/optimize:




```
# Constellation points
>> const_points = tf.Variable(qam(M), trainable = True)
```

Adding the *learning* part

And for the variables we aim to learn/optimize:




```
# Demapper
>> inputs = tf.keras.Input(shape=(2,))
>> outputs = tf.keras.layers.Dense(M, activation="relu")(inputs)
>> outputs = tf.keras.layers.Dense(M, activation="softmax)(outputs)
>> demapper = tf.keras.Model(inputs=inputs, outputs=outputs)
```

Adding the *learning* part

Each of the variables to optimize has its optimizer:

```
>> optimizer_log_probs = tf.keras.optimizers.Adam(learning_rate=lr_probs)
>> optimizer_const_points = tf.keras.optimizers.Adam(learning_rate=lr_const)
>> optimizer_demapper = tf.keras.optimizers.Adam(learning_rate=lr_dmappr)
```

Which optimize the variables to minimize a loss function:

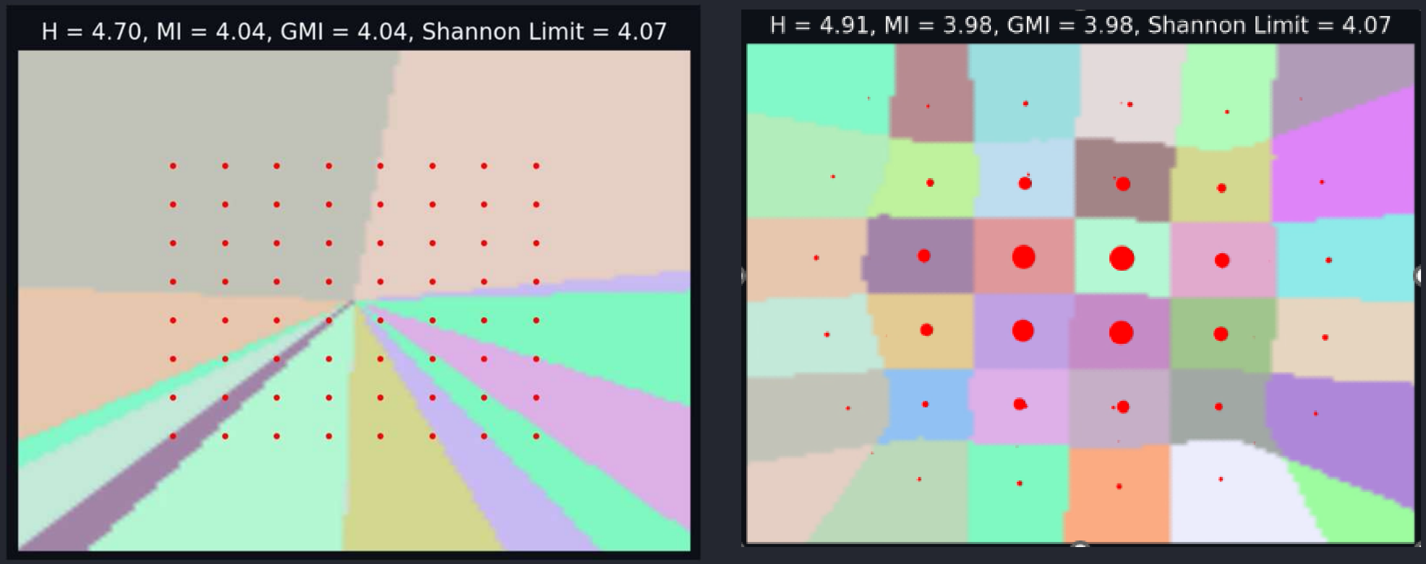
```
# Performance metrics
>> H, MI, GMI, MSE, CE = metrics_fcn(probs,
                                     const_points_n,
                                     sampled_syms_idx,
                                     syms_noisy,
                                     rx_syms)
```

Adding the *learning* part

So the complete flow is:

```
>> while(learning):
>>     # A gradient tape allows to record the gradients of the
>>     # operations performed seamlessly:
>>     with tf.GradientTape() as tape:
>>           <run one batch, pick loss function>
>>           # Update each variable, var, to learn like:
>>           grads_var = tape.gradient(loss_value, var)
>>           optimizer_var.apply_gradients([(grads_var, var)])
```

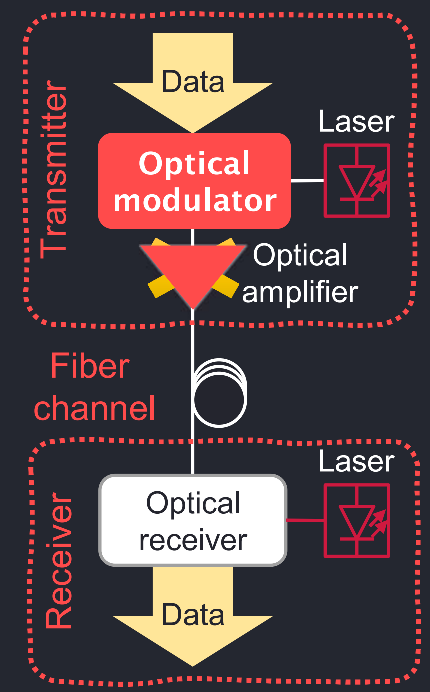
First Demo – Hands on



Github: **github.com/msneves/ConstellationShapingWizard/**

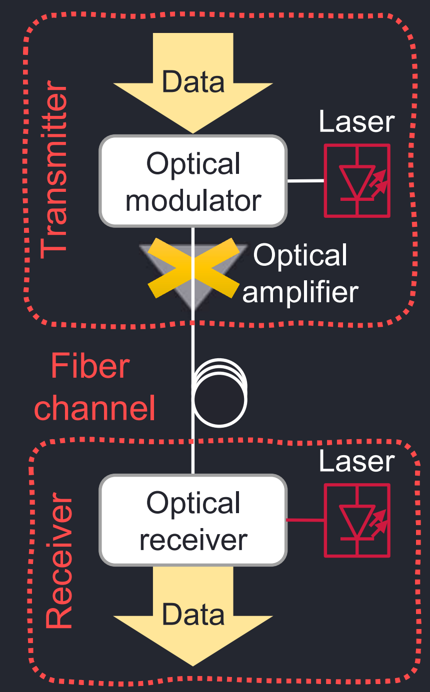
Use Case: *Unamplified* Links

- The optical modulator is limited by the peak power of the signal
- Up to now, coherent systems were used only for long range systems, requiring amplification
- By using the optical amplifier, the system is now limited by the average power, which is a well-known constraint (APC)
- Recently, unamplified short-reach coherent links have been standardized
- Because there is no optical amplifier, the system is governed by a peak power constraint (PPC) that has been under research focus



Use Case: *Unamplified* Links

- Targeting short-reach deployment, the removal of the optical amplifier shifts the paradigm
- Unamplified systems are peak power constrained (as opposed to average power, a well-known constraint)
- Because the peak power has a big impact, legacy constellations geometries are suboptimal
- A *tailored* solution is required!



Use Case: *Unamplified* Links (PPC)

Forcing a PPC is a matter of signal normalization

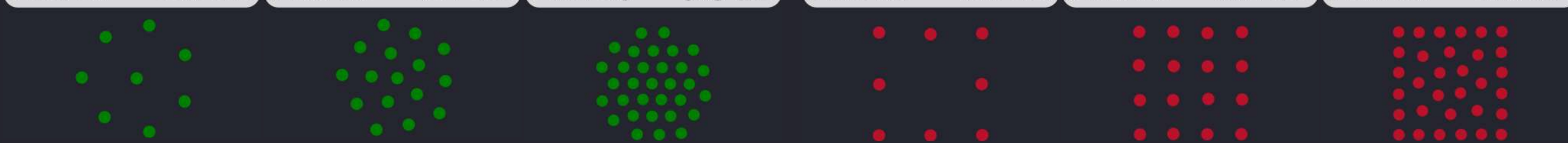
APC

```
>> const = const/tf.math.sqrt(const_pow(const,probs))
```

PPC

```
>> const = const/(tf.math.reduce_max(tf.math.abs(const),axis=0))
```

8-AE-APC	16-AE-APC	32-AE-APC	8-AE-PPC	16-AE-PPC	32-AE-PPC
PAPR = 8.9 dB	PAPR = 9.7 dB	PAPR = 9.8 dB	PAPR = 7.1 dB	PAPR = 8.2 dB	PAPR = 8.5 dB



Second Demo –
Unknown Optimal Solution

Github: **github.com/msneves/ConstellationShapingWizard/**

Thank you for your attention!
Questions?

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References of interest:

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