Pacific Ballroom #137

Neural Inverse Knitting: From Images to Manufacturing Instruction

Alexandre Kaspar*, Tae-Hyun Oh*, Liane Makatura,
Petr Kellnhofer and Wojciech Matusik

MIT CSAIL

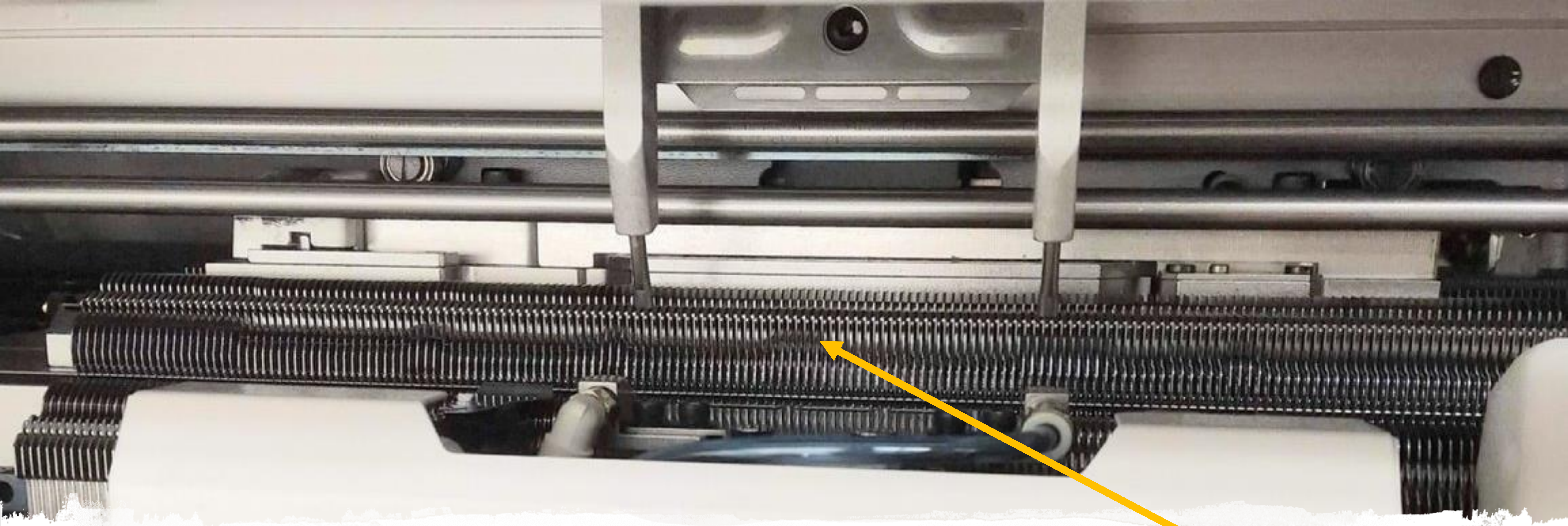
Industrial Knitting

Pacific Ballroom #137, http://deepknitting.csail.mit.edu

Industrial Knitting

- Whole garments from scratch

Pacific Ballroom #137, http://deepknitting.csail.mit.edu



Industrial Knitting

- Control of individual needles
- Whole garments from scratch

Pacific Ballroom #137, http://deepknitting.csail.mit.edu

Knitted Garment & Patterns

Many garments are knitted:

- Beanies, scarves
- Gloves, socks and underwear
- Sweaters, sweatpants

Current machines can create those garments **seamlessly** (no sewing needed).

Knitted Garment & Patterns

Those garments have **various types** of surface **patterns** (knitting patterns).

These can be fully controlled by industrial knitting machine.

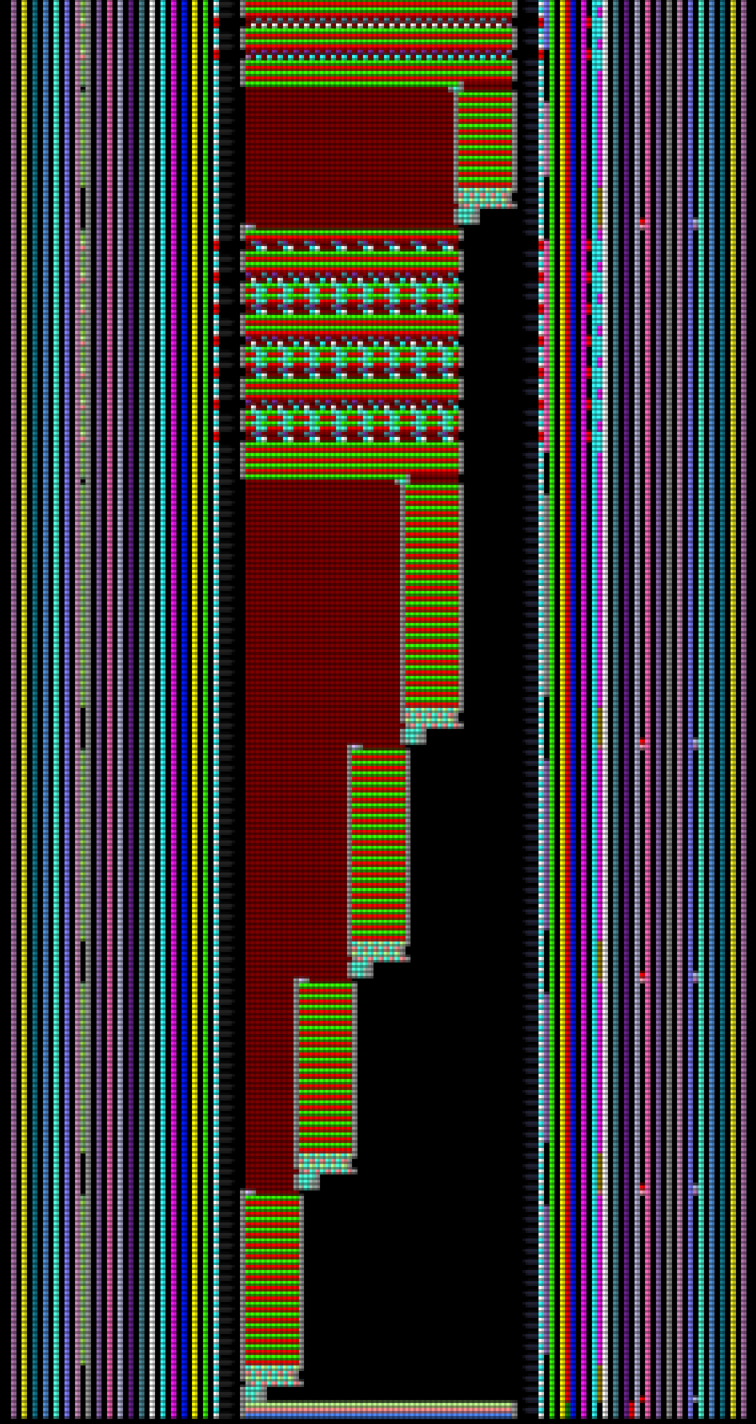
= User customization!

Machine Knitting Programming

Low-level machine code
requires skilled experts
= knitting masters

Good news

- Many hand knitting patterns available online and in books
- Online communities of knitting enthusiasts sharing patterns



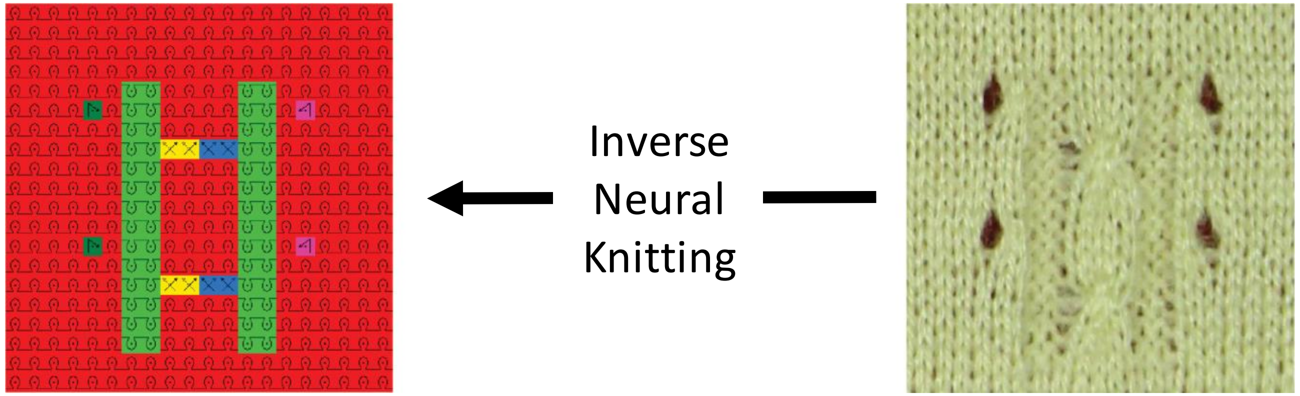
Pacific Ballroom #137, http://deepknitting.csail.mit.edu

Scenario

1. User takes picture of knitting pattern

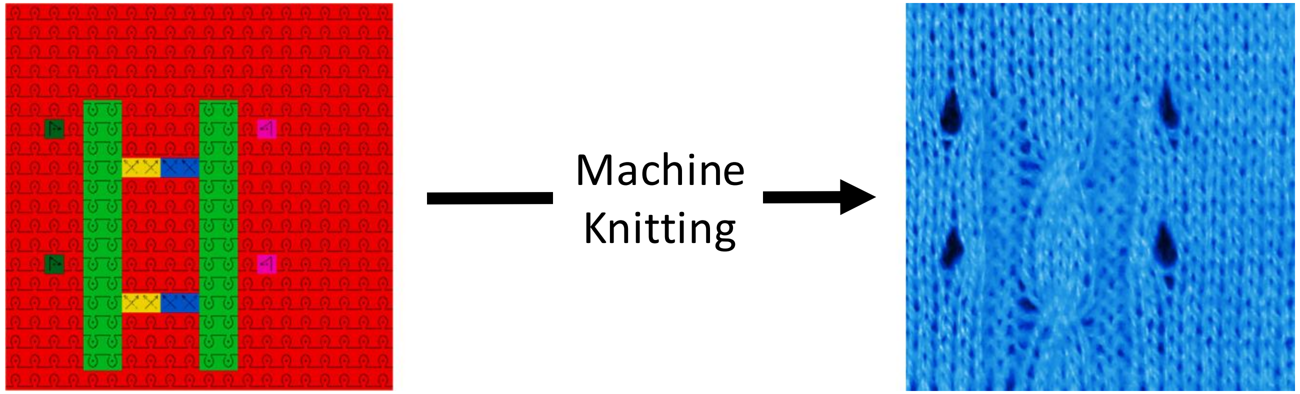
Scenario

1. User takes picture of knitting pattern
2. System creates knitting instructions



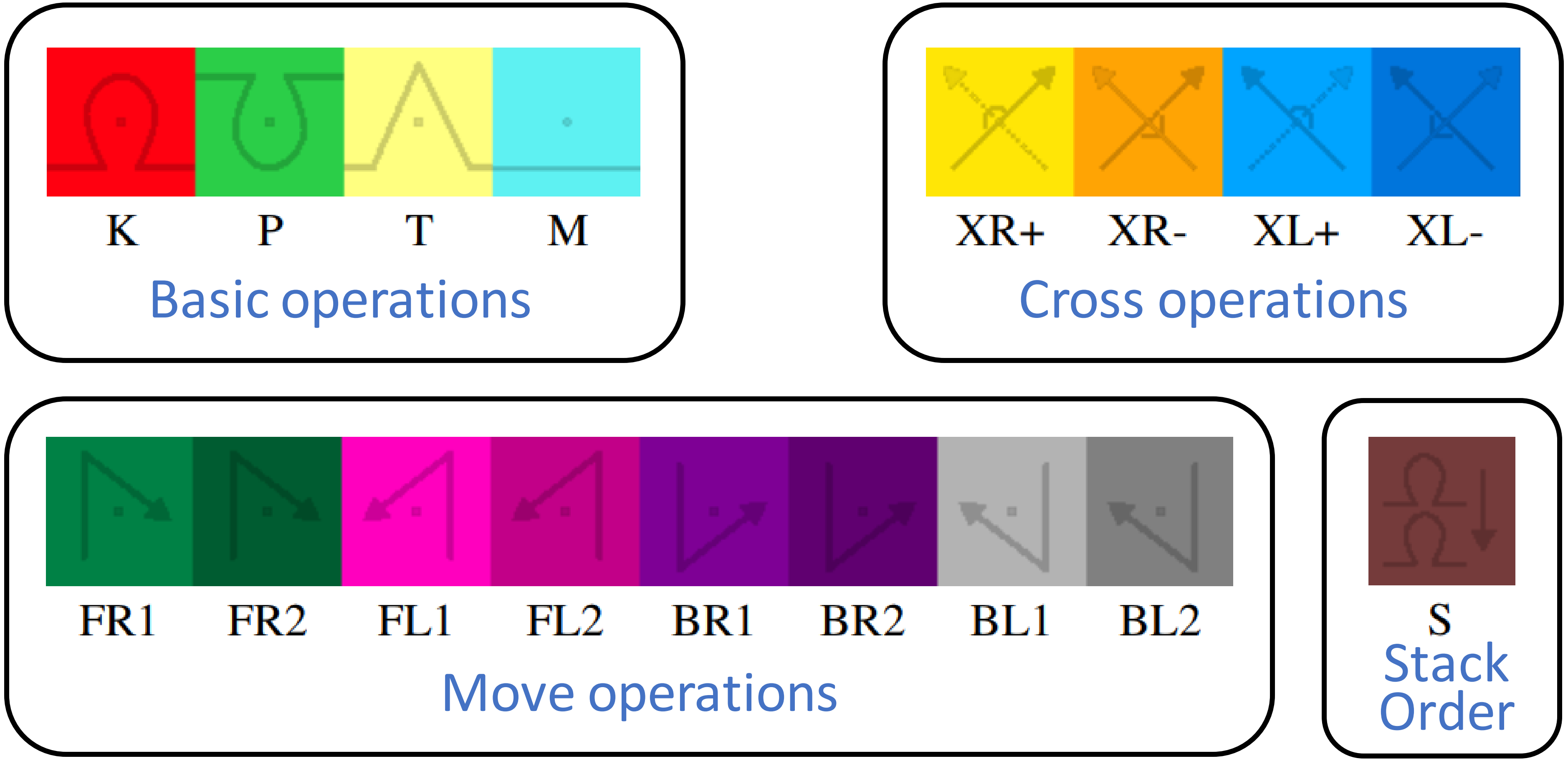
Scenario

1. User takes picture of knitting pattern
2. System creates knitting instructions
3. User reuses pattern for new garment



Dataset: DSL

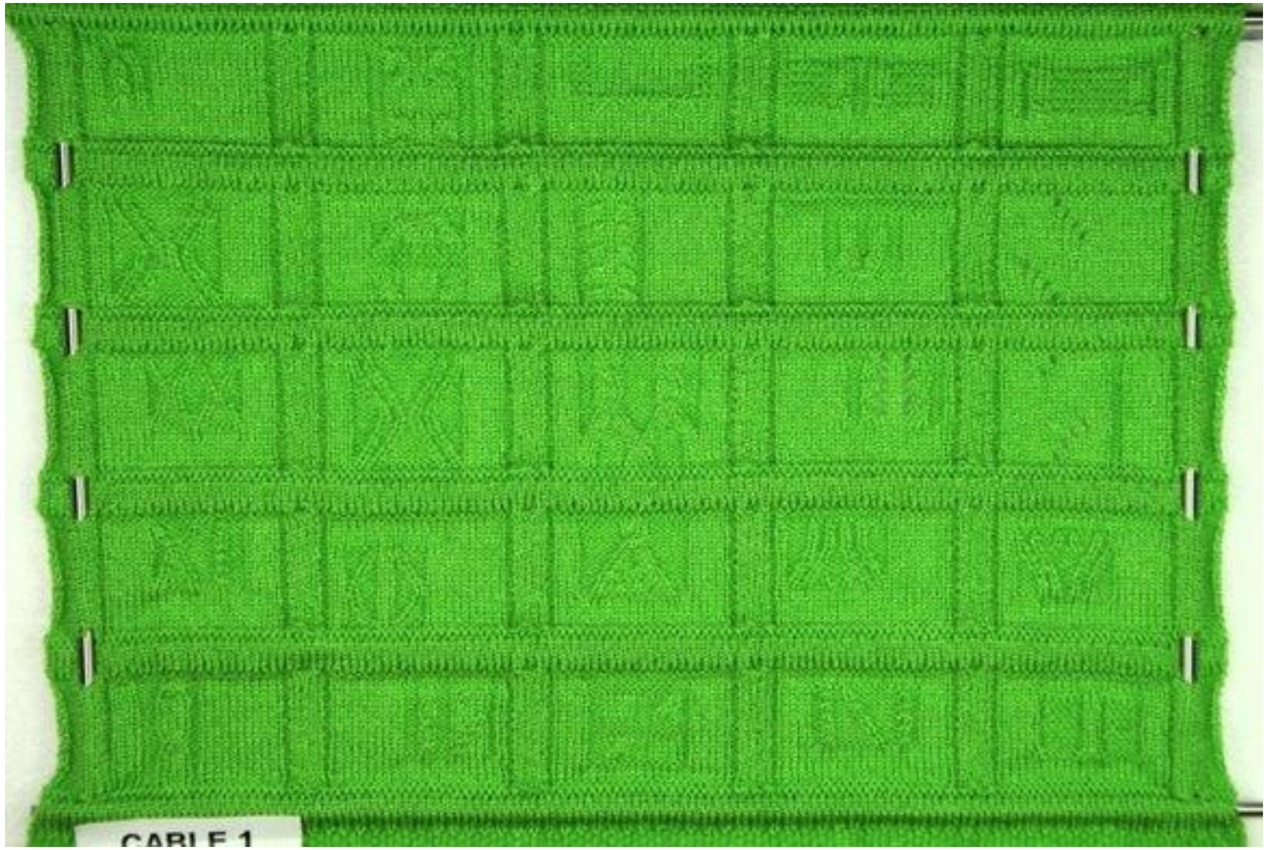
Domain Specific Language (DSL) for regular knitting patterns



Pacific Ballroom #137, http://deepknitting.csail.mit.edu

Dataset: Capture

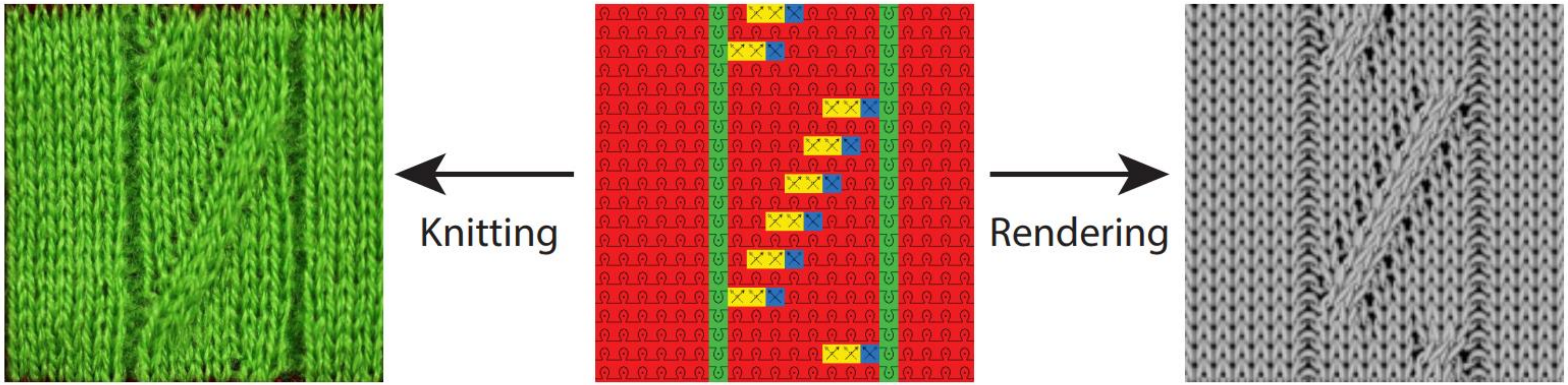
Capture setup with steel rods to normalize tension



Pacific Ballroom #137, http://deepknitting.csail.mit.edu

Dataset Content

- Paired instructions with real (2,088) and synthetic (14,440) images.
- Available on project page.



Learning Problem

Mapping **images** to discrete **instruction maps**

= CE loss minimization

Using two domains of input data (one real, one synthetic)

= How to best combine both

Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2}\underbrace{|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)|}_{\text{Generalization gap}} \leq \alpha\left(\mathrm{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) + \lambda\right) + \epsilon$$

Ideal min.

Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2}\left|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)\right| \leq \alpha\left(\mathrm{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) + \lambda\right) + \epsilon$$

Generalization gap

Ideal min.

Empirical min. $\arg\min_h \alpha \mathcal{L}_{\hat{S}}(h, y) + (1 - \alpha)\mathcal{L}_{\hat{T}}(h, y)$

Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2}|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)| \leq \alpha \left(\text{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) + \lambda\right) + \epsilon$$

Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2}|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)|$$

$$\leq \alpha\left(\mathrm{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) + \lambda\right) + \epsilon$$

$$\epsilon(m, \alpha, \beta, \delta) = \sqrt{\frac{1}{2m}\left(\frac{\alpha^2}{\beta} + \frac{(1-\alpha)^2}{1-\beta}\right)\log(\frac{2}{\delta})},$$

Parameter dependent term

Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2}|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)| \leq \alpha\left(\text{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) + \lambda\right) + \epsilon$$

$$\lambda = \min_{h \in \mathcal{H}} \mathcal{L}_S(h, y) + \mathcal{L}_T(h, y).$$

Ideal error of the combined losses

Generalization Bound with Two Domains

With probability at least $1 - \delta$

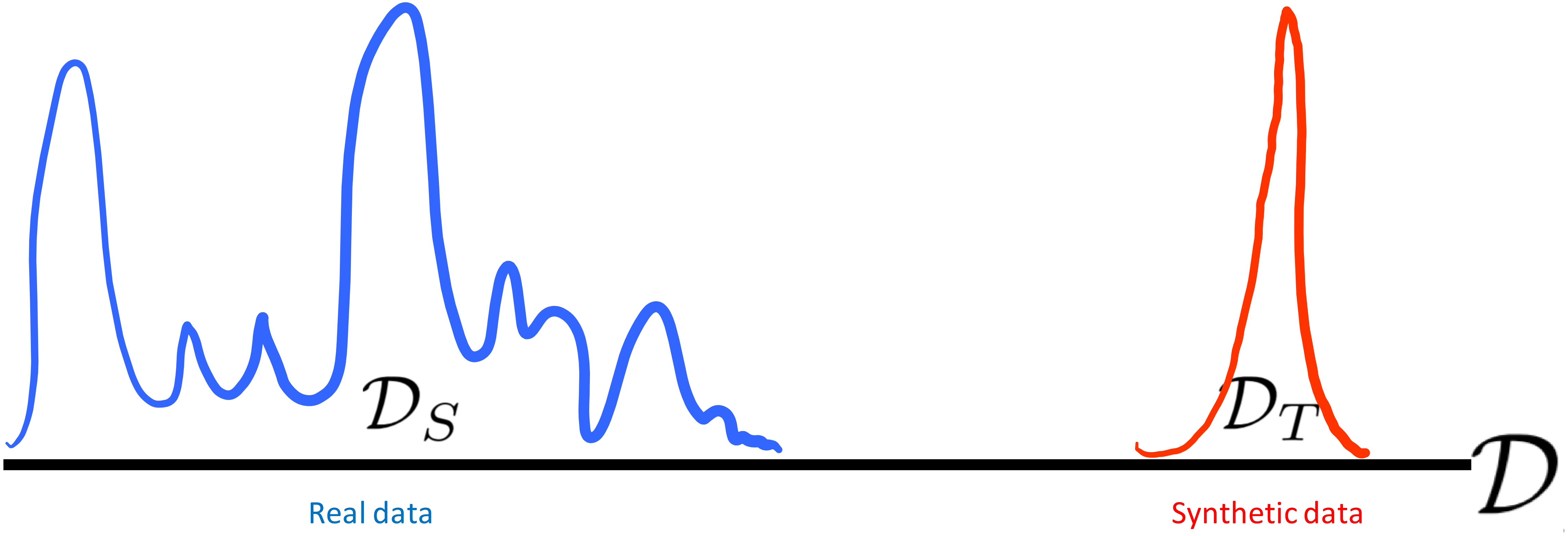
$$\frac{1}{2}|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)|$$
$$\leq \alpha\left(\mathrm{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) + \lambda\right) + \epsilon$$

Discrepancy between distributions

$$\mathrm{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T) = \max_{h, h' \in \mathcal{H}} |\mathcal{L}_{\mathcal{D}_S}(h, h') - \mathcal{L}_{\mathcal{D}_T}(h, h')|$$

Data distributions

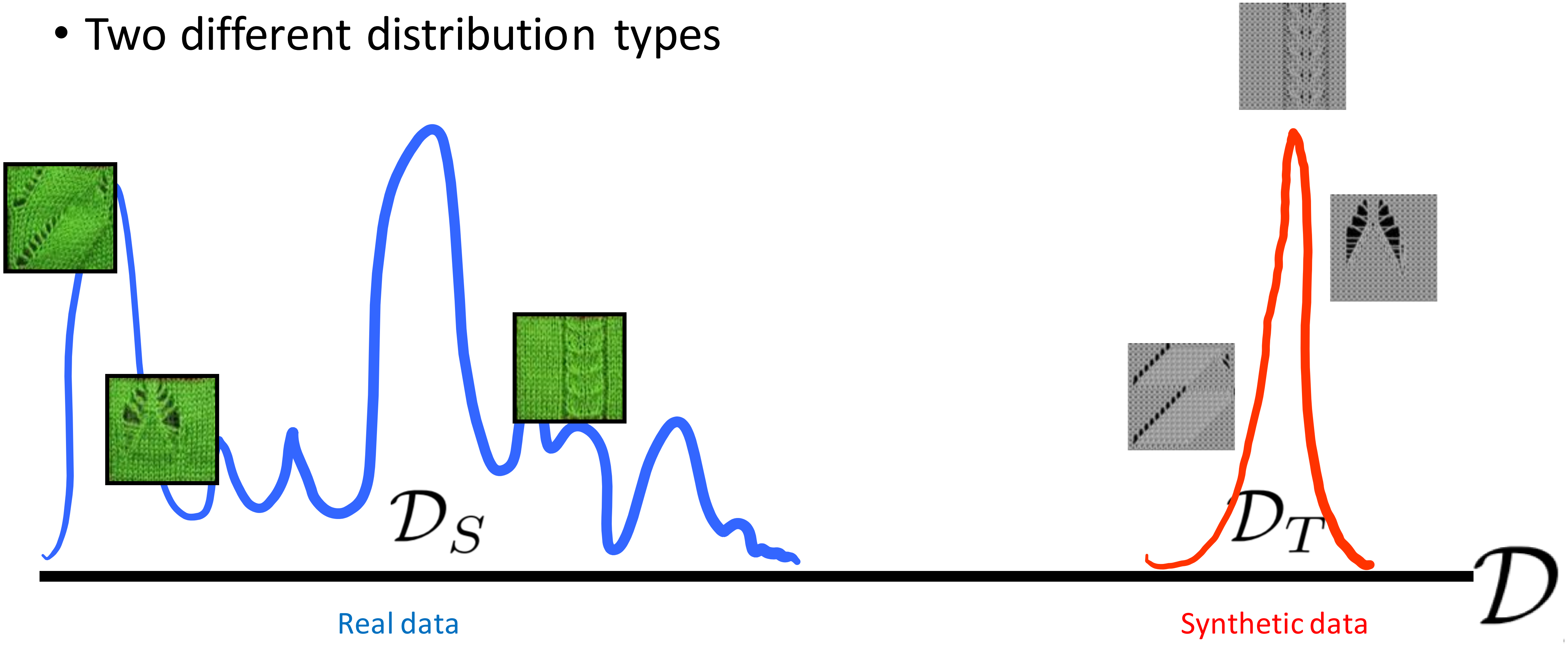
- Two different distribution types



Pacific Ballroom #137, http://deepknitting.csail.mit.edu

Data distributions

- Two different distribution types

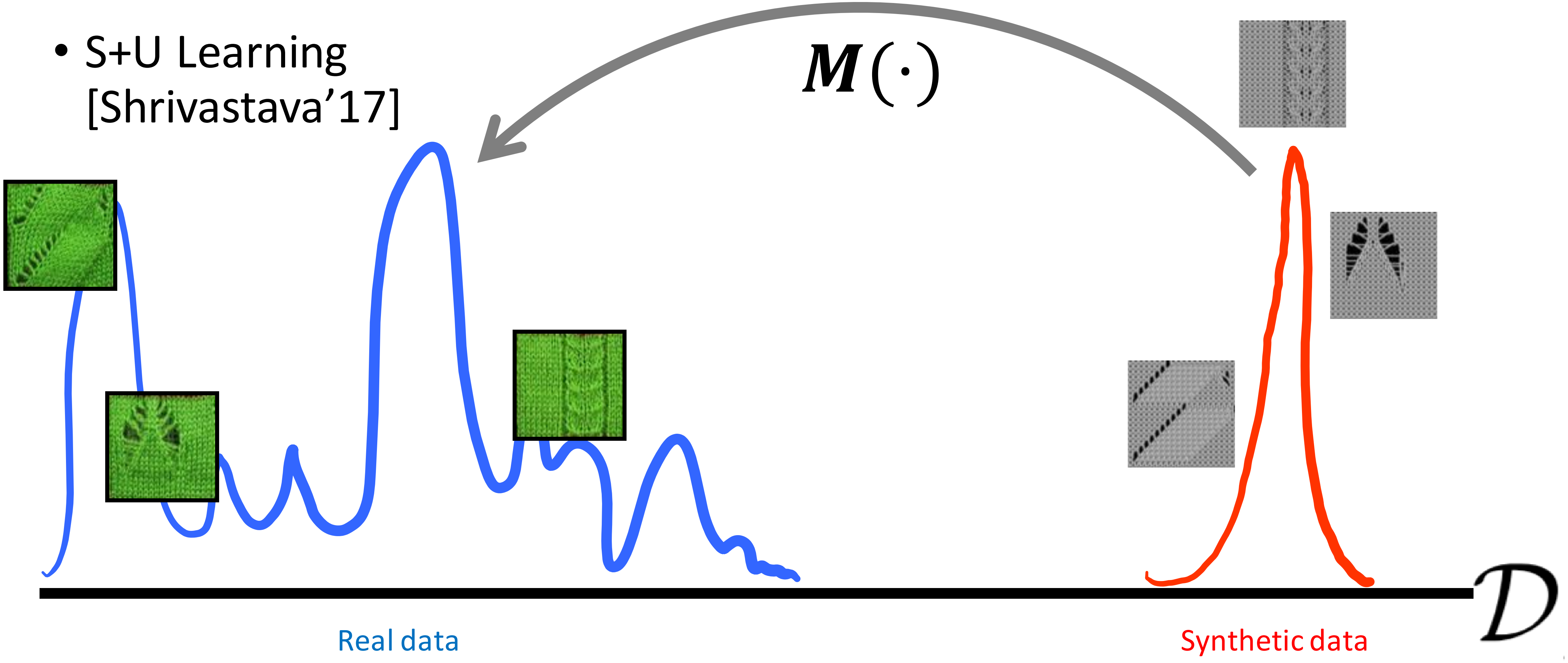


Pacific Ballroom #137, http://deepknitting.csail.mit.edu

From synthetic to real

$$\min_{M} \operatorname{disc}(\mathcal{D}_S, \underset{S \Leftarrow T}{M(\mathcal{D}_T)})$$

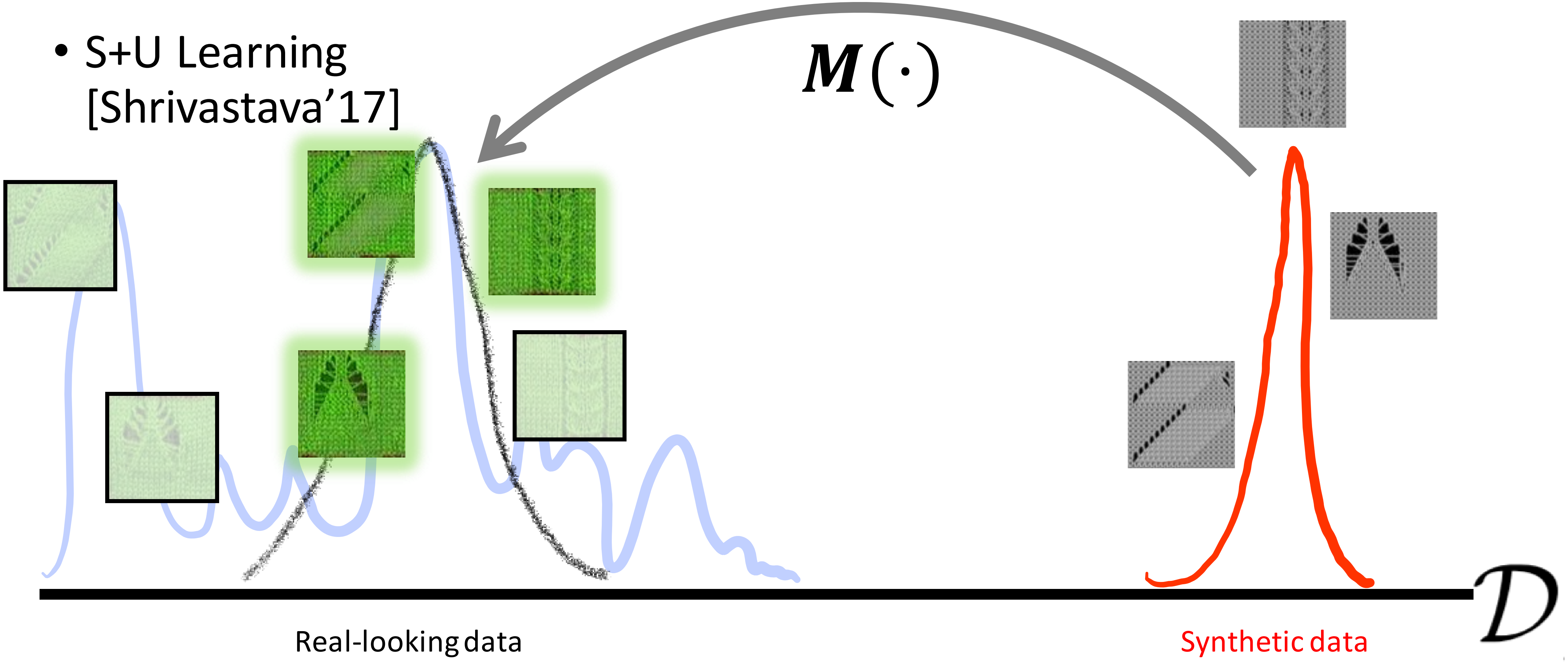
- S+U Learning [Shrivastava'17]



From synthetic to real

$$\min_{M} \operatorname{disc}(\mathcal{D}_S, \underbrace{M(\mathcal{D}_T)}_{S \Leftarrow T})$$

- S+U Learning [Shrivastava'17]

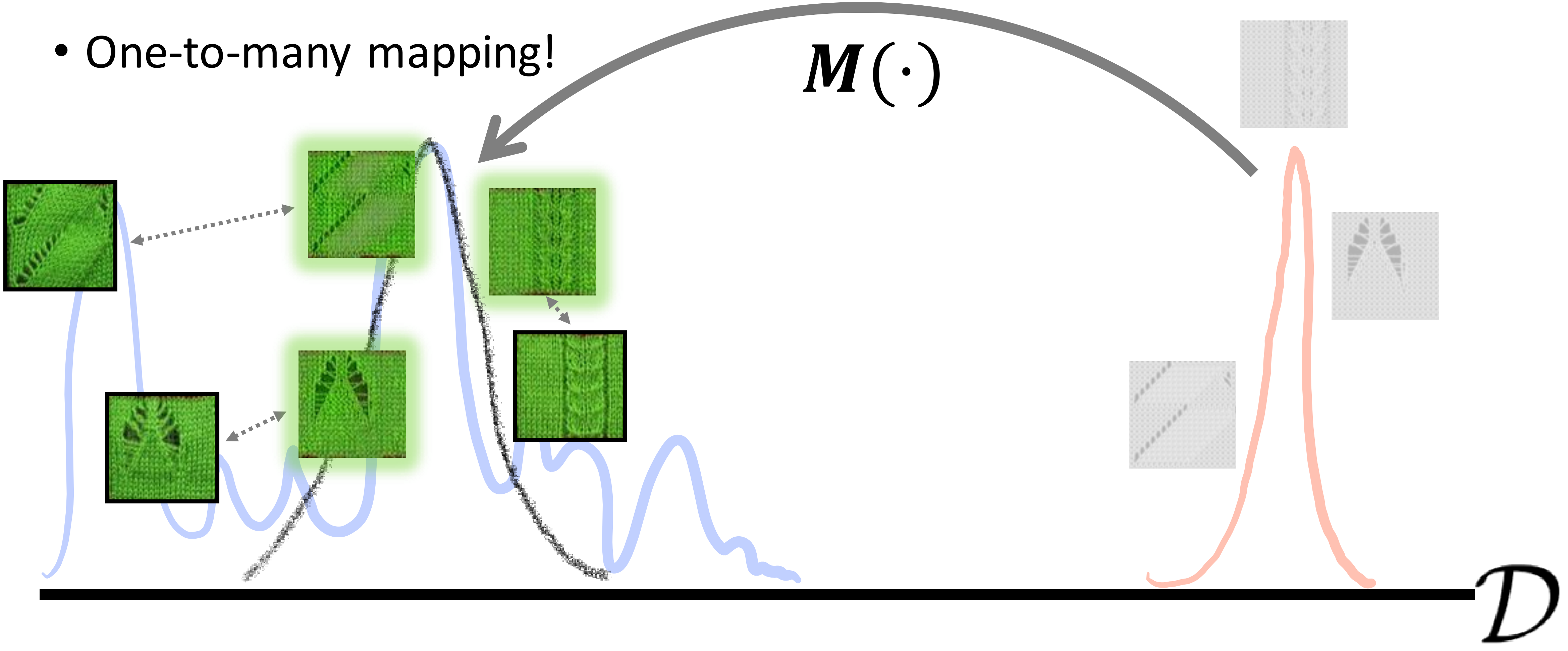


Pacific Ballroom #137, http://deepknitting.csail.mit.edu

From synthetic to real

$$\min_{M} \operatorname{disc}(\mathcal{D}_S, \underset{S \Leftarrow T}{M(\mathcal{D}_T)})$$

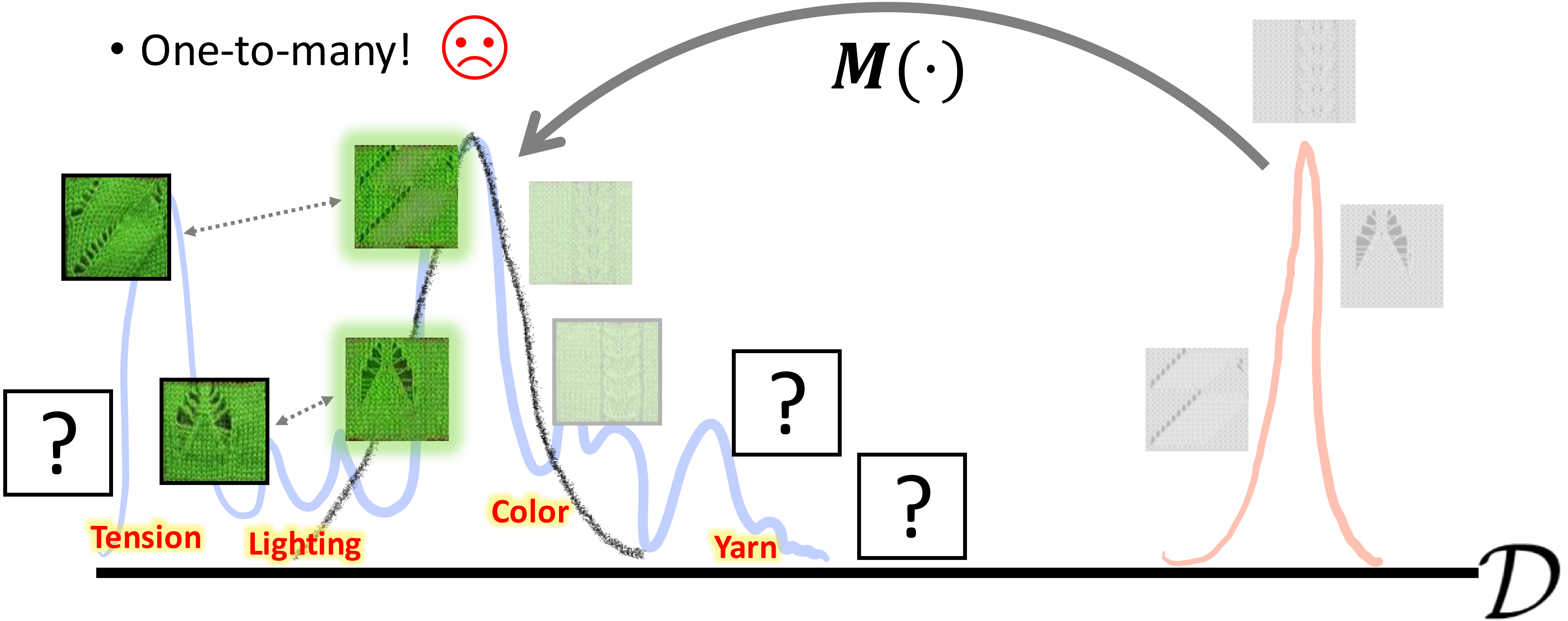
- One-to-many mapping!



From synthetic to real

$$\min_{M} \operatorname{disc}(\mathcal{D}_S, M(\mathcal{D}_T))_{S \Leftarrow T}$$

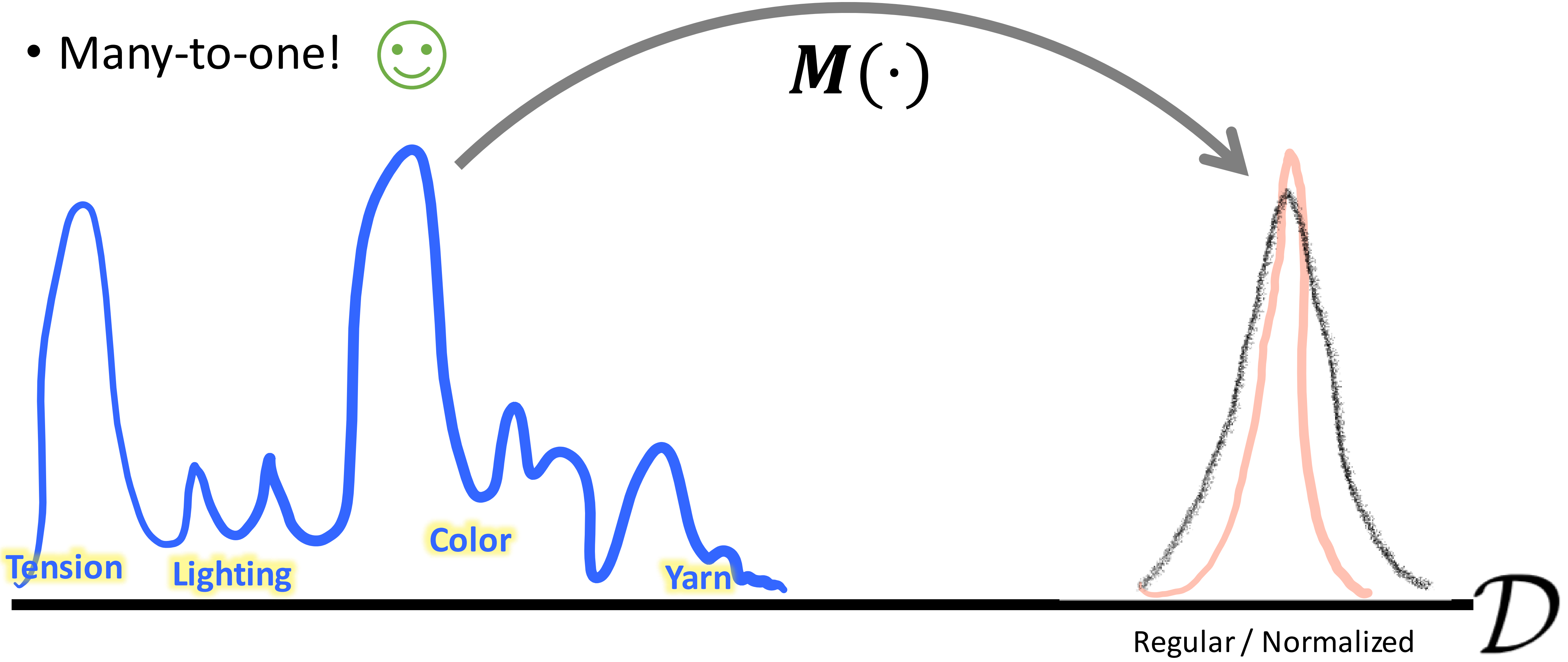
- One-to-many! ☹



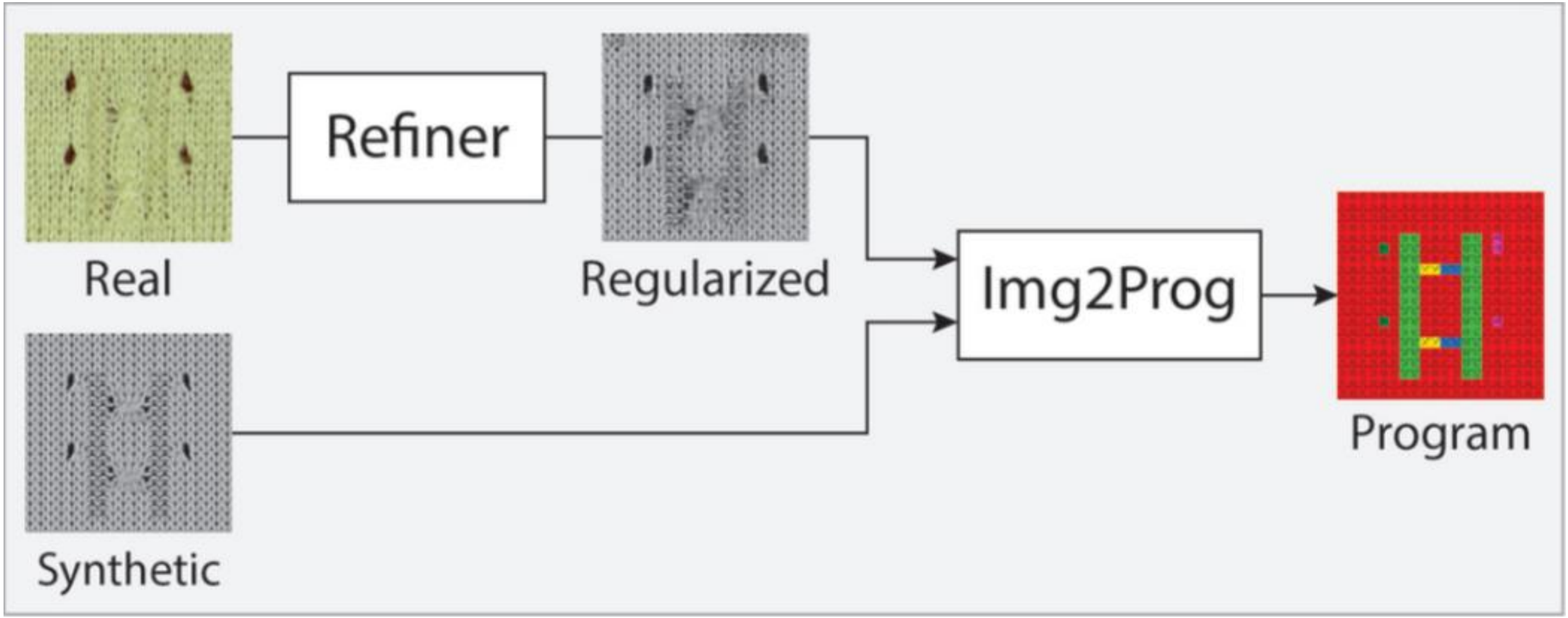
From real to synthetic

$$\min_{M} \operatorname{disc}_{S \Rightarrow T}(M(\mathcal{D}_S), \mathcal{D}_T)$$

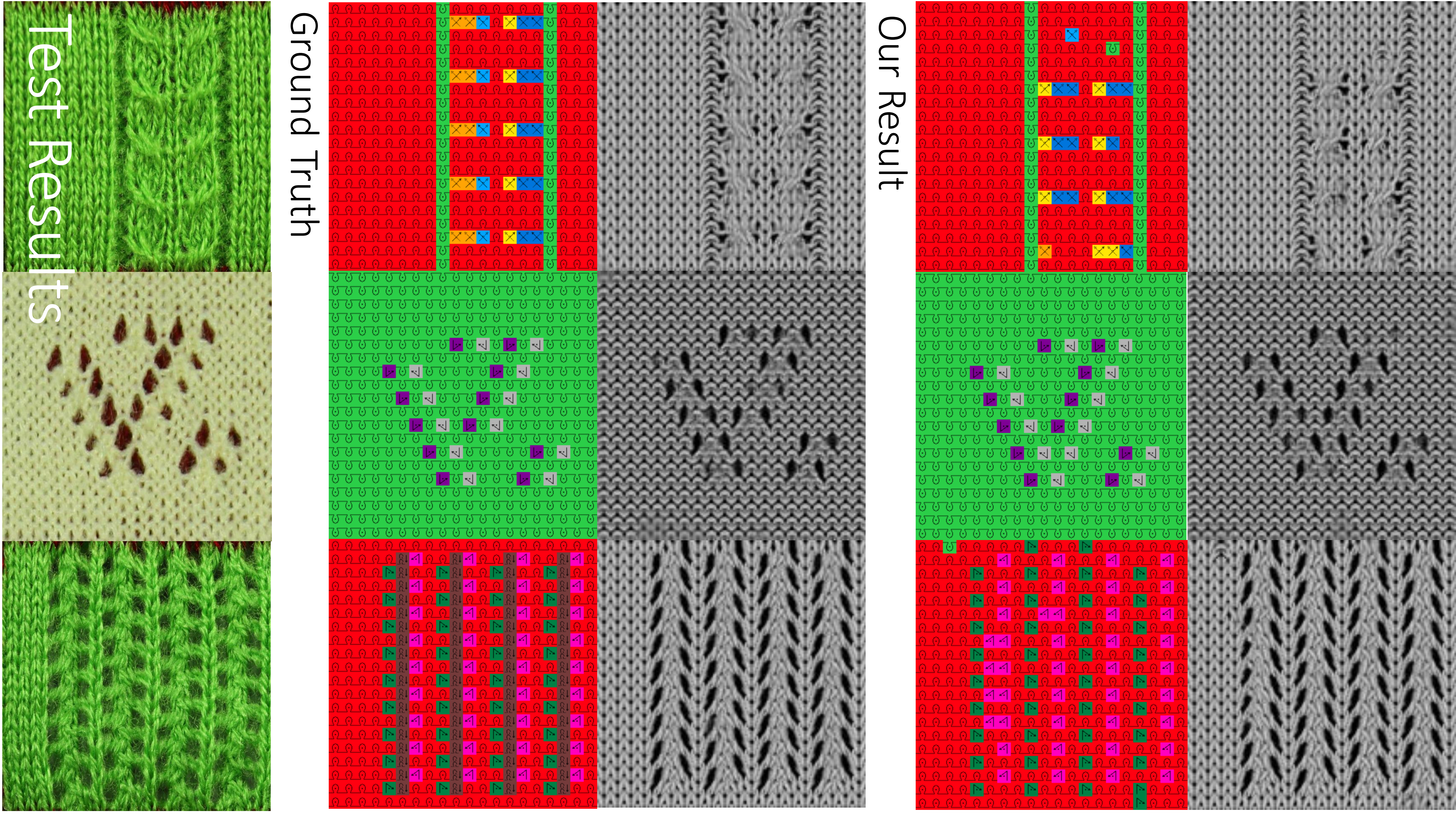
- Many-to-one! ☺



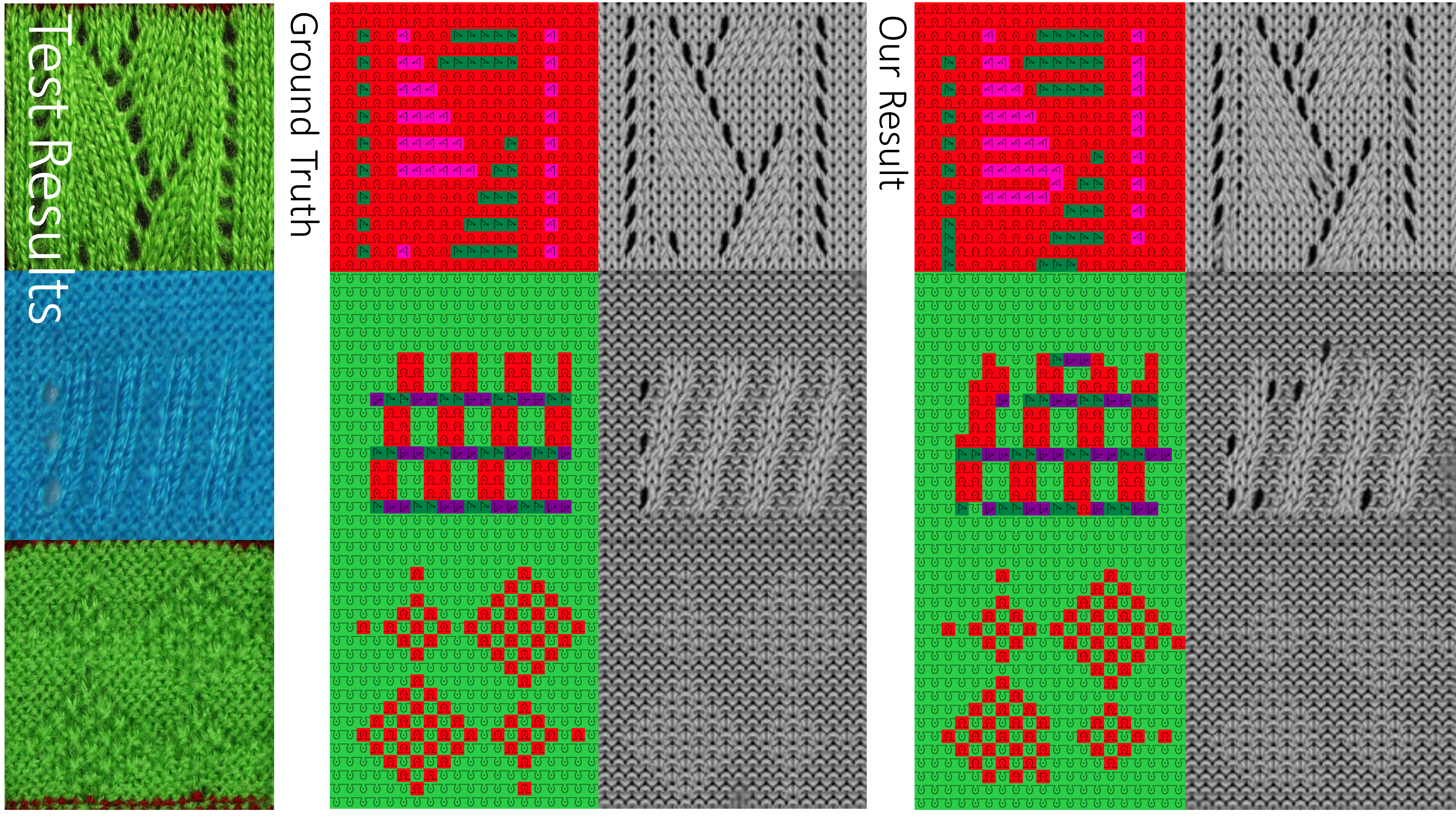
Network composition



Pacific Ballroom #137, http://deepknitting.csail.mit.edu



Test Results
Ground Truth
Our Result


Test Results
Ground Truth
Our Result

Pacific Ballroom #137

http://deepknitting.csail.mit.edu

Pacific Ballroom #137

http://deepknitting.csail.mit.edu