Neural Inverse Knitting: From Images to Manufacturing Instruction

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Industrial Knitting

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

• Whole garments from scratch

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Industrial Knitting

- Control of individual needles
- Whole garments from scratch
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

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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

Basic operations

Cross operations

Move operations

Stack Order

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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.
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

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Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} | \mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h_T^*, y) | \leq \alpha (\text{disc}_H(D_S, D_T) + \lambda) + \epsilon$$

Ideal min.
Generalization Bound with Two Domains

With probability at least $1 - \delta$

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

Generalization gap

$$\leq \alpha (\text{disc}_H(D_S, D_T) + \lambda) + \epsilon$$

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 $1 - \delta$

\[
\frac{1}{2} | \mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y) | \leq \alpha (\text{disc}_\mathcal{H}(\mathcal{D}_S, \mathcal{D}_T) + \lambda) + \epsilon
\]
Generalization Bound with Two Domains

With probability at least $1 - \delta$

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

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

Parameter dependent term
Generalization Bound with Two Domains

With probability at least $1 - \delta$

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

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

Ideal error of the combined losses
Generalization Bound with Two Domains

With probability at least $1 - \delta$

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

Discrepancy between distributions

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

- Two different distribution types

$D_S$  
Real data

$D_T$  
Synthetic data
Data distributions

- Two different distribution types

Real data

Synthetic data
From synthetic to real

• S+U Learning [Shrivastava’17]

$$\min_M \text{disc}(\mathcal{D}_S, M(\mathcal{D}_T))_{S \leftarrow T}$$

Real data

Synthetic data

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From synthetic to real

- S+U Learning [Shrivastava'17]

\[ \min_M \text{disc}(\mathcal{D}_S, M(\mathcal{D}_T)) \]

Real-looking data

Synthetic data
From synthetic to real

- One-to-many mapping!

\[ \min_{M} \text{disc}(\mathcal{D}_S, M(\mathcal{D}_T)) \]
From synthetic to real

• One-to-many! 😞

\[
\min_{M} \text{disc}(D_S, M(D_T))
\]

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From real to synthetic

• Many-to-one!

\[ \min_{M} \text{disc}(M(\mathcal{D}_S), \mathcal{D}_T) \]

\[ M(\cdot) \]

\[ D \]

Regular / Normalized

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Network composition

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