Pacific Ballroom #137

Neural Inverse Knitting: From Images to Manufacturing Instruction

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MIT CSAIL

Industrial Knitting

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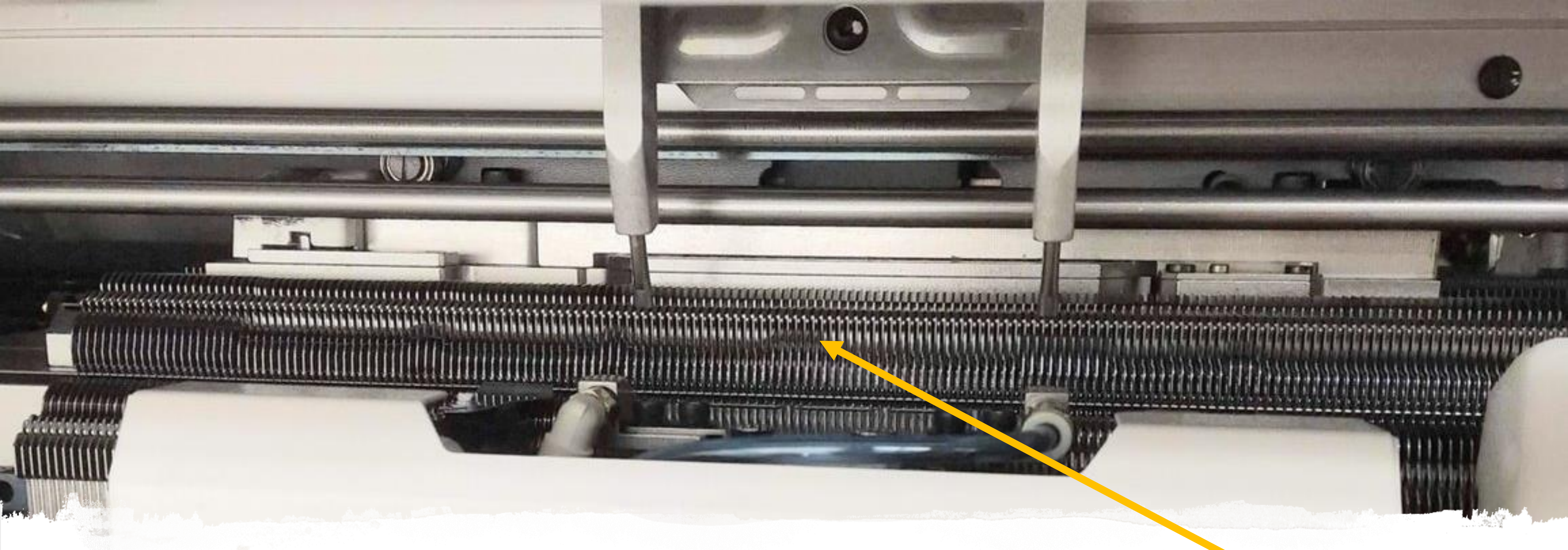
Industrial Knitting

- Whole garments from scratch



Industrial Knitting

- Control of individual needles
- Whole garments from scratch

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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).

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Knitted Garment & Patterns

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

These can be fully controlled by industrial knitting machine.

= User customization!

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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

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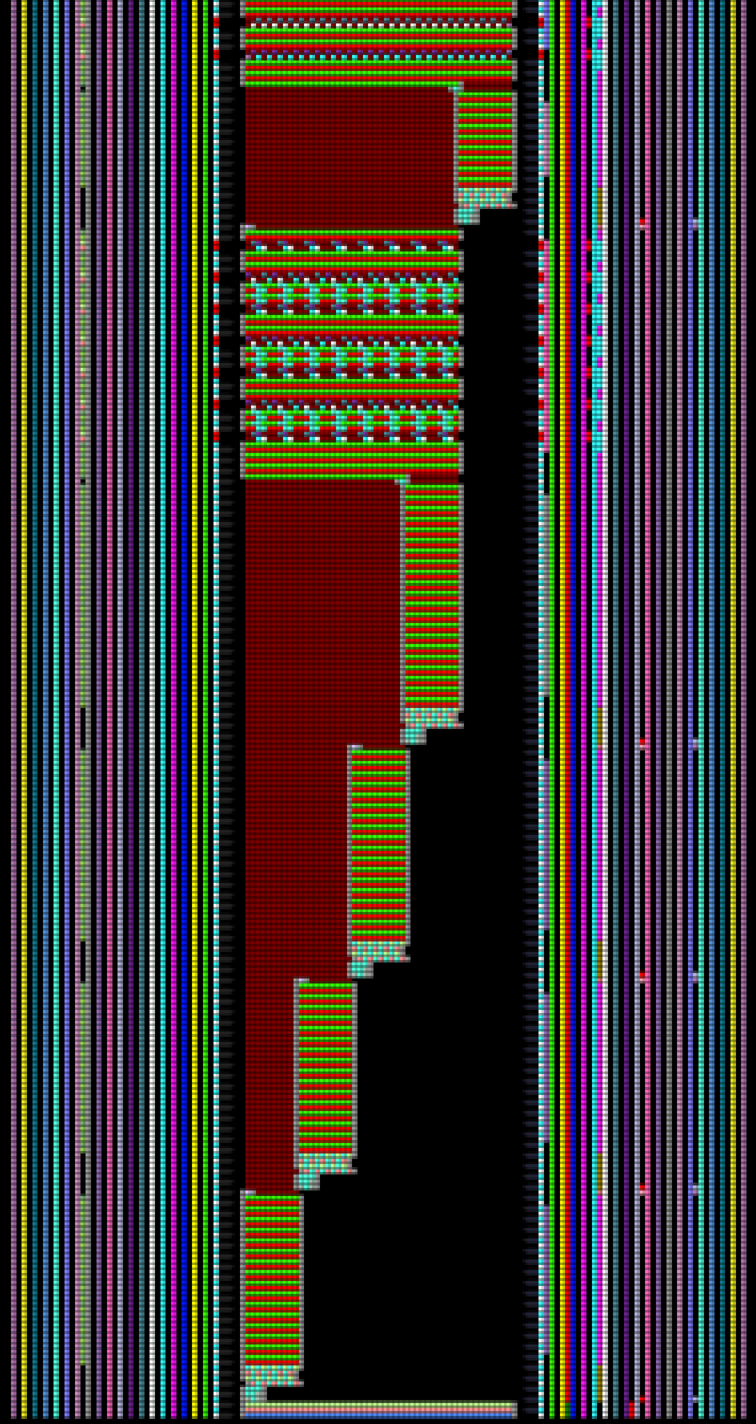
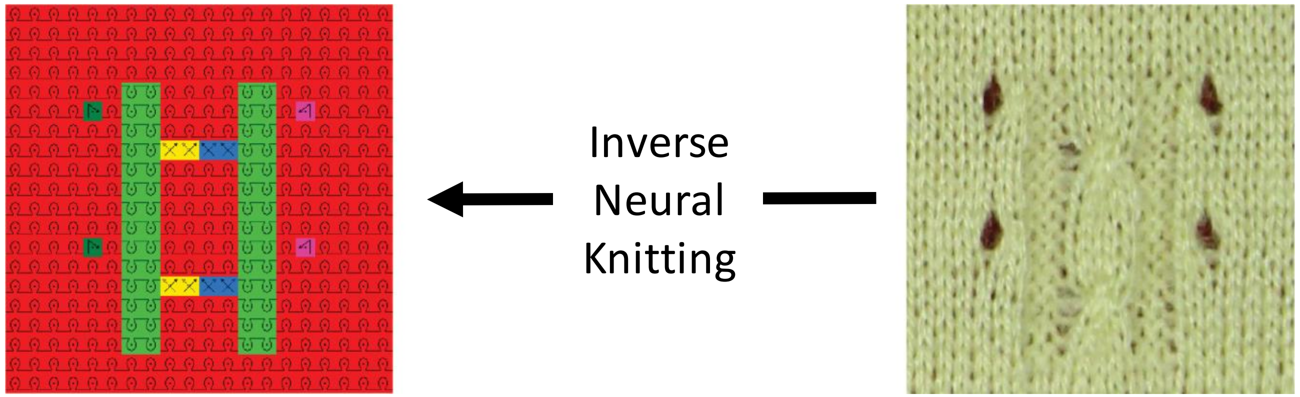


Scenario

1. User takes picture of knitting pattern

Scenario

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



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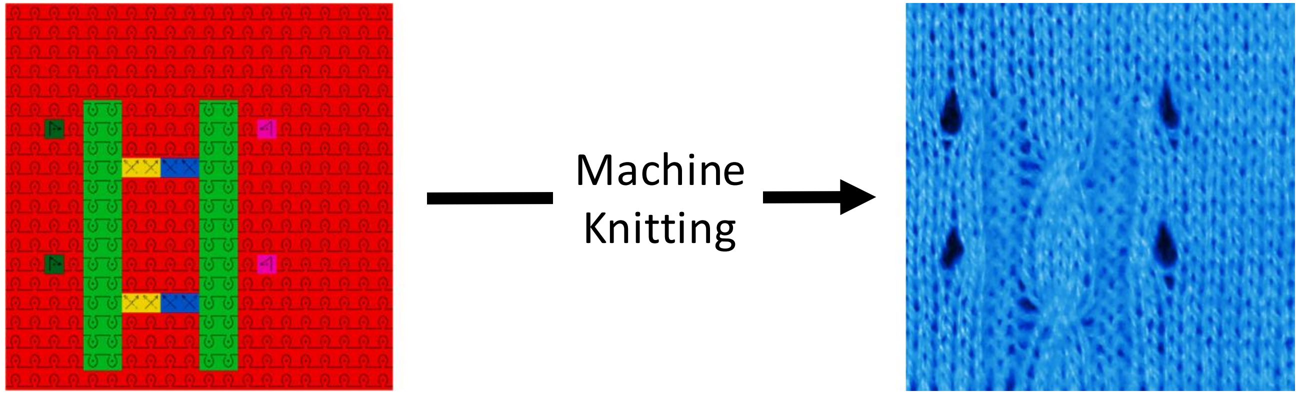
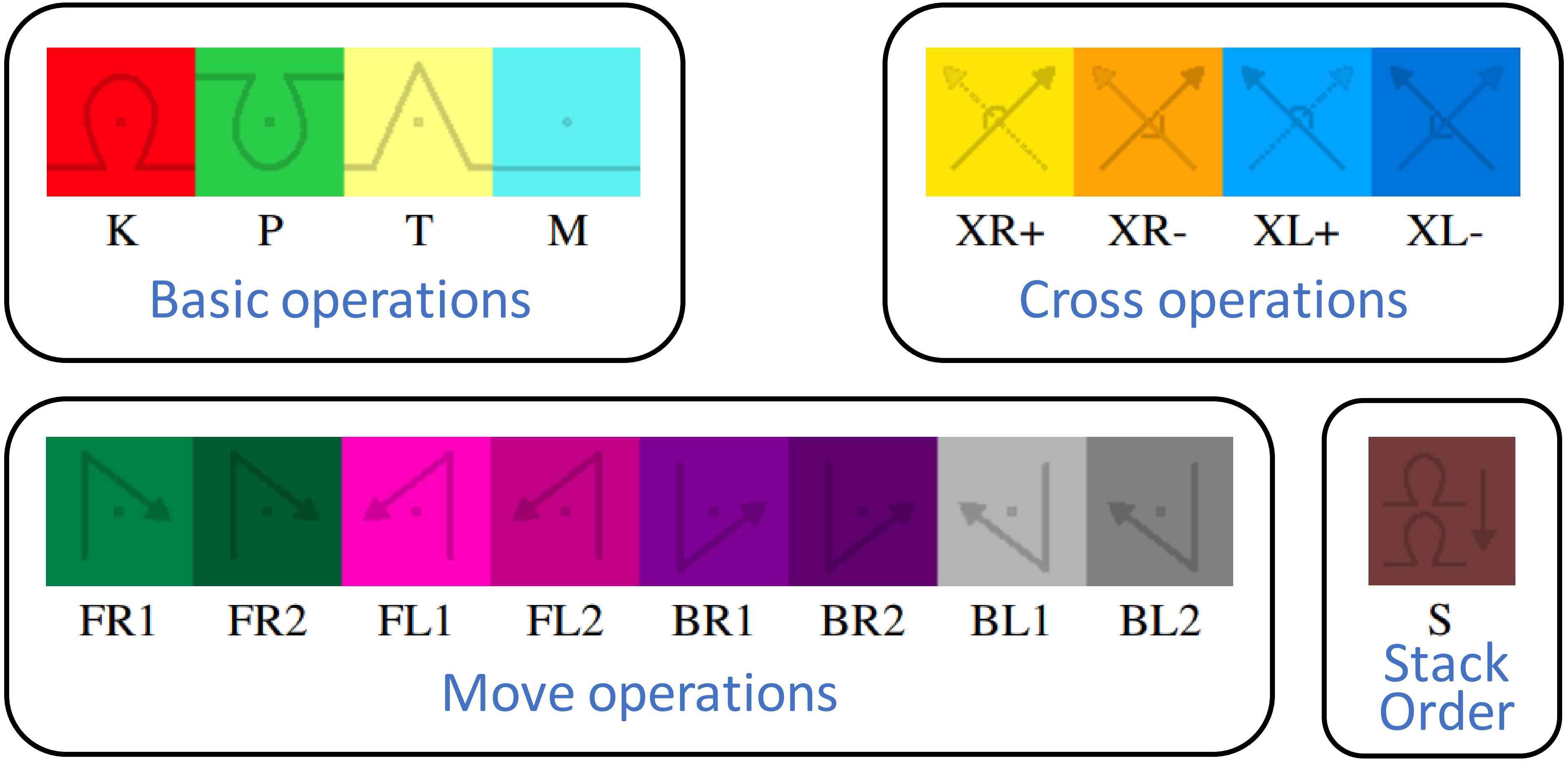
Scenario

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



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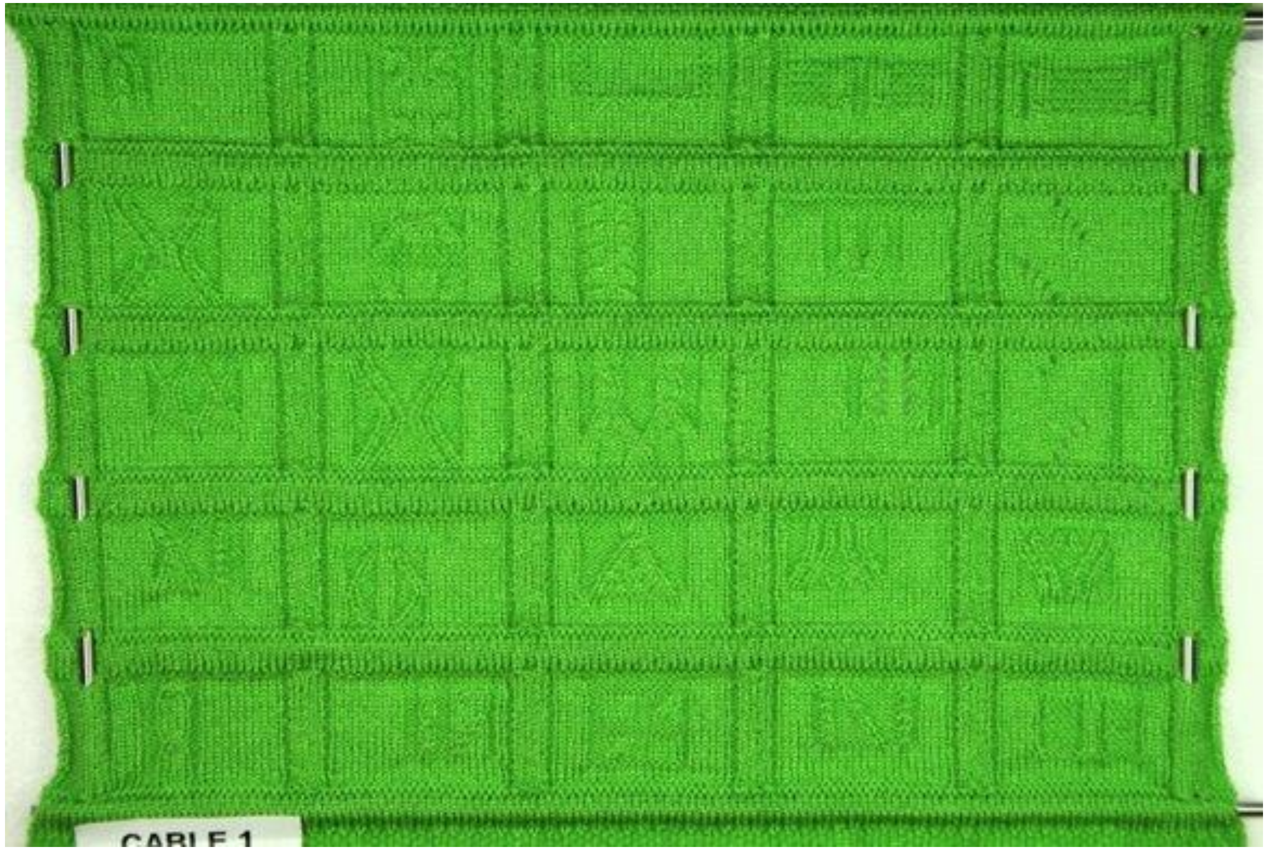
Dataset: Capture

Capture setup with steel rods to normalize tension



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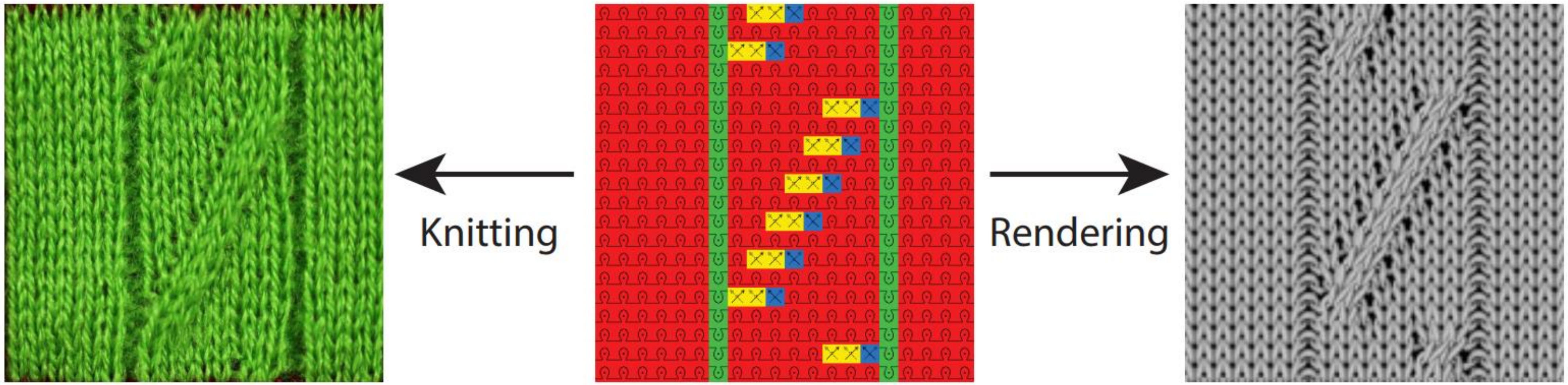
Dataset Content

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



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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 $1-\delta$

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

Ideal min.

Generalization Bound with Two Domains

With probability at least $1-\delta$

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

Ideal min.

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 $1-\delta$

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

Generalization Bound with Two Domains

With probability at least $1 - \delta$

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

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

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

Parameter dependent term

Generalization Bound with Two Domains

With probability at least $1 - \delta$

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

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

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

Ideal error of the combined losses

Generalization Bound with Two Domains

With probability at least $1-\delta$

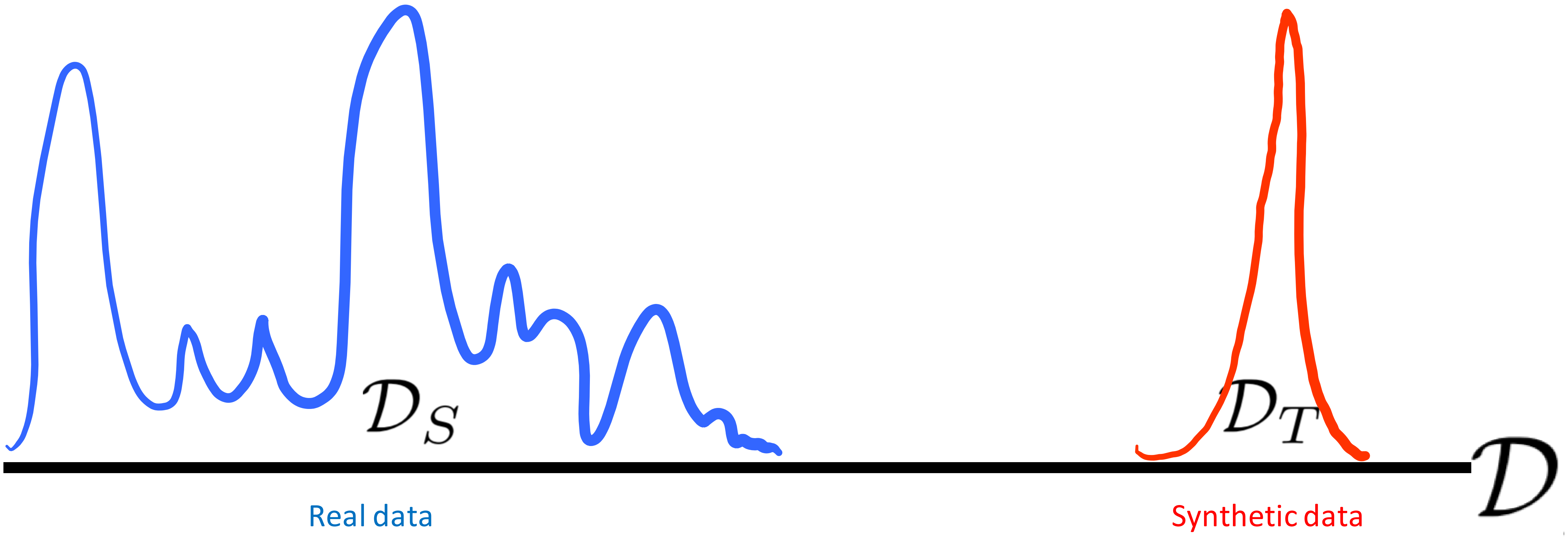
$$\frac{1}{2}\left|\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y)\right| \leq \alpha\left(\boxed{\mathrm{disc}_{\mathcal{H}}(\mathcal{D}_S, \mathcal{D}_T)} + \lambda\right) + \epsilon$$

Discrepancy between distributions

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

Data distributions

- Two different distribution types



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Data distributions

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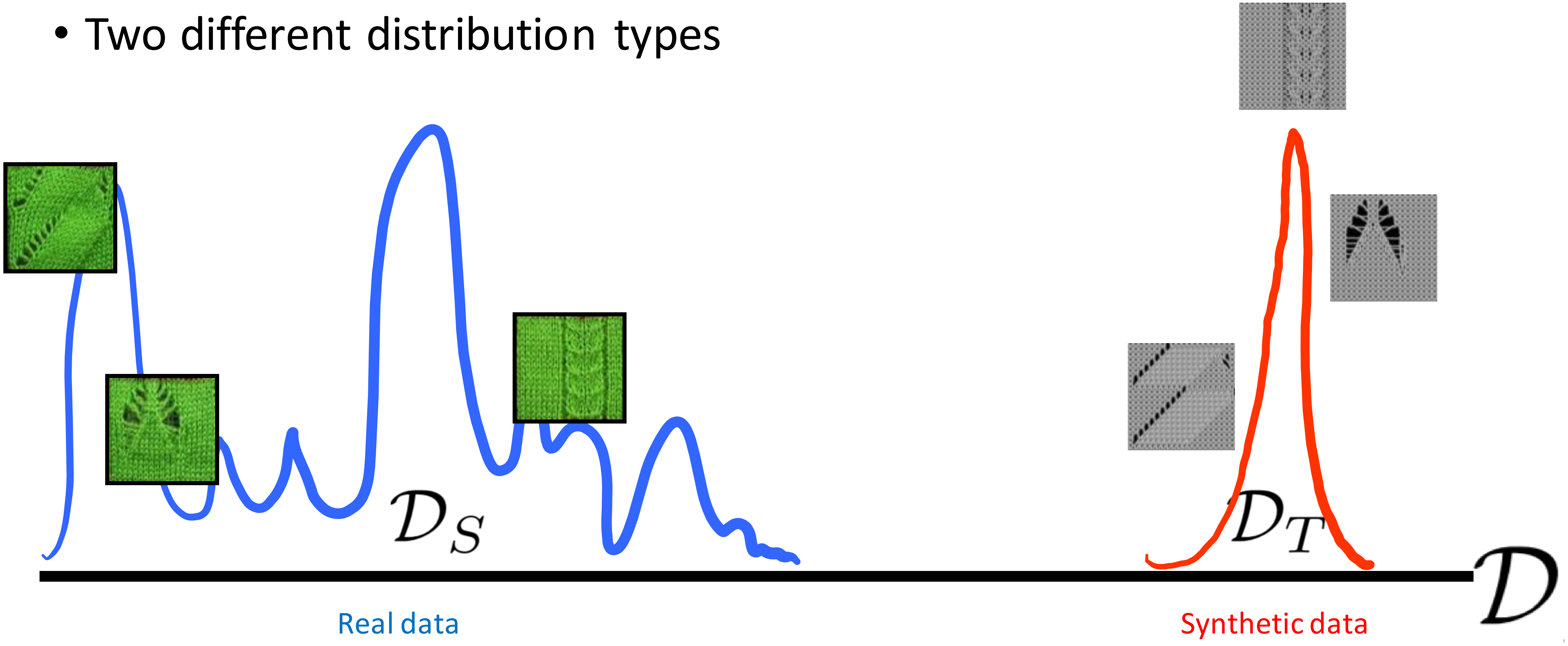

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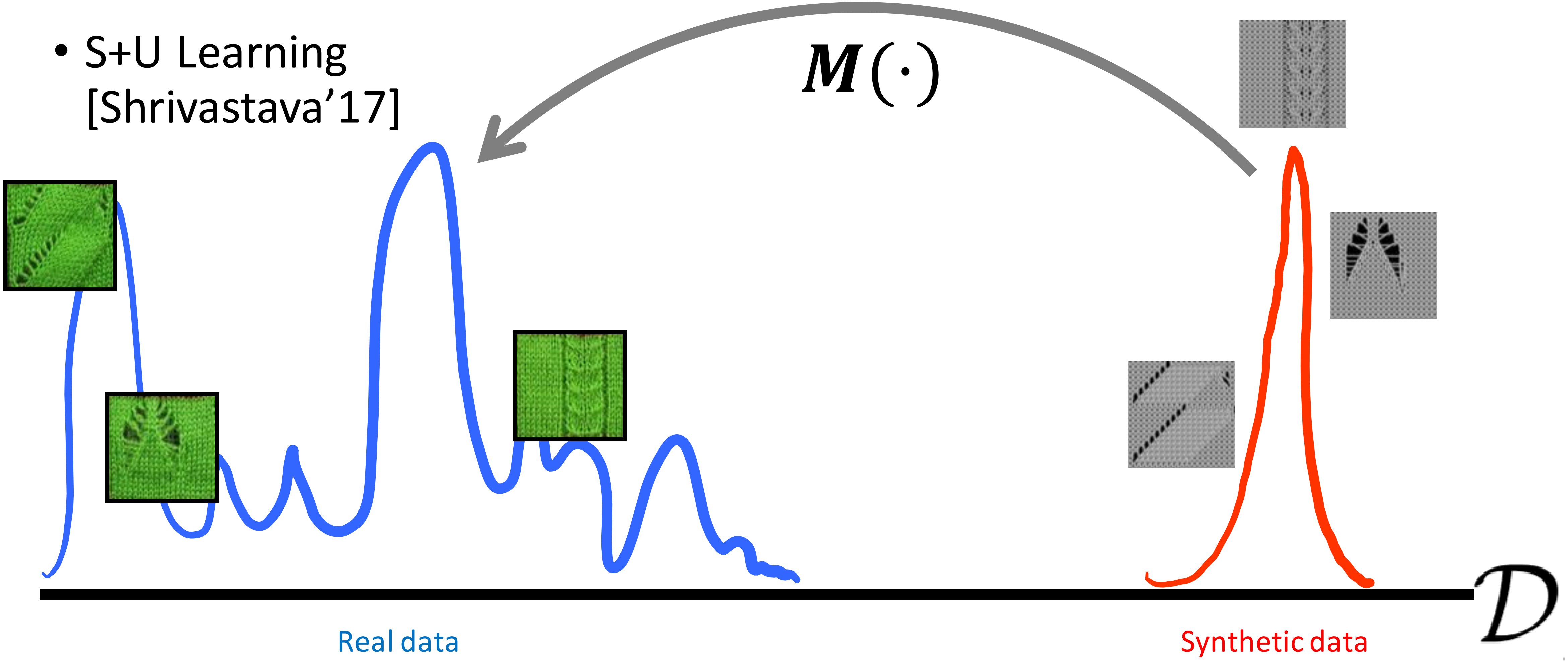
From synthetic to real

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

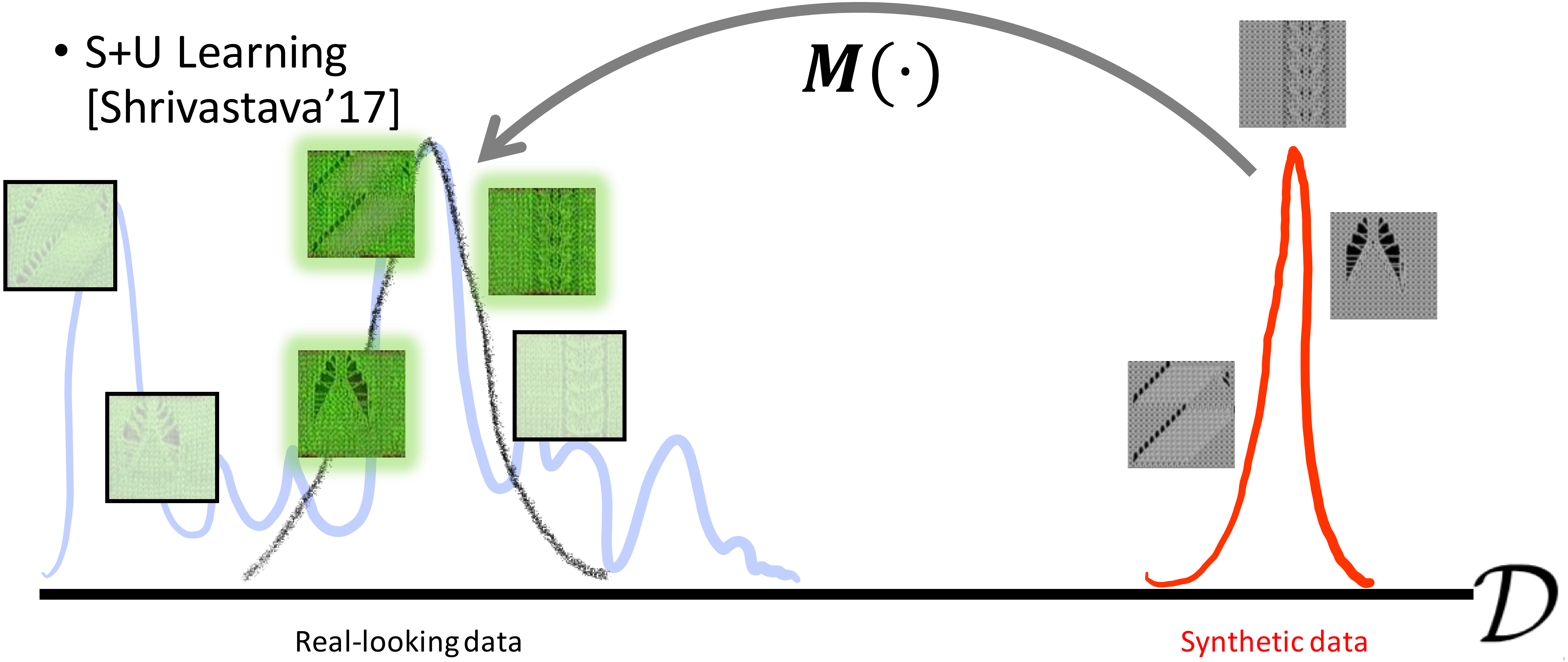
- S+U Learning [Shrivastava'17]



From synthetic to real

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

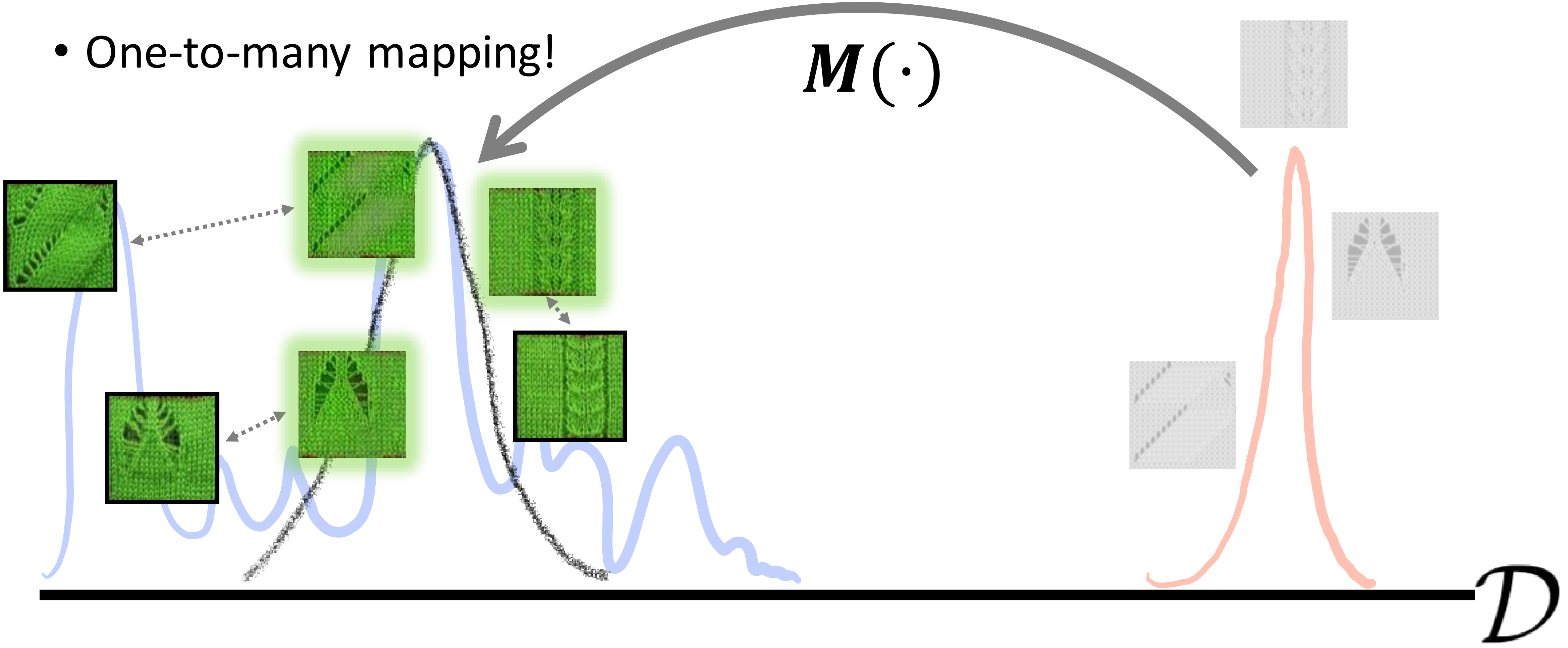
- S+U Learning [Shrivastava'17]



From synthetic to real

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

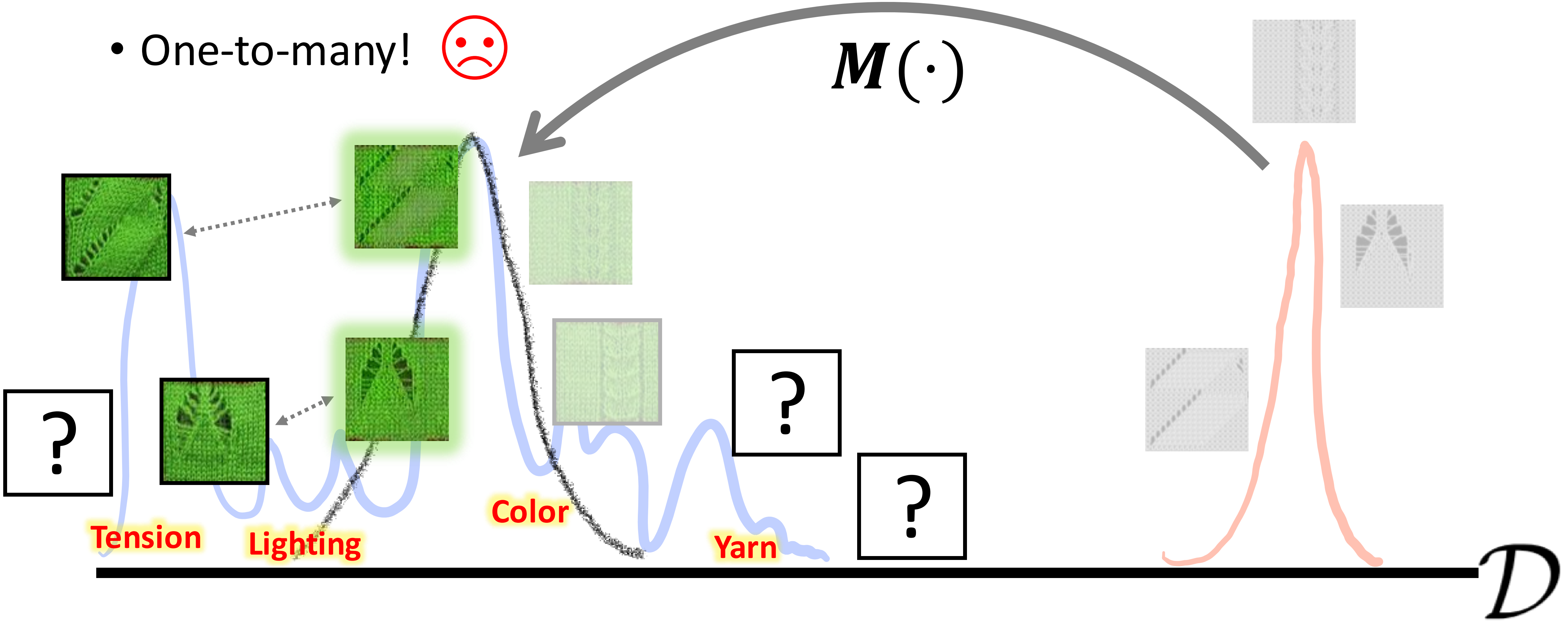
- One-to-many mapping!



From synthetic to real

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

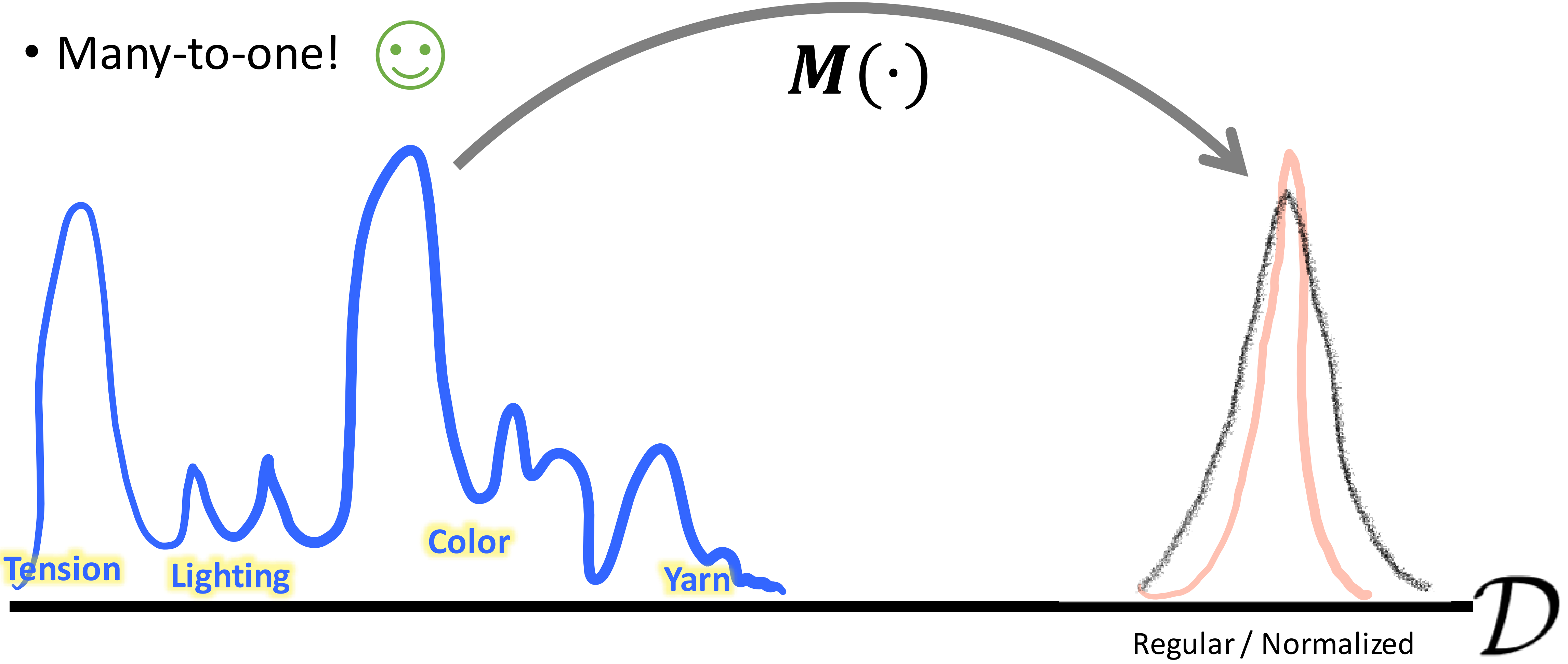
- One-to-many! ☹



From real to synthetic

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

- Many-to-one! ☺



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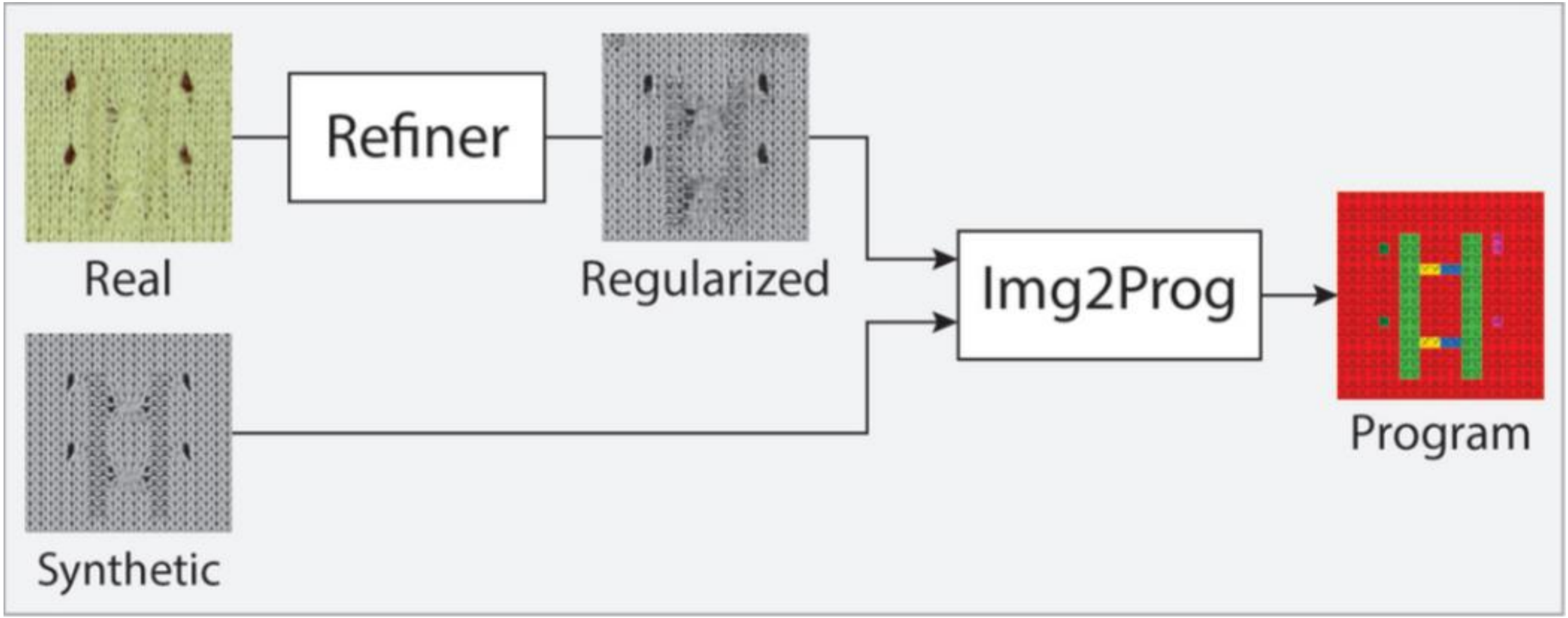
Network composition



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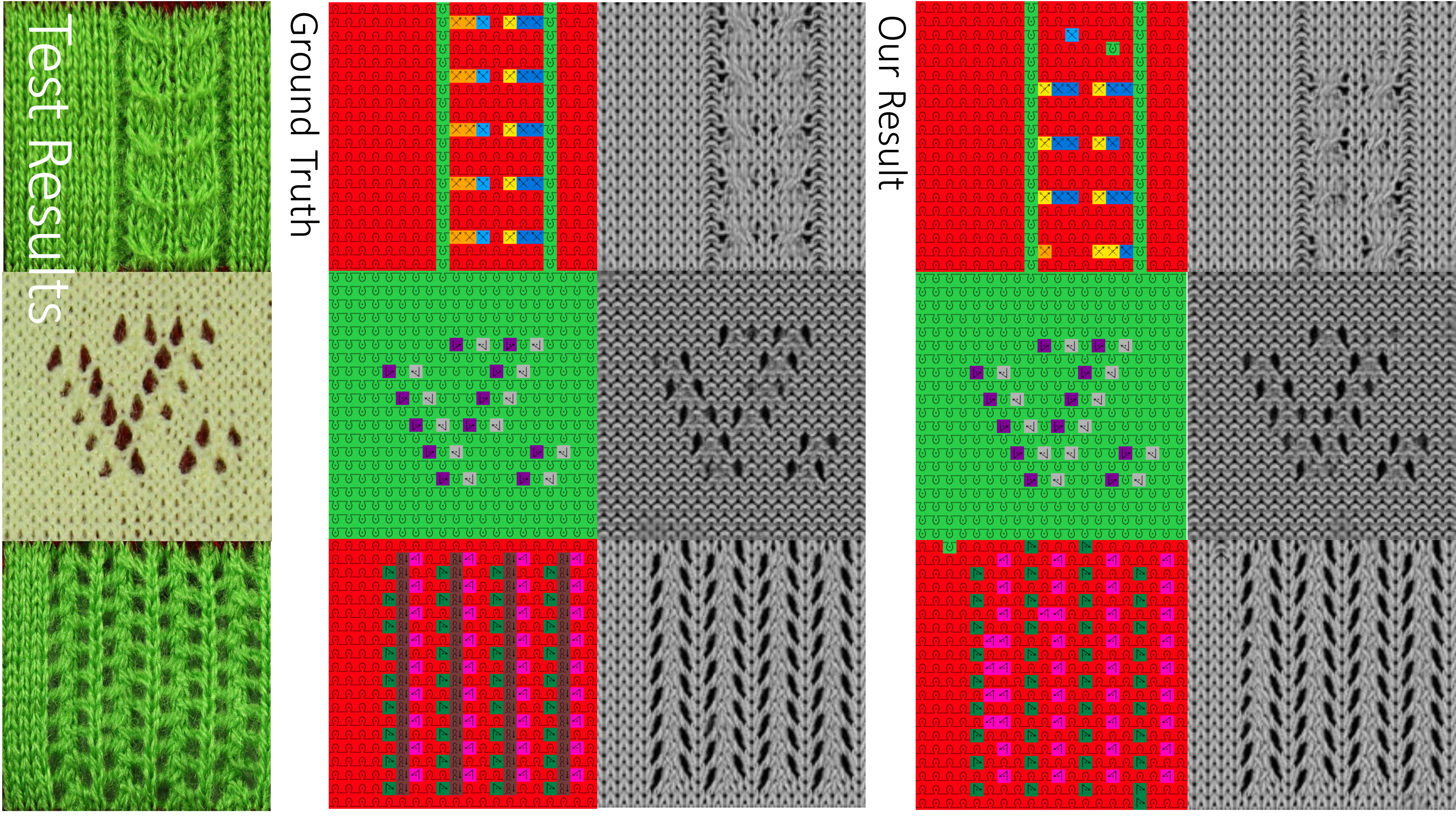
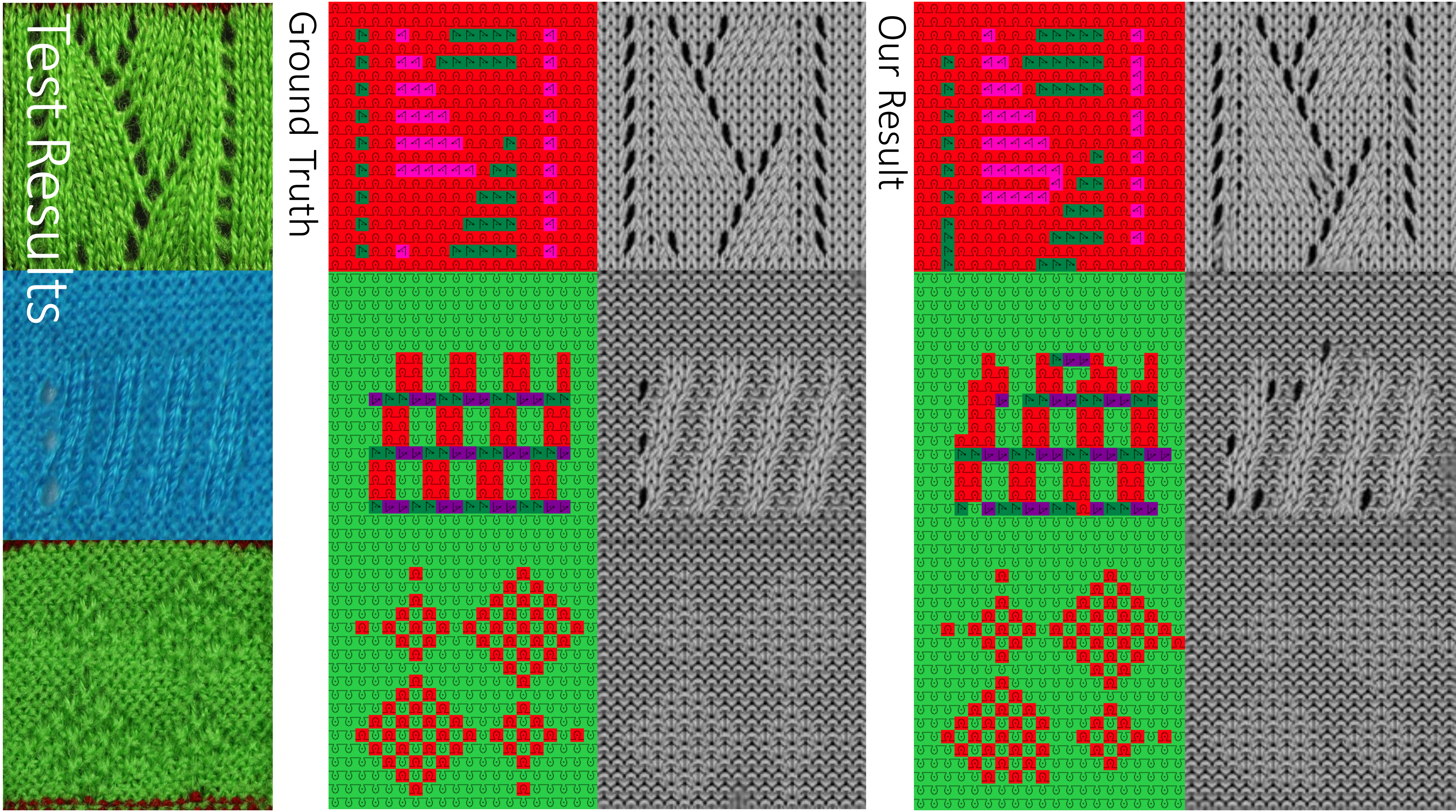


Test Results
Ground Truth
Our Result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